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# IMPACT OF ARTIFICIAL INTELLIGENCE ON HR PROCESS ENGINEERING IN THE PUBLIC ADMINISTRATION SYSTEM

# ВПЛИВ ШТУЧНОГО ІНТЕЛЕКТУ НА ІНЖИНІРИНГ HR-ПРОЦЕСІВ В СИСТЕМІ ПУБЛІЧНОГО УПРАВЛІННЯ

**Summary.** The study demonstrates that artificial intelligence is transforming human resource management in the public sector, shifting it from an administrative system to an analytical model based on predictive insights and digital trust. The research analyzes scientific approaches to the use of artificial intelligence in public administration and establishes a coherent framework for transforming the entire HR lifecycle. It identifies that the use of predictive analytics, automated recruitment systems, virtual assistants, and explainable algorithms enhances transparency, objectivity, and public trust in governmental decision-making. A comparative analysis of implementation barriers in the public and private sectors revealed key differences between profit-oriented and value-driven management approaches. The study outlines the main risks associated with algorithmic decision-making in HR processes and proposes mechanisms to mitigate them. As a result, an integrated concept of adaptive HR engineering in public administration was developed, combining ethical, technological, and competence-based dimensions to ensure a gradual transition toward a new culture of collaboration between humans and artificial intelligence.

**Keywords:** artificial intelligence, public administration, HR engineering, ethical governance, predictive analytics, algorithmic transparency, digital transformation.

**Formulation of the problem.** The system of public administration is currently undergoing a fundamental crisis driven by a dual pressure. On

the one hand, there is a strong societal and political demand for digital transformation, improved efficiency, and higher quality of public services. On the other hand, the governmental apparatus remains constrained by outdated administrative approaches to personnel management, where the HR function has historically focused on administration, paperwork, and regulatory compliance rather than on strategic partnership or human capital development. The emergence of artificial intelligence technologies is not simply another incremental tool for automation comparable to the introduction of basic HRMIS systems. AI acts as a transformative force that will not merely automate but will fully reengineer and augment the cognitive processes involved in personnel decision making. However, this is precisely where the core problem lies, because the public sector is institutionally built on determinism, strict adherence to procedures, and risk minimization. AI, in contrast, introduces unprecedented ethical, legal, and operational risks, especially in a sensitive domain such as HR. At the center of the challenge is a fundamental paradox between the operational logic of AI and the value foundations of public administration. AI engineering optimizes efficiency by relying on probabilistic and often opaque black-box algorithms to achieve outcomes. Public administration, in contrast, requires legitimacy that is grounded in deterministic, transparent, accountable, and objectively fair processes. Consequently, any attempt to directly engineer HR processes such as recruitment, evaluation, or promotion through AI creates a direct threat to public trust and legal guarantees. While algorithmic bias in the private sector results in lawsuits and reputational damage, in the public sector it translates into violations of constitutional rights, delegitimization of state authority, and risks of social destabilization. Therefore, the central problem that requires resolution is how to integrate artificial intelligence tools into the public administration system in a way that preserves efficiency, legality, and fairness in decision making.

**Analysis of recent achievements and publications.** Modern research on integrating artificial intelligence into personnel management focuses primarily on ethical, legal, and technical aspects, yet it overlooks the systematic combination of these dimensions within public administration. Hunkenschroer A.L., Kriebitz A. [1] examine AI-recruitment through the lens of human rights, demonstrating its compatibility with the principles of validity, autonomy, non-discrimination, privacy, and transparency. However, the authors do not propose operational mechanisms for implementing these standards in the public sector. The integrated concept of adaptive HR-engineering presented in this study addresses this gap by introducing ethical auditing, risk management, and documented algorithmic control. Capasso M., Arora P., Sharma D., Tacconi C. [2] concentrates on the protection of fundamental rights within algorithmic HRM, identifying risks of hidden discrimination, yet does not outline practical means for preventing it. The concept developed in this work enhances this approach by integrating decision explainability and human involvement in critical stages of candidate selection. Dima J., Gilbert M.H., Dextras-Gauthier J., Giraud L. [3] identifies five effects of AI on HR, but does not describe how these effects can be structurally implemented in public administration. In contrast, the article achieves this through a three-component architecture that includes "Governance and Ethics", "Technology and Data", and "People and Competencies", forming a coherent sequence from strategy formulation to its implementation. Wang A., Jiang D. [4] propose a tripartite framework for technological governance, although they leave it without an applied mechanism. In the proposed concept, this framework is elaborated through algorithmic auditing, an ethics council, and ethical performance indicators. Maake G., Schultz C.M. [5] describe success factors for AI adoption in local governance, yet they do not cover the full life cycle of HR processes. The concept presented in this study compensates for this by establishing an ecosystem that integrates managerial, technological, and competency-based elements. Soleimani M., Intezari A., Arrowsmith J., Pauleen D.J., Taskin N. [6] highlight the need for cooperation between HR departments and developers but do not define governmental audit standards. This gap is addressed in the proposed concept by developing internal regulatory procedures and ethical evaluation systems. Căvescu A.M., Popescu N. [7] focus on predictive talent analytics while disregarding the institutional and legal dimension, which in this study is incorporated through data transparency controls. Fenwick A., Molnar G., Frangos P. [8] describe the evolutionary phases of AI-HRM but do not provide criteria for transitioning between these phases. The concept developed in this study fills this gap by defining clear readiness parameters, risk levels, and performance indicators for each stage. Overall, previous international studies have provided essential individual components of ethical, technical, and managerial approaches, yet none has offered an integrated solution. The concept developed in this research resolves these gaps by combining legal standards, technological

interoperability, and competency development within a unified HR-transformation cycle. This ensures the scientific novelty and practical relevance of the study, since it introduces for the first time an integrated concept of adaptive HR-engineering in the field of public administration.
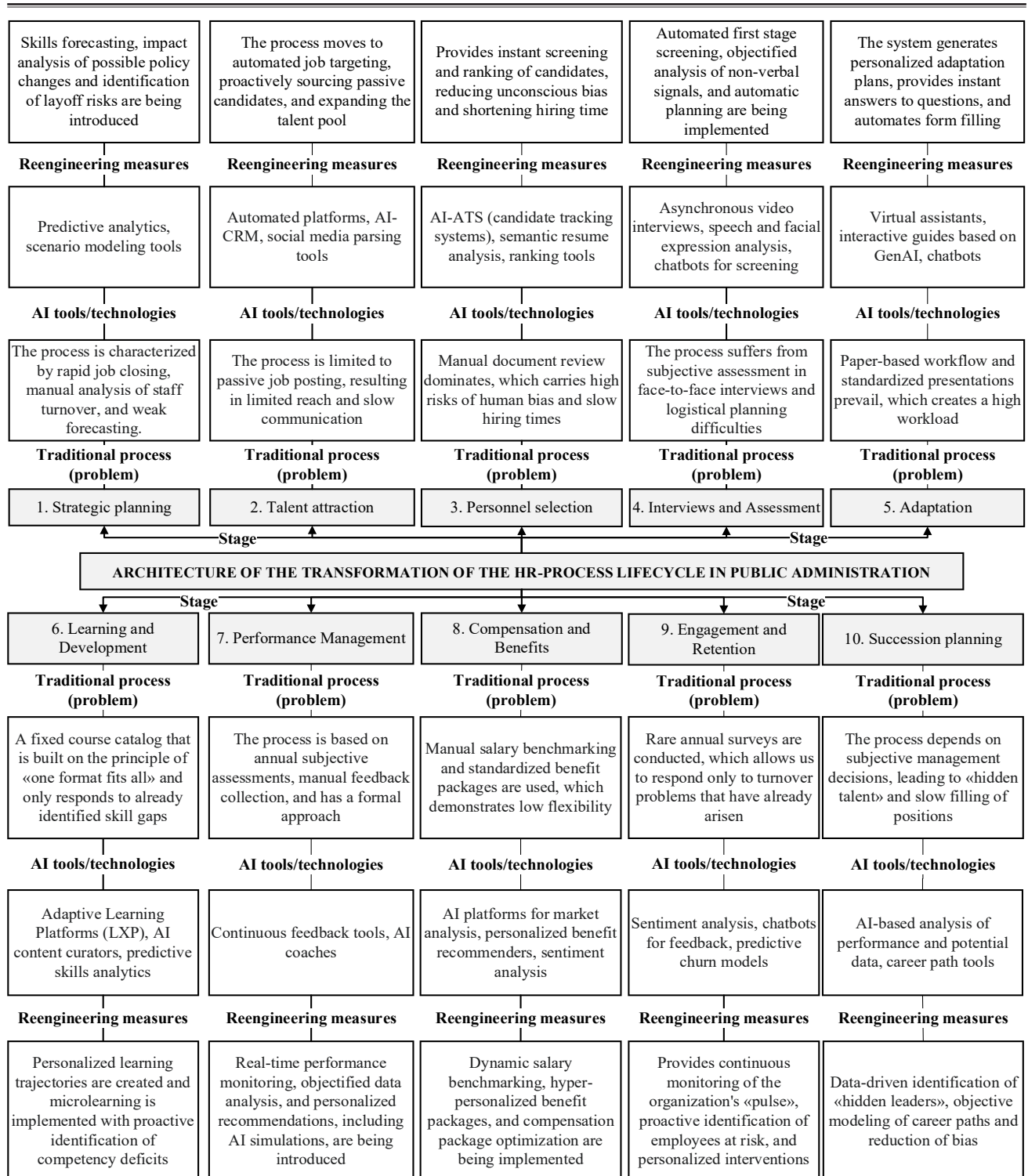
**The purpose of the article** is to develop a holistic concept for integrating artificial intelligence into the public administration personnel system by designing an adaptive HR-engineering framework that combines managerial, technological, and ethical components within a unified architecture of digital HR transformation.

**Presentation of the main material.** Improving the architecture of state personnel management requires a shift from fragmented digital initiatives to a holistic engineering of the HR-process lifecycle in which artificial intelligence functions as a system integrator connecting strategic management, technological analytics, and workforce competency development. Therefore, it is essential to establish a transformation architecture for the HR-process lifecycle in public administration, as shown in Figure 1.

The defined architecture of HR-process lifecycle transformation in public administration, illustrated in Figure 1, will need to create an integrated digital-analytical system [3] in which all stages of personnel management operate as interconnected components. Whereas previous decisions were made with delays, the future architecture must rely on predictive analytics [4], ensuring synchronization between data, technologies, and the strategic priorities of the state. At the stage of strategic planning, the public administration system will gradually move away from slow manual analysis and inefficient assessments, as it will require more predictable and manageable decisions. For this reason, personnel policy will rely on intelligent forecasting that will provide timely managerial actions. At the stage of strategic planning, the public administration system will gradually move away from slow manual analysis, since the growing complexity of government processes will require more controlled and predictable decisions. For this reason, the use of predictive analytics and scenario modelling will transform the traditional statistical approach into a system of anticipatory forecasting [7], which will create a foundation for decision making based on computational models rather than retrospective data. As a result of this transformation, the logic of talent acquisition will also evolve, because the need for accuracy and speed in selection will drive a shift from passive vacancy posting toward algorithmic platforms that analyse the professional and behavioural profiles of candidates [1].

Since greater selection accuracy will require deeper automation, the further development of candidate assessment will rely on systems for analysis and ranking, which will provide semantic interpretation of profiles and minimise the risks of bias [2]. Consequently, the selection process will gradually become more objective and manageable. Within the same logic, digital modernisation will reshape the format of interviews, as the proliferation of asynchronous video interviews and algorithmic analysis of non-verbal and speech signals [8] will create a standardised evaluation architecture that enhances the accuracy and representativeness of results. At the same time, the growing need for rapid integration of new employees will drive the digitalisation of onboarding, where intelligent assistants will provide personalised support and continuous information exchange. This, in turn, will form the basis for updating systems of learning and development, since effective integration will require flexible mechanisms for upskilling. Therefore, adaptive learning platforms and predictive skill analytics will generate personalised learning trajectories integrated directly into real work processes [3]. The renewal of approaches to personnel development will naturally influence performance management, which will shift from episodic evaluations to continuous monitoring through intelligent coaching and analysis of employees' communicative and emotional signals. As a result, the management system will provide leaders with up-to-date information and support timely decision making. Simultaneously, the domain of compensation and benefits will undergo evolution as well, because the rising demand for individualisation will stimulate the use of personalised reward packages [5] adjusted through market analytics. The consistent development of these elements will form a new approach to employee retention, in which algorithmic sentiment analysis and predictive models [6] will identify early signs of burnout, creating conditions for preventive management of team stability. The logical conclusion of this transformation will be the formation of strategic succession planning, as the increasing complexity of state institutions will require predictable models of personnel development. Algorithmic potential assessment will gradually perform the function of a tool that ensures continuity of career trajectories and transparency of managerial decisions. Ultimately, the updated HR architecture will function as an analytical ecosystem in which all stages of the personnel

| Stage 1 | Stage 2 | Stage 3 | Stage 4 | Stage 5 |
|---|---|---|---|---|
| Skills forecasting, impact analysis of possible policy changes and identification of layoff risks are being introduced | The process moves to automated job targeting, proactively sourcing passive candidates, and expanding the talent pool | Provides instant screening and ranking of candidates, reducing unconscious bias and shortening hiring time | Automated first stage screening, objectified analysis of non-verbal signals, and automatic planning are being implemented | The system generates personalized adaptation plans, provides instant answers to questions, and automates form filling |
| **Reengineering measures** | **Reengineering measures** | **Reengineering measures** | **Reengineering measures** | **Reengineering measures** |
| Predictive analytics, scenario modeling tools | Automated platforms, AI-CRM, social media parsing tools | AI-ATS (candidate tracking systems), semantic resume analysis, ranking tools | Asynchronous video interviews, speech and facial expression analysis, chatbots for screening | Virtual assistants, interactive guides based on GenAI, chatbots |
| **AI tools/technologies** | **AI tools/technologies** | **AI tools/technologies** | **AI tools/technologies** | **AI tools/technologies** |
| The process is characterized by rapid job closing, manual analysis of staff turnover, and weak forecasting. | The process is limited to passive job posting, resulting in limited reach and slow communication | Manual document review dominates, which carries high risks of human bias and slow hiring times | The process suffers from subjective assessment in face-to-face interviews and logistical planning difficulties | Paper-based workflow and standardized presentations prevail, which creates a high workload |
| **Traditional process (problem)** | **Traditional process (problem)** | **Traditional process (problem)** | **Traditional process (problem)** | **Traditional process (problem)** |
| 1. Strategic planning | 2. Talent attraction | 3. Personnel selection | 4. Interviews and Assessment | 5. Adaptation |

Stage

**ARCHITECTURE OF THE TRANSFORMATION OF THE HR-PROCESS LIFECYCLE IN PUBLIC ADMINISTRATION**

Stage

| Stage 6 | Stage 7 | Stage 8 | Stage 9 | Stage 10 |
|---|---|---|---|---|
| 6. Learning and Development | 7. Performance Management | 8. Compensation and Benefits | 9. Engagement and Retention | 10. Succession planning |
| **Traditional process (problem)** | **Traditional process (problem)** | **Traditional process (problem)** | **Traditional process (problem)** | **Traditional process (problem)** |
| A fixed course catalog that is built on the principle of «one format fits all» and only responds to already identified skill gaps | The process is based on annual subjective assessments, manual feedback collection, and has a formal approach | Manual salary benchmarking and standardized benefit packages are used, which demonstrates low flexibility | Rare annual surveys are conducted, which allows us to respond only to turnover problems that have already arisen | The process depends on subjective management decisions, leading to «hidden talent» and slow filling of positions |
| **AI tools/technologies** | **AI tools/technologies** | **AI tools/technologies** | **AI tools/technologies** | **AI tools/technologies** |
| Adaptive Learning Platforms (LXP), AI content curators, predictive skills analytics | Continuous feedback tools, AI coaches | AI platforms for market analysis, personalized benefit recommenders, sentiment analysis | Sentiment analysis, chatbots for feedback, predictive churn models | AI-based analysis of performance and potential data, career path tools |
| **Reengineering measures** | **Reengineering measures** | **Reengineering measures** | **Reengineering measures** | **Reengineering measures** |
| Personalized learning trajectories are created and microlearning is implemented with proactive identification of competency deficits | Real-time performance monitoring, objectified data analysis, and personalized recommendations, including AI simulations, are being introduced | Dynamic salary benchmarking, hyper-personalized benefit packages, and compensation package optimization are being implemented | Provides continuous monitoring of the organization's «pulse», proactive identification of employees at risk, and personalized interventions | Data-driven identification of «hidden leaders», objective modeling of career paths and reduction of bias |

**Figure 1. Architecture of the Transformation of the HR-Process Lifecycle in Public Administration**

*Source: formed by the author based on the following sources [1, 2, 3, 4, 5, 6, 7, 8]*

lifecycle are aligned through data, forecasting, and strategic foresight, forming a stable, transparent, and controllable personnel policy.

The next step involves conducting a comparative analysis of the barriers to implementing AI in HR in the public and private sectors, as shown in Figure 2.

The analysis of these barriers, presented in Figure 2, demonstrates a profound asymmetry between the two spheres, since each is guided by different managerial logics. Consequently, while profitability and rapid adaptation serve as determining factors for business, the public sector remains constrained by legal restrictions, complex hierarchical structures, and the requirements of public trust [2], which immediately directs attention to the need for analysing institutional and regulatory
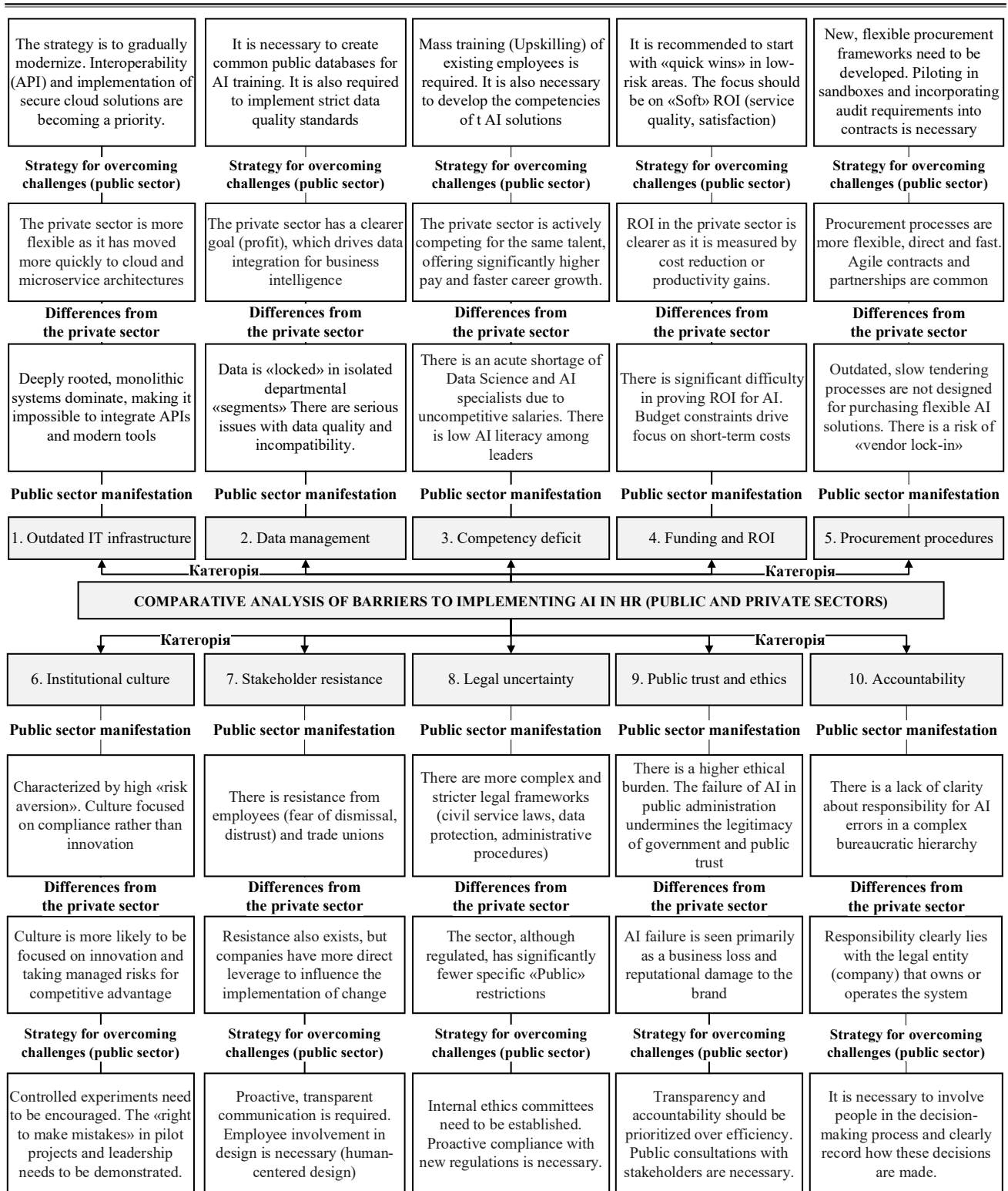
preconditions. In this context, the outdated IT infrastructure of government agencies emerges as the most persistent barrier, because its monolithic and technologically obsolete nature stands in sharp contrast to the flexibility of the private sector, which already operates on microservices and cloud architectures [5]. For this reason, modernising state systems will require a gradual transition toward interoperable modules and the phased implementation of secure cloud solutions, which logically links technical limitations to the need for a coherent managerial strategy. Furthermore, the problem of data management in the public sector is intensified by departmental isolation, which makes it impossible to create comprehensive analytics. In contrast, the private sector overcomes such barriers through a unified economic incentive, whereas public institutions must focus on building interagency databases, compatible standards, and unified quality frameworks [7]. This requirement naturally leads to the issue of competencies, as the lack of skills in working with data and modern AI tools becomes a critical factor slowing down digital transformation [8]. Unlike private companies that can attract specialists through highly competitive working conditions, the public sector will often lose talent due to limited compensation opportunities. Consequently, the strategic solution will involve the development of large-scale upskilling programs, the creation of internal data academies, and the formation of a competent public-sector customer capable of selecting and supervising AI solutions effectively [3].

Yet even with growing competencies, financial capacity remains a critical requirement, and this significantly differentiates the public sector from business [5], where efficiency is measured by profit. For this reason, public institutions will find it rational to pursue a strategy of gradual implementation through small "quick wins" and a focus on soft performance indicators, including service quality and citizen satisfaction. This positioning naturally leads to an analysis of procurement mechanisms, since traditional tender procedures remain incompatible with the flexibility required for modern IT solutions [4]. In contrast to businesses that can operate through agile contracts, the state will require modernisation of its procurement policy by introducing pilot sandboxes, transparent audit models, and safeguards against excessive vendor lock-in. This institutional dimension is inseparable from cultural constraints, as public service is characterised by a high degree of risk aversion [8], which contradicts the nature of algorithmic innovation. Therefore, creating a managerial environment where controlled experimentation and acceptable failure are permitted will become a key condition for building innovative trust [3]. However, cultural changes cannot occur without addressing social resistance, since public-sector employees are more likely to express concerns regarding automation, algorithmic decision making, and changes in roles. In this case, the state must implement a strategy of open communication, involve employees in co-designing solutions, and publicly explain the principles of the AI-HR model [8], which directly links cultural aspects with legal challenges. Since legal uncertainty creates additional barriers for public AI projects [4], it will be necessary to introduce ethical committees and alignment procedures that ensure compliance of AI initiatives with GDPR and the European AI Act [2]. Ultimately, the issues of public trust and ethics will determine the stability of all transformation components [1], because an algorithmic mistake in public administration affects not a company's reputation but the legitimacy of the state. For this reason, the formation of transparency, accountability, and ethical justification of decisions will become a foundational requirement for all stages of AI implementation [8]. The logical final step will involve embedding the principle of human control over algorithms through documented decision-making chains, which will ensure the controllability of technologies and guarantee the human right to the final say.

The next step is to identify the key risks associated with implementing AI in public-sector HR processes, as shown in Figure 3.

The risks presented in Figure 3 form a comprehensive system of threats, as they combine technical, legal, and ethical consequences that simultaneously influence citizen trust and the legitimacy of managerial decisions. For this reason, unlike in the private sector where risks are treated as operational parameters, in the public sector they acquire political and societal significance, since any algorithmic error is interpreted as a violation of the principle of fairness [1], which naturally reinforces the need to integrate risk management into the legal and ethical foundations of public service [2]. Within this logic, one of the most critical risks is algorithmic bias, as it reproduces discriminatory patterns against protected groups and simultaneously undermines the meritocratic nature of public recruitment [6]. Therefore, mitigating this threat requires not isolated technical fixes but a comprehensive approach that combines human involvement in decisive stages with regular bias auditing that ensures transparency in candidate evaluation [8]. This, in turn, logically

| Category | Public sector manifestation | Differences from the private sector | Strategy for overcoming challenges (public sector) |
|---|---|---|---|
| 1. Outdated IT infrastructure | Deeply rooted, monolithic systems dominate, making it impossible to integrate APIs and modern tools | The private sector is more flexible as it has moved more quickly to cloud and microservice architectures | The strategy is to gradually modernize. Interoperability (API) and implementation of secure cloud solutions are becoming a priority. |
| 2. Data management | Data is «locked» in isolated departmental «segments» There are serious issues with data quality and incompatibility. | The private sector has a clearer goal (profit), which drives data integration for business intelligence | It is necessary to create common public databases for AI training. It is also required to implement strict data quality standards |
| 3. Competency deficit | There is an acute shortage of Data Science and AI specialists due to uncompetitive salaries. There is low AI literacy among leaders | The private sector is actively competing for the same talent, offering significantly higher pay and faster career growth. | Mass training (Upskilling) of existing employees is required. It is also necessary to develop the competencies of t AI solutions |
| 4. Funding and ROI | There is significant difficulty in proving ROI for AI. Budget constraints drive focus on short-term costs | ROI in the private sector is clearer as it is measured by cost reduction or productivity gains. | It is recommended to start with «quick wins» in low-risk areas. The focus should be on «Soft» ROI (service quality, satisfaction) |
| 5. Procurement procedures | Outdated, slow tendering processes are not designed for purchasing flexible AI solutions. There is a risk of «vendor lock-in» | Procurement processes are more flexible, direct and fast. Agile contracts and partnerships are common | New, flexible procurement frameworks need to be developed. Piloting in sandboxes and incorporating audit requirements into contracts is necessary |

**COMPARATIVE ANALYSIS OF BARRIERS TO IMPLEMENTING AI IN HR (PUBLIC AND PRIVATE SECTORS)**

| Category | Public sector manifestation | Differences from the private sector | Strategy for overcoming challenges (public sector) |
|---|---|---|---|
| 6. Institutional culture | Characterized by high «risk aversion». Culture focused on compliance rather than innovation | Culture is more likely to be focused on innovation and taking managed risks for competitive advantage | Controlled experiments need to be encouraged. The «right to make mistakes» in pilot projects and leadership needs to be demonstrated. |
| 7. Stakeholder resistance | There is resistance from employees (fear of dismissal, distrust) and trade unions | Resistance also exists, but companies have more direct leverage to influence the implementation of change | Proactive, transparent communication is required. Employee involvement in design is necessary (human-centered design) |
| 8. Legal uncertainty | There are more complex and stricter legal frameworks (civil service laws, data protection, administrative procedures) | The sector, although regulated, has significantly fewer specific «Public» restrictions | Internal ethics committees need to be established. Proactive compliance with new regulations is necessary. |
| 9. Public trust and ethics | There is a higher ethical burden. The failure of AI in public administration undermines the legitimacy of government and public trust | AI failure is seen primarily as a business loss and reputational damage to the brand | Transparency and accountability should be prioritized over efficiency. Public consultations with stakeholders are necessary. |
| 10. Accountability | There is a lack of clarity about responsibility for AI errors in a complex bureaucratic hierarchy | Responsibility clearly lies with the legal entity (company) that owns or operates the system | It is necessary to involve people in the decision-making process and clearly record how these decisions are made. |

**Figure 2. Comparative analysis of barriers to implementing AI in HR (public and private sectors)**

*Source: formed by the author based on the following sources [1, 2, 3, 4, 5, 6, 7, 8]*

shifts attention to the next risk associated with the opacity of algorithmic models. The black-box effect creates a situation in which it becomes impossible to explain how a personnel decision was formed, which automatically reduces the accountability of the public service [4]. Since the absence of explainability undermines trust in algorithms, an effective control mechanism requires the application of XAI technologies and contractual obligations for vendors to provide full documentation of model logic [5]. This, in turn, leads to an examination of risks associated with the processing of personal

data. The risk of privacy violations becomes critically important because public-sector systems operate with large volumes of confidential citizen information, and any data breach results in political and reputational consequences. Therefore, privacy protection requires not only technological safeguards but also strict policies of data minimisation, dataset encryption, and adherence to internal security protocols [7], which logically connects to the issue of preserving human autonomy in decision making.

The effect of automation bias shows that excessive reliance on algorithms can reduce the quality of managerial judgment, creating dependence on automated systems and dehumanising the selection process [8]. In response, the control mechanism requires clear legal reinforcement of the role of the human as the final decision maker and positioning AI exclusively as a support tool rather than a substitute [3]. This leads to the structural problem of diffuse responsibility. Accountability becomes even more uncertain within the complex hierarchy of public institutions, where the boundaries of responsibility between HR units, developers, and leadership remain unclear [4]. Consequently, effective control requires regulatory definition of roles, mandatory logging of all algorithmic

| Apply the «Human-in-the-loop» (HITL) principle to all high-risk decisions. Regular bias audits should be implemented. | Use of Explainable AI (XAI) technologies. Require vendors to provide documentation of model logic | Strict adherence to the principle of data minimization. Implementation of strong encryption and clear data management policies | Maintaining human contact at critical points (final interview). Positioning AI as a support tool, not a solution replacement | Clear definition of responsibility in regulations. Mandatory auditing and logging of all AI solutions |
|---|---|---|---|---|
| **Control mechanisms and risk reduction** | **Control mechanisms and risk reduction** | **Control mechanisms and risk reduction** | **Control mechanisms and risk reduction** | **Control mechanisms and risk reduction** |
| AI tool systematically discriminates against protected groups. This violates equal opportunity laws and undermines trust in fair hiring | The inability to explain why an AI made a certain personnel decision makes appeals and accountability procedures impossible. | AI systems process vast amounts of sensitive personal data, which poses a risk of leakage or misuse. | Candidates and employees are being evaluated by machines, not humans. Managers are overly reliant on AI (automation bias) | In the event of a wrong decision (e.g., wrongful dismissal), it is unclear who is responsible the HR manager, the AI developer, or the government agency |
| **Threat to public legitimacy** | **Threat to public legitimacy** | **Threat to public legitimacy** | **Threat to public legitimacy** | **Threat to public legitimacy** |
| Algorithmic bias | Opacity («Black Box») | Violation of privacy and data security | Erosion of human autonomy and dehumanization | Ambiguous accountability |
| **Risk Detailing** | **Risk Detailing** | **Risk Detailing** | **Risk Detailing** | **Risk Detailing** |
| 1. Ethical and legal | 2. Ethical and operational | 3. Legal and operational | 4. Ethical and operational | 5. Legal and administrative |

Risk type ——— Risk type

**KEY RISKS WHEN IMPLEMENTING AI IN PUBLIC ADMINISTRATION PERSONNEL PROCESSES**

Risk type ——— Risk type

| 6. Social and operational | 7. Operating | 8. Legal | 9. Ethical | 10. Operating |
|---|---|---|---|---|
| **Risk Detailing** | **Risk Detailing** | **Risk Detailing** | **Risk Detailing** | **Risk Detailing** |
| Deskilling and displacement of personnel | False or inaccurate information generated by AI | Non-compliance with the new legislative framework | Hidden discrimination | Excessive observation |
| **Threat to public legitimacy** | **Threat to public legitimacy** | **Threat to public legitimacy** | **Threat to public legitimacy** | **Threat to public legitimacy** |
| Automation of routine tasks leads to loss of skills. This creates fear of mass layoffs | HR professionals use GenAI to create policies, but AI generates factually incorrect or fabricated information | Ignoring or misunderstanding new laws (EU AI Act) leads to fines and lawsuits | The algorithm does not use prohibited characteristics, but uses «hidden discrimination» correlated with them (place of residence, type of educational institution) | Performance monitoring tools create «digital surveillance». This destroys trust and causes stress. |
| **Control mechanisms and risk reduction** | **Control mechanisms and risk reduction** | **Control mechanisms and risk reduction** | **Control mechanisms and risk reduction** | **Control mechanisms and risk reduction** |
| Implementing strategic reskilling. Focus on augmentation, not replacement | Mandatory human verification. Use of «Closed» models trained on verified internal data | Constant monitoring of legislation. Creation of internal compliance matrices and training of legal and HR staff | Conducting a deep audit of input data. Testing the model for fairness (fairness testing). | Clearly inform employees about what and how is being monitored. Prohibition of invasive monitoring and anonymization of data |

**Figure 3. Key risks when implementing AI in public administration personnel processes**

*Source: formed by the author based on the following sources [1, 2, 3, 4, 5, 6, 7, 8]*

decisions, and regular independent audits, which logically opens the path to analysing social risks. The automation of routine operations generates the risk of staff de-skilling, where employees gradually lose competencies while simultaneously experiencing increased fear of technological replacement [8]. To mitigate this threat, the control mechanism is based on a strategic reskilling policy and an augmentation model in which AI strengthens rather than replaces human labour. This leads to operational risks associated with generative models. Inaccuracies of generative AI create the threat of decisions being made on the basis of unreliable or fabricated information, which in the public sector has particularly critical consequences [5]. Managing this threat requires the use of models trained on verified internal datasets and mandatory human verification, which naturally transitions to the legal dimension of risks. Non-compliance with regulations, including the requirements of the European AI Act, creates a direct legal threat because public institutions are subject to enhanced oversight. To minimize this risk, continuous monitoring of regulatory changes, the development of internal compliance matrices, and training staff in the legal aspects of AI use [2] are required, which highlights the importance of ethical risks. The ethical risk of proxy discrimination arises when a model uses correlates of prohibited attributes, resulting in hidden structural unfairness [6]. Control is exercised through auditing input data and fairness testing, which identifies indirect discriminatory patterns, logically concluding the analysis and transitioning to the issue of digital surveillance. Excessive monitoring creates the risk of AI platforms becoming instruments of employee control, which in the public sector directly affects the level of public trust [1]. To mitigate this, clear boundaries of monitoring, transparent employee notification, and the use of anonymized datasets are implemented, which finally forms a comprehensive approach to AI risk management in public-sector HR.

Having analyzed the results of Figures 1–3, it has been demonstrated that HR-engineering in the private sector is based on simple automation and replication of solutions, whereas in public administration such an approach is both impossible and dangerous because it ignores the fundamental barriers (Figure 2) and existential risks (Figure 3) that are rooted in the very essence and principles of public legitimacy. Consequently, the only viable path is a controlled, phased, human-centred, and ethically grounded approach that integrates risk management, technological modernization, and human capital development into a unified process.

In response to these challenges, we propose the "Integrated Concept of Adaptive HR-Engineering" (Table 1), which synthesizes the previous conclusions from Figures 1–3 and structures the key components of re-engineering (Figure 1) through staged implementation, overcoming the barriers identified in Figure 2 and ensuring effective risk management as outlined in Figure 3.

The presented "Integrated Concept of Adaptive HR-Engineering" (Table 1) establishes a coherent logic for introducing artificial intelligence into public-sector personnel processes by synchronizing managerial, technological, and human components. It defines a consistent sequence of stages from preparation to transformation, where each step ensures an organic transition from regulatory governance to technological integration and the development of workforce competencies. At the «Preparation and Strategy» stage, the primary focus is placed on building an ethical foundation through the creation of an interdisciplinary AI council that unites legal experts, HR specialists, IT professionals, and civil society representatives to balance stakeholder interests. At the same time, an audit of HR processes is conducted to identify high-risk areas, and a regulatory risk-management framework is developed, which becomes the ethical reference point for the entire transformation process. In the technological dimension, outdated systems are audited and an interoperability strategy is defined, aimed at data cleansing and standardization, thereby creating the prerequisites for establishing a security architecture that will underpin all subsequent decisions. In parallel, competency development begins as public institutions launch AI-literacy programs and cultivate a new generation of HR specialists.

At the "Piloting and Validation" stage, the focus shifts from preparation to practical testing. Pilot projects in low-risk domains allow algorithms to be tested without creating critical threats. Trade unions and employee representatives are mandatorily involved to ensure social trust. From the technological perspective, piloting occurs within regulatory sandboxes where tools are tested on verified datasets and assessed for compatibility with HRMIS. At the organisational level, competency centres are established, training sessions on mitigating operator bias are conducted, and user feedback is systematically collected for further system enhancement. The "Scaling and Re-engineering" stage shifts managerial priorities toward transitioning from pilots to full-scale implementation. Continuous monitoring of high-risk systems is introduced, and an employee appeal

Table 1

**Integrated concept of adaptive HR engineering**

| Implementation stages | Components | | |
|---|---|---|---|
| | Governance and Ethics | Technology and Data | People and Competencies |
| Preparation and Strategy | – Create an interdisciplinary AI Ethics Council (HR, lawyers, IT, public representatives). <br>– Conduct an audit of existing HR processes to identify «high-risk» areas. <br>– Develop a legislative framework for AI risk management. | – Conduct data obsolescence and quality audits. <br>– Develop a data interoperability and cleansing strategy. <br>– Define data security architecture. | – Launch a department-wide AI literacy program for all employees. <br>– Start training HR professionals as "as informed digital-service customers" |
| Piloting and Validation | – Launch pilots only in "low-risk" areas (interview planning, L&D curation). <br>– Conduct a mandatory bias audit before launching a pilot. <br>– Involve unions/staff in monitoring the pilot. | – Use "regulatory sandboxes" to test tools. <br>– Test tools on verified internal data. <br>– Assess integration with existing systems (HRMIS). | – Form "competence centers" from among the pilot participants. <br>– Conduct bias mitigation training for HITL operators. <br>– Collect feedback from end users. |
| Scaling and Re-engineering | – Implement ongoing monitoring and auditing of "high-risk" AI systems. <br>– Create a transparent appeal mechanism for employees/candidates <br>– Ensure full compliance with the EU AI Act and other regulations. | – Start phasing out legacy systems. <br>– Scale only validated and transparent tools. <br>– Implement XAI (explainable AI) for all decisions that affect people. | – Launch mass Reskilling/Upskilling programs. <br>– Officially redesign HR roles <br>– Cultivate a "people-centric" innovation culture. |
| Optimization and Integration | – Implement KPIs for monitoring AI ethics (level of bias correction). <br>– Move from static auditing to dynamic real-time risk monitoring. <br>– Ensure full integration of the ethics framework into all HR workflows. | – Fully integrate AI tools with HRMIS and other government registries. <br>– Use AI analytics to optimize HR ROI and prove investment effectiveness. <br>– Implement digital twins to model HR processes. | – Deepen skills, managing a portfolio of AI agents. <br>– Use AI to hyper-personalize employee experience and well-being. <br>– Shift L&D focus to "soft skills" (critical thinking, empathy) that complement AI. |
| Trans-formation and Innovation | – Governments should become leaders and exporters of ethical AI standards for the public sector. <br>– Audit and accountability mechanisms should be built directly into the AI architecture. <br>– Create public registries of AI systems to ensure public transparency. | – Deploying autonomous AI agents to provide new, proactive HR services to employees. <br>– Using AI to create new talent management models that were not possible before. <br>– Creating common AI platforms and models for use by different government agencies. | – HR function completely transitions from operational support to strategic forecasting and innovation. <br>– Transition from the "human-in-the-loop" model (control) to "human-and-AI" (co-creation). <br>– Freed up HR resources are directed to complex human aspects: leadership, culture, well-being. |

*Source: developed by the authors themselves*

mechanism is instituted. Technologically, gradual decommissioning of legacy systems begins, and explainable AI is integrated into all HR decisions affecting personnel management, with scaling limited to those tools that demonstrated transparency during pilot testing. In parallel, HR roles undergo official redesign, and large-scale reskilling and upskilling programs are launched to ensure employee adaptation to working symbiotically with algorithms.

The "Optimisation and Integration" stage consolidates stability and translates it into measurable efficiency. Management focuses on creating KPI systems for evaluating AI ethics, dynamic real-time risk monitoring, and full integration of ethical frameworks into HR processes. The technological component concentrates on fully connecting HRMIS with state registries, performing analytical ROI control, and modelling HR processes through digital twins. Simultaneously, at the

organisational level, a specialised competency in managing portfolios of AI agents is formed, aimed at personalising employee experience and developing skills that complement algorithmic tools, such as critical thinking, empathy, and ethical leadership. The final stage, Transformation and Innovation, establishes the foundation of a new governance paradigm. The public authority evolves into an exporter of ethical standards and AI practices, where audits and explainability are embedded into the system architecture. Technologically, an "agentic state" emerges, in which autonomous AI agents deliver a new level of HR services and an interagency ecosystem supports the shared use of platforms. Meanwhile, the HR function shifts into the domain of strategic forecasting where human AI co-creation becomes the basis of managerial decisions formed not through control but through partnership, and human capital becomes the central investment of the digital state.

In conclusion, the developed "Integrated Concept of Adaptive HR-Engineering" constitutes a roadmap for the ethical transformation of public institutions, in which technology, ethics, and people are unified into a single system of sustainable development, and artificial intelligence becomes both an automation instrument and a driver of governmental innovation culture.

**Conclusions.** The conducted research demonstrates that directly replicating business models of artificial intelligence implementation within public administration is ineffective and poses risks to public legitimacy. The proposed integrated concept of adaptive HR-engineering provides a scientific foundation for constructing an ethically calibrated system of managing the state's human capital, where algorithmic decisions become part of a trust-building mechanism rather than a source of threat. The practical value of the study lies in creating a phased model capable of guiding public institutions toward the safe and effective use of AI in HR practices through bias audits, ethics councils, testing sandboxes, and appeal mechanisms. The theoretical significance of the research consists in forming a new managerial paradigm that transforms rigid control and determinism into human-technology co-creation. Future scientific work will focus on developing the regulatory and legal foundations for AI implementation in public administration, adapting the provisions of the European AI Act to the national context, and establishing a system of independent ethical oversight for governmental algorithmic decision-making.

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**Анотація.** У дослідженні було встановлено, що штучний інтелект суттєво змінює логіку управління людськими ресурсами у публічному секторі, поступово трансформуючи його з адміністративної функції в аналітичну систему, засновану на прогнозних моделях і принципах цифрової довіри. Проаналізовано сучасні наукові підходи до використання штучного інтелекту у сфері управління персоналом, зокрема правові, етичні та технологічні виміри, які до сьогодні розвивалися ізольовано, без узгодженої управлінської нормативно-правової бази. На підставі виконаного аналізу сформовано структуру трансформації життєвого циклу кадрових процесів у системі публічного управління, у межах якої етапи від стратегічного планування до утримання персоналу, поєднуються через єдину цифрово-аналітичну платформу. Розширено розуміння того, як інструменти прогнозної аналітики, системи автоматизованого відбору кандидатів, віртуальні асистенти та технології пояснюваного штучного інтелекту забезпечують підвищення прозорості, зниження ризику упередженості та підвищення об'єктивності кадрових рішень у державному секторі. Виконано компаративний аналіз бар'єрів впровадження технологій штучного інтелекту у державному та приватному управлінні, що дозволило окреслити глибинні відмінності

між орієнтованою на прибуток логікою бізнесу та ціннісною природою державної служби, у якій визначальною є довіра громадян. Сформовано перелік ключових ризиків і механізми їх контролю, що виникають під час впровадження алгоритмічних рішень у кадрових процесах, зокрема ризики непрозорості ШІ моделей, втрати правової автономії людини, дискримінаційних ефектів та надмірного нагляду. За результатами дослідження було створено інтегровану концепцію адаптивного інжинірингу управління персоналом, яка поєднує управлінсько-етичний, технологічний та компетентнісний рівні. Запропонована модель дозволила описати послідовний процес впровадження цифрової трансформації ШІ-HR від початкового етапу пов'язаного з підготовкою та експериментальним тестування до масштабування систем і формування нової культури взаємодії людини та штучного інтелекту у публічному секторі.

**Ключові слова:** штучний інтелект, публічне управління, HR-інжиніринг, етичне врядування, прогнозна аналітика, алгоритмічна прозорість, цифрова трансформація.