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ARTIFICIAL INTELLIGENCE IN RECRUITMENT SYSTEMS: EVALUATION METHODOLOGY AND PRACTICAL APPLICATIONS

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Purpose: This study develops an original methodology for evaluating AI-based employee selection systems, grounded in the AIPT maturity model (Assist–Inform–Predict–Transform), and verifies its usefulness through a comparative analysis of two recruitment solutions representing different technological classes.
Design/methodology/approach: The study adopts a conceptual-empirical approach. The theoretical part draws on maturity models in management and HR, including People CMM and HR-AIMM, as well as frameworks of algorithmic HRM. On this basis, the AIPT model was applied to assess four levels of AI maturity in recruitment systems: operational support, information-based decision support, prediction and recommendations, and transformation of HR processes. The empirical part compares eRecruiter and SAP SuccessFactors Recruiting using criteria aligned with the AIPT dimensions.
Findings: The analysis confirms the usefulness of the AIPT model for evaluating AI applications in recruitment systems. Both systems demonstrate high maturity in the Assist and Inform dimensions, offering automation of recruitment workflows and support for data-driven decision-making. Differences are more visible at the Predict and Transform levels, especially in predictive functionalities, integration with HR architecture, and the extent to which AI influences process design and user roles.
Research limitations/implications: The study is exploratory and covers only two systems, which limits generalizability. The analysis is based mainly on vendor materials and organizational documentation, which may create information asymmetry. Future research should include more systems and primary data on recruitment effectiveness, decision quality, and candidate experience.
Practical implications: The proposed methodology may support HR managers in selecting and implementing AI-based recruitment systems by enabling a structured assessment of system functionalities, organizational fit, and maturity level. It may also reduce implementation risks resulting from misalignment between technology and HR processes.
Social implications: The study supports transparent and responsible implementation of AI in recruitment, contributing to reducing algorithmic discrimination and strengthening candidate trust.

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Originality/value: The originality of the study lies in integrating maturity-model logic with a practical evaluation method for AI-based recruitment systems and demonstrating its applicability to systems from different technological classes.
Keywords: maturity model, recruitment systems, AI in employee selection, AIPT model, AI system evaluation.
Category of the paper: Research paper.

1. Introduction

The contemporary discourse on the use of artificial intelligence (AI)[1] in human resource management is characterized by a holistic approach, in which not only algorithmic efficiency is analyzed, but also the impact of technology on the functioning of HR processes, decision-making mechanisms, candidate experience, and ethical and regulatory aspects (Bąk-Grabowska, Bartkowiak, 2026, pp. 4-6). Taking these interrelated perspectives into account creates a need to refer to multidimensional maturity models, which can serve as a framework for methodologies for evaluating systems using AI in employee selection across technological, organizational, social, and legal dimensions. These models, adopting a multi-criteria approach, focus on a sequence of stages from an evolutionary perspective, which enables the categorization of the level of advancement of AI-based solutions. Consequently, maturity models primarily serve a diagnostic and decision-support function (Lahrmann, Marx, 2010, pp. 522-525).

In the context of this study, recruitment is understood as the process of attracting and identifying potential candidates for employment, while selection refers to the process of evaluating and choosing the most suitable candidates from the applicant pool. These processes are increasingly supported and transformed by AI-based systems, which affect both operational efficiency and the quality of decision-making.

A variety of AI tools are available on the market, covering nearly every aspect of human resource management, including more than one hundred dedicated to employee selection (Zhang, 2025, pp. 1-35). This raises the question of how to facilitate decision-making for HR practitioners regarding the adoption of a given solution. At the theoretical and methodological level, the answer to this question may be linked to the use of maturity model assumptions to develop a methodology for evaluating solutions that adopt AI and are applied in employee selection.

The aim of the study was to develop an original methodology for evaluating employee selection systems utilizing AI, based on the AIPT maturity model (Assist-Inform-Predict-Transform), and to verify its usefulness through a comparative analysis of two selected

[1] In this study, it was decided to use the abbreviation AI from the English term artificial intelligence, because the abbreviation SI, and especially the expression "SI system", is used to describe the International System of Units.

solutions. The AIPT model was developed as a conceptual and operational representation of the development of AI applications in human resource management, with particular emphasis on employee selection (Bąk-Grabowska, Bartkowiak, 2026, pp. 39-50). The application of the evaluation methodology was exemplified using two solutions: eRecruiter and SAP SuccessFactors Recruiting. The analyzed solutions represent different classes of technological systems- a local ATS-type system and a global ERP-class solution. The empirical data concerning the systems selected for analysis, used in this study, were derived from organizational documentation, including publicly available data provided by system vendors.

In the study, the theoretical part presents maturity models serving as a reference point for developing the evaluation methodology for AI-based employee selection systems. The assumptions of the proposed evaluation methodology are presented. A comparative analysis of two employee selection systems is conducted based on selected evaluation criteria. The conclusion focuses on presenting the findings from the application of the evaluation methodology, indicating its advantages, including its potential for practical application, as well as the limitations of the conducted study.

2. Maturity models as a source of guidelines for the methodology y of evaluating AI-based employee selection systems

The methodology for evaluating systems utilizing artificial intelligence requires grounding in reference frameworks that enable the determination of the level of development and advancement of the analyzed solutions. One of the well-established approaches in this area is maturity models, whose origins in the organizational context can be traced back to the concept proposed by P. Crosby (1979, pp. 14-18). This concept serves as a point of reference for numerous subsequent approaches assessing the level of development, capabilities, and improvement potential of domains within organizations.

Maturity models enable the systematic identification of strengths and weaknesses within the analyzed area, as well as the comparison of the current state with the desired level (Lahrmann and Marx, 2010, pp. 312-315). Their essence lies in their iterative nature and the division of the examined domain into archetypal levels reflecting stages of development and professionalization (Mettler and Rohner, 2009, pp. 5-7). In the literature, the term “maturity” primarily refers to:

- process maturity (the degree of process definition and effectiveness),
- object maturity (the level of sophistication of a technical product),
- people competencies (the ability of the workforce to create knowledge) (Mettler, Rohner, 2009, p. 6).

Maturity models serve descriptive, explanatory, or predictive functions. All of them reflect the state of a given domain, regardless of whether they describe the current situation or suggest a target state. It is important to distinguish between a model ("what" constitutes the ideal state) and a method ("how" to achieve it), which represents a key methodological distinction (Lahrmann, Marx, 2010, p. 314). Methods are systematic, purposeful, and repeatable, which makes them more practical in diagnosis and in supporting managerial decision-making. The literature shows a growing interest in the application of maturity models in information systems (Mettler, Rohner, 2009, pp. 3-4). In the context of human resource management, this evolution includes the assessment of process maturity and the analysis of technological advancement, including the use of solutions based on AI algorithms (Duggan et al., 2020, pp. 115-118; Kellogg, Valentine, Christin, 2020, pp. 368-372).

Maturity models have become a tool for structuring the degree of formalization of HR processes and the integration of digital technologies with HRM practices. Among the key approaches are the People Capability Maturity Model (People CMM), which constitutes the foundation of thinking about HR maturity, and the Artificial Intelligence Maturity Model for Human Resources (HR-AIMM), which responds to the challenges of the fourth industrial revolution and the algorithmization of HR processes.

The People CMM model is an organizational change model and originates from software engineering. It assumes that sustainable improvement in HR requires simultaneous changes in organizational behaviors, management structures, and decision-making processes (Curtis, Hefley, Miller, 1995, pp. 3-10; 2001, pp. 27-34; 2009, pp. 41-52). The People Capability Maturity Model distinguishes five stages of human capital development:

- Level 1 (Initial – Inconsistent Management) – HR practices are inconsistent and reactive, dependent on individual decisions.
- Level 2 (Managed – People Management) – the organization repeats effective practices, including in recruitment, and managers assume responsibility for basic processes.
- Level 3 (Defined – Competency Management) – HR practices are standardized and integrated with strategy; coherent competency management develops.
- Level 4 (Predictable – Capability Management) – process effectiveness is measured quantitatively using HR analytics.
- Level 5 (Optimizing – Change Management) – human capital management is subject to continuous improvement, and innovation and learning become a permanent element of the organization (Curtis, Hefley, Miller, 2001, pp. 27-34).

In the context of implementing AI-based employee selection systems, People CMM constitutes an important point of reference. Level 3 is particularly critical, as the standardization of processes and their integration with strategy create the conditions for effective AI implementation. The absence of this level fosters fragmented use of technology and limits the organization's ability to derive value from advanced algorithmic systems.

An extension of the process maturity-based approach in HR is represented by models that directly address the use of artificial intelligence in human resource management. One of the most comprehensive is the Artificial Intelligence Maturity Model for Human Resources (HR-AIMM) developed by Armutat, Wattenberg, and Mauritz (2024, pp. 50-55). It was created in response to the limitations of general AI maturity models, which do not account for the specificity of HR processes and the role of HR in the context of digital transformation (HR 4.0, HR 5.0). The authors emphasize that implementing AI in HR is not purely a technological endeavor, but a complex organizational process encompassing strategy, structure, culture, competencies, and data management. HR-AIMM is multidimensional and serves to assess the readiness and advancement of organizations in adopting AI within the HR function, supporting the analysis of factors determining its effective application. The model includes eleven dimensions reflecting technical, social, and organizational aspects, including: integration of AI with strategy, scope of application in HR processes (including recruitment), ethical principles, data management, infrastructure, implementation organization, development of HR competencies, attitudes toward AI, organizational experience, accountability, and the perceived impact of AI on HR function performance. It distinguishes four levels of maturity:

- Level 1 (Curious start) – interest in AI without operational implementation.
- Level 2 (Learning experimentation) – experiments and pilot projects in selected HR areas.
- Level 3 (Project-related implementation) – project-based implementations with a defined scope.
- Level 4 (Holistic integration) – sustained integration of AI with HR processes and organizational strategy (Armutat, Wattenberg, Mauritz, 2024, pp. 55-56).

An important feature of HR-AIMM is the possibility of assessing multiple dimensions simultaneously, which allows for the identification of both advanced areas and those requiring development. The model allows for varying levels of maturity across different HR areas and does not assume uniform progress.

It is also worth noting commercial models that strongly influence business practice. The Deloitte model (Bersin, 2017, pp. 42-45) describes an evolution from “systems of record” to “systems of intelligence”, in which AI not only collects data but also generates recommendations. The Gartner model emphasizes the transition from the automation of simple tasks to the transformation of the HR operating model (Gartner, 2023, pp. 4-7). At the same time, approaches are being developed that do not meet the criteria of maturity models sensu stricto but serve as analytical frameworks and diagnostic tools supporting the qualitative assessment of AI use in HR. These include the concept of algorithmic human resource management (Meijerink, Bondarouk, Lepak, 2021, pp. 3-8). The authors do not reconstruct sequential stages of development but instead analyze the relationships between algorithms, decision-making processes, and the roles of organizational actors in conditions of HR automation. They emphasize the degree of delegation of decisions to algorithms,

the autonomy of AI systems, and the implications for responsibility, control, and human agency. This approach captures the social and normative dimension of algorithmization but does not enable comparative evaluation of systems or their classification according to maturity levels.

An example of a diagnostic approach is also the method for assessing organizational progress in the use of AI in HR (Ulrich et al., 2024, pp. 6-12). It includes, among others, business justification, value creation for stakeholders, accountability, development of AI competencies, principles of responsible technology use, metrics, and integration with business processes. It has a practical character and supports managerial reflection; however, similarly to algorithmic HRM frameworks, it is not based on the formal logic of maturity models nor on clearly defined stages of development. It enables the diagnosis of selected dimensions of AI but does not allow for systematic comparison of systems or their multidimensional assessment of advancement.

3. The AIPT model as a foundation for the methodology of evaluating AI-based employee selection systems

The AIPT model was developed as a conceptual and operational representation of the development of artificial intelligence applications in human resource management, with particular emphasis on recruitment and selection processes (Bąk-Grabowska, Bartkowiak, 2026, pp. 39-50). In the context of employee selection, characterized by high decision sensitivity, a direct impact on candidates' professional situations, and increasing regulatory and ethical requirements, it becomes justified to apply a methodology that combines the logic of maturity models with the possibility of multidimensional evaluation of AI systems. In response to this need, an original methodology for evaluating AI-based recruitment systems was developed, based on the AIPT maturity model (Assist–Inform–Predict–Transform).

The fundamental assumption of AIPT is the staged nature of AI implementation and use, ranging from operational support to the strategic transformation of the HR function. The model does not describe only the increase in technological advancement, but primarily the change in the role that artificial intelligence plays in decision-making, organizational, and relational processes. The AIPT model distinguishes four stages of maturity:

- Assist – at this stage, artificial intelligence performs a supporting function in the execution of routine and repetitive tasks in the recruitment process. AI systems are primarily used to automate operational activities such as initial application screening, scheduling interviews, and handling communication with candidates. Recruitment decisions remain fully on the human side, and the role of AI is instrumental.

- Inform – this stage is characterized by the use of artificial intelligence for data analysis and the provision of information supporting the decision-making process. AI systems generate reports, summaries, and data visualizations, enabling recruiters and HR managers to make decisions based on empirical evidence. However, AI does not formulate autonomous recommendations, and its role is limited to informing and structuring knowledge.
- Predict – at this stage, AI systems use predictive models to forecast the outcomes of recruitment processes, such as candidate–job fit, probability of hiring success, or risk of turnover. Algorithms formulate recommendations that have a real impact on recruitment decisions, and the role of humans shifts toward interpreting results and supervising the operation of the system.
- Transform – the highest level of maturity, at which artificial intelligence becomes an integral element of the architecture of HR processes and organizational strategy. AI not only supports recruitment decisions but also co-shapes process design, redefines the roles of recruiters and HR managers, and influences value creation for the organization and its stakeholders. At this stage, a transformation of the recruitment operating model as a whole becomes possible.

The AIPT model has a framework-based and analytical character. It does not assume uniform progress across all areas of system functioning, nor does it require achieving the same level of maturity in every organization. Instead, it enables the structuring and comparison of recruitment systems in terms of the way artificial intelligence is utilized, as well as the identification of their current level of maturity and development potential.

4. Comparative analysis of systems: eRecruiter and SAP SuccessFactors Recruiting within the AIPT framework

The AIPT model was used as the basis for the methodology of comparative evaluation of two recruitment systems representing different technological classes. This made it possible to empirically verify the usefulness of the model as a tool for analyzing AI systems in employee selection. A synthetic characterization of the individual stages of the AIPT model, taking into account the role of AI, the scope of its impact on the recruitment process, and the evolving role of humans, is presented in Table 1.

Table 1.
Characteristics of the stages of the AIPT model (Assist–Inform–Predict–Transform)

Model stage	Dominant role of AI	Scope of impact on the recruitment process	Role of humans	Significance for system maturity
Assist	Operational support	Automation of individual, repetitive tasks (e.g., CV pre-screening, communication)	Main decision-maker	Low level of maturity - AI as a tool
Inform	Providing information	Data analysis, reporting, visualization of the recruitment process	Decision-maker supported by information	Medium level of maturity - data-driven decisions
Predict	Forecasting and recommendations	Prediction of recruitment outcomes, candidate ranking, recommendations	Supervisor and interpreter of AI outputs	High level of maturity - AI influences decisions
Transform	Co-shaping processes	Reorganization of the recruitment process, changes in HR roles, strategic integration	Strategic partner of AI	Very high level of maturity - AI transforms the HR function

Source: Own elaboration based on (Curtis, Hefley, Miller, 2001; Armutat, Wattenberg, Mauritz, 2024).

In the comparative analysis, the AIPT model (Assist–Inform–Predict–Transform) was adopted as a framework for assessing the maturity of AI applications in recruitment systems. The model enables the structuring of AI functions according to their increasing impact: from the automation of operational tasks (Assist), through data-driven decision support (Inform), to prediction and recommendations (Predict), and finally to the transformation of HR roles and processes (Transform). The subject of comparison consisted of two IT systems:

- eRecruiter, a product of eRecruitment Solutions, representing a mature ATS system strongly embedded in the Polish market, developed as SaaS and extended with AI functionalities (including pre-screening, tagging, generative content, and an AI assistant) (eRecruiter, 2025, 4.02.2026),
- SAP SuccessFactors Recruiting, an enterprise-class solution (HCM/ERP) offered by SAP, in which the Recruiting component functions as an ATS supporting the entire process from requisition to candidate selection, and whose AI functionalities include, among others, AI-assisted skills matching/applicant screening, role recommendations based on CV analysis, and the generative assistant Joule within the SuccessFactors ecosystem (SAP SuccessFactors Recruiting, 2025, 4.02.2026).

Table 2 presents a comparison of eRecruiter and SAP SuccessFactors Recruiting based on the AIPT model.

Table 2.
Comparison of eRecruiter and SAP SuccessFactors Recruiting based on the AIPT model

AIPT dimension	Evaluation criterion	eRecruiter (ATS SaaS)	SAP SuccessFactors Recruiting (enterprise ATS / HCM)
Assist	Operational automation of recruitment (workflow, communication, process organization)	Automation of routine recruitment tasks: application handling, candidate communication, organization of submissions. AI performs a tool-based role, with decisions remaining on the recruiter's side.	Automation of recruitment processes within a standardized workflow (requisitions, applications, interviews, offers) as part of a broader HCM system.
Inform	Reporting, dashboards, process insights, source analysis	Analysis of process data and reporting (candidate sources, time-to-hire, channel effectiveness). Support for data-driven decisions.	Use of candidate and job data within a skills-based approach; information embedded in HR processes and system reports.
Predict	Prediction and recommendations supporting recruitment decisions (candidate–job fit, outcome forecasting)	Pre-selection and matching of candidates using AI (semantic matching, shortlists, generative profile summaries).	AI-assisted applicant screening and skills matching; recommendations of roles and candidates based on CV and competency analysis.
Transform	Integration of AI with HR processes and impact on recruitment design and decision-making roles	Development of AI toward supporting the entire recruitment cycle and improving candidate experience; transformation is gradual and functional.	Integration of AI with the HCM ecosystem (SuccessFactors + Joule); AI influences the way HR processes are carried out and user roles at the organizational scale.

Source: Own elaboration based on source materials from official websites (eRecruiter, 2025; SAP SuccessFactors Recruiting, 2025, 4.02.2026)

The comparison of eRecruiter and SAP SuccessFactors Recruiting within the AIPT framework indicates that both solutions follow the logic of the staged development of AI applications in recruitment, although they do so within different organizational and technological contexts. At the Assist and Inform levels, both systems demonstrate a high degree of maturity, offering advanced mechanisms for operational automation and process data analysis that support recruitment decision-making. Differences become more pronounced at the Predict stage, where both eRecruiter and SAP SuccessFactors use matching and pre-selection algorithms, but differ in scope and scale—eRecruiter focuses on supporting the operational work of recruiters, whereas SAP SuccessFactors embeds prediction within a broader, skills-based approach characteristic of enterprise-class solutions.

The most significant differences emerge at the Transform stage, which in the AIPT model refers not to the mere increase in technological advancement, but to changes in the design of recruitment processes and the role of the HR function. In the case of eRecruiter, transformation is gradual and functional, aimed at improving the entire recruitment cycle and enhancing user experience. In contrast, SAP SuccessFactors realizes the transformational dimension through the integration of artificial intelligence within the HCM ecosystem and the introduction of a conversational layer, which fosters the redefinition of user roles and the way HR processes are executed at the organizational level.

5. Conclusion

The analysis of both classical maturity models and conceptual and diagnostic frameworks revealed a research gap. On the one hand, maturity models offer a structured development framework and enable the classification of organizations according to their level of advancement; on the other hand, they often abstract from the detailed evaluation of specific AI systems, their algorithmic quality, their impact on users, and their compliance with ethical and regulatory requirements. In turn, diagnostic frameworks and concepts of algorithmic HRM provide in-depth qualitative insights but do not offer coherent comparative criteria or tools enabling the evaluation of systems across different technological classes. These limitations justified the need to develop a methodology for evaluating AI systems in recruitment that would integrate the logic of maturity models with a multi-criteria approach encompassing technological, organizational, user-related, and ethical-legal dimensions.

The identified gap is addressed by the original methodology based on the AIPT model, which describes four stages of maturity of AI applications in employee selection: Assist, Inform, Predict, and Transform. The conducted analysis confirms the usefulness of the AIPT model for identifying the maturity level of AI applications in recruitment, as well as for capturing qualitative differences between systems representing different technological classes. Both analyzed systems demonstrated a high level of maturity in the Assist and Inform dimensions, offering advanced operational automation and data-driven decision support. At the same time, differences were identified at the Predict and Transform levels, where both the scale of predictive use and the degree of integration of AI with HR process architecture and organizational strategy differ. Further operationalization of the AIPT model in the form of measurement scales enabling the quantitative assessment of maturity levels is possible.

The developed methodology may serve as a tool supporting decision-makers in the process of selecting and implementing AI-based recruitment systems. Its application may contribute to more informed investment decisions, reduce the risk of implementing solutions misaligned with the organization's maturity level, and improve the management of digital transformation within the HR function. From an economic perspective, this may result in the optimization of recruitment costs, improved candidate-job fit, and increased efficiency of HR processes. It should be noted, however, that the study is exploratory in nature and is based on the analysis of two systems representing specific technological classes, which limits the generalizability of the results. The data sources consisted primarily of vendor materials and organizational documentation, which may involve the risk of information asymmetry and a lack of full insight into algorithmic functioning.

In conclusion, the use of artificial intelligence (AI) in recruitment systems may contribute to increased efficiency of the selection process, particularly through faster data processing, improved matching accuracy, and enhanced decision support. However, the actual effectiveness

of these systems depends on the quality of input data, model design, and the degree of human oversight. In addition to data-related limitations, the implementation of AI in recruitment systems involves a number of challenges, including the risk of algorithmic errors, a lack of transparency in decision-making processes, and potential resistance from users. Furthermore, regulatory requirements and ethical considerations may limit the scope and manner of AI deployment in HR processes.

Future research directions should include expanding the empirical scope of the proposed methodology by analyzing a larger and more diverse set of recruitment systems representing different technological classes and organizational contexts. An important direction is also the operationalization of the AIPT model in the form of measurable indicators enabling the quantitative assessment of AI maturity levels. It would also be valuable to investigate the impact of AI-based recruitment systems on recruitment effectiveness, decision quality, and candidate experience using primary data. Further analyses should also consider ethical and regulatory aspects, particularly in the context of transparency, fairness, and the risk of algorithmic discrimination.

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