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**PROMPT ENGINEERING AS A NEW PERSONNEL COMPETENCY:  
IMPACT ON THE STRUCTURE OF PROFESSIONS  
AND THE COMPANY'S HR STRATEGY****PROMPT ENGINEERING ЯК НОВА КОМПЕТЕНЦІЯ ПЕРСОНАЛУ:  
ВПЛИВ НА СТРУКТУРУ ПРОФЕСІЙ  
ТА HR-СТРАТЕГІЮ КОМПАНІЇ**

**Summary.** The article substantiates prompt engineering as a new professional skill and examines its impact on job structure and HR strategy under the integration of generative AI into business processes. The methodology combines systemic, structural-functional and comparative analysis, as well as generalization of analytical reports and modelling of HR processes. The study identifies key elements of prompt engineering and levels of competency development, showing its role in transforming professional functions. It is established that its adoption leads to hybridization of roles, changes in competency profiles, and transformation of hiring, training and performance evaluation. Key risks are outlined, including responsibility ambiguity, information security threats and knowledge management issues. The results can be used to develop HR strategies and training systems.

**Keywords:** generative artificial intelligence, personnel management, personnel retraining, knowledge management, information security, risk management.

**Анотація.** У статті здійснено теоретико-методологічне обґрунтування prompt engineering як нової професійної компетенції персоналу та визначено його вплив на трансформацію структури професій і HR-стратегії компанії в умовах інтеграції генеративного штучного інтелекту в бізнес-процеси. Методологія дослідження ґрунтувалася на поєднанні системного, структурно-функціонального та порівняльного аналізу, що дозволило розглянути prompt engineering як елемент складної системи організаційних змін, а також на узагальненні сучасних аналітичних звітів міжнародних організацій і консалтингових компаній щодо впровадження штучного інтелекту в корпоративному секторі. Додатково застосовано методи логічного узагальнення, класифікації та моделювання HR-процесів, що забезпечило формування цілісної аналітичної рамки дослідження. У результаті дослідження визначено структурні елементи prompt engineering (формалізація завдання, контекстуалізація, ітеративне уточнення, валідація результату), обґрунтовано рівні сформованості компетенції та встановлено її функціональні прояви у різних підрозділах організації, зокрема в управлінні, аналітиці, маркетингу та операційній діяльності. Доведено, що інтеграція цієї компетенції спричиняє гібридизацію професійних ролей, зміну профілів компетенцій, трансформацію підходів до найму, навчання та оцінювання результативності працівників, а також посилює міжфункціональну взаємодію в організації. Виявлено ключові ризики впровадження prompt engineering, зокрема невизначеність професійної відповідальності,

загрози інформаційній безпеці, обмеження контролю якості результатів і проблеми управління знаннями, пов'язані з використанням генеративних моделей. Запропоновано їх систематизацію у формі аналітичної моделі управління ризиками, що враховує організаційні, технологічні та поведінкові чинники. Практична значимість результатів полягає у можливості використання запропонованої моделі інтеграції *prompt engineering* для формування довгострокової HR-стратегії компаній, розроблення програм перекваліфікації та підвищення кваліфікації персоналу, удосконалення системи оцінювання результативності та створення внутрішніх стандартів управління якістю і безпекою використання генеративного штучного інтелекту в корпоративному середовищі.

**Ключові слова:** генеративний штучний інтелект, управління персоналом, перекваліфікація персоналу, управління знаннями, інформаційна безпека, управління ризиками.

**Problem statement.** The rapid introduction of AI systems based on Large Language Models (LLMs) has caused profound changes in the ways of organizing work, the distribution of functional responsibilities and the requirements for professional competences of personnel. The use of such tools as ChatGPT, Gemini or Microsoft Copilot is gradually moving from the experimental level to the operational practice of companies in the field of law, marketing, finance, logistics, human resource (HR) management, and public administration. Under such conditions, human interaction with algorithmic systems becomes not an auxiliary, but an integrated part of production and management processes.

In this context, a new applied competency is being formed – *prompt engineering*, which is the ability to create queries to AI systems in such a way as to obtain relevant, structured, and analytically suitable results. The initial stage of development of generative models the emphasis was placed on the technical aspects of their development, while the key factor of efficiency turns to be the quality of user interaction with the algorithm. Accordingly, competency in the field of creating queries, contextualizing tasks, specifying parameters, and critically evaluating the received answers is becoming a new element of the employee's professional profile.

The relevance of the study is determined by the failure of traditional profession classification models built on the stability of functional roles and a clear hierarchy of qualifications to take into account the phenomenon of hybridization of competencies. *Prompt engineering* is not reduced to the field of information technology; it is integrated into the activities of lawyers, analysts, marketers, risk management specialists, teachers, and HR managers. This creates the prerequisites for the transformation of the structure of professions: new roles are emerging (AI coordinator, AI business process integrator, specialist in interaction with generative models), while the content of existing job descriptions is changing.

#### **Analysis of recent research and publications.**

The existing knowledge on the impact of GenAI on HR management is formed at the intersection of digitalization of the HR function, algorithmic labour management, and the integration of generative models in intellectual tasks. O. Kots et al. [1] show

that AI shifts HR strategy toward proactive human capital management, emphasizing competency forecasting and productivity growth. O. M. Vaskiv and I. V. Borshchuk [2] demonstrate that ChatGPT increases efficiency in routine HR tasks, raising issues of quality standardization. In the public sector, O. Parkhomenko-Kutsevil [3] highlights the need for regulatory consistency, transparency, and accountability, while N. I. Chernenko [4] emphasizes the redistribution of functions between humans and AI and the growing demand for new competencies.

S. V. Obikhod [5] links HR innovation with organizational adaptability, while Strohmeier S. [6] conceptualizes the transition to data-driven Smart HR. J. Duggan et al. [7] focus on risks of algorithmic control, including reduced transparency and responsibility conflicts. P. Budhwar et al. [8] and H. Aguinis et al. [9] show that GenAI enhances productivity but requires quality control, ethical regulation, and strong *prompt* formulation skills. E. Brynjolfsson et al. [10] confirm that GenAI increases productivity and transforms task structures and skill requirements.

Despite extensive research, *prompt engineering* remains insufficiently conceptualized as an integrated HR competency affecting job architecture, performance evaluation, and knowledge management. This study addresses this gap by: (1) conceptualizing *prompt engineering* as an applied HR competency; (2) proposing a model of its integration into HR architecture; (3) systematizing key risks of its corporate use.

**The aim of the study.** The aim of the article was to provide a theoretical and methodological justification for *prompt engineering* as a new professional skill of personnel and determine its impact on the transformation of the structure of professions.

The study is conceptual and analytical in nature and focuses on the transformation of employee interaction with generative AI and the emergence of *prompt engineering* as an applied skill within HR systems. The methodological basis includes the analysis and synthesis of contemporary academic literature on GenAI, *prompt*-based interaction, and digital competencies, which allows for the conceptualization of the structure, functions, and levels of *prompt engineering*. Comparative and classification methods are applied to systematize approaches to integrating

this competence into HR processes, while modelling is used to develop a generalized framework for embedding prompt engineering into organizational HR architecture.

**Summary of the main research material.**

The evolution of employee interaction with digital intelligent systems should be considered as a sequential transition from tools with fixed logic to systems whose behaviour is determined by textual instructions from the user. Software solutions in which the result was set by predefined rules and formalized commands dominated in the early stages of labour automation. The employee interacted with the system through an interface, where the content of the request was strictly limited by form fields, directories and business rules, and any deviation from the scenario required developer intervention. In this model, knowledge of the regulations and the ability to work with the functionality of the software product remained the key competencies, while the quality of the request was not an independent factor of performance.

The next stage is associated with the spread of statistical methods of natural language processing (NLP) and the emergence of large pre-trained language models capable of performing tasks based on text context without specialized retraining for each task. The study [11] shows that scaling language models increases the ability to perform various tasks in zero-shot and few-shot modes, when the user gives instructions and examples without changing the code. In the applied dimension, this meant changing the point of control from programming to the textual problem statement: the result began to depend significantly on how the employee describes the goal, constraints, response format, and output data in a single message.

A critical prerequisite for the transition from experimental interaction to mass use was the emergence of models optimized for executing instructions. The researchers [12] described an approach to further training models using human feedback, which increased the controllability of responses, their relevance to instructions, and their suitability for practical user tasks. As a result, natural language has actually become a universal control interface for performing analytical, textual, and partially procedural operations. For the employees, this changed the nature of the interaction: instead of selecting commands from a menu, they began to “construct a task” in the text, and the system interpreted it taking into account the context.

A further shift occurred with the launch of dialog products, which established the conversational format as a standard form of interaction and made iterative refinement of the query a typical work action. The OpenAI announcement [13] about the launch of ChatGPT explicitly states that the model is trained to

interact in a dialog format, respond to refinements, and work with follow-up queries, i.e., to support the step-by-step refinement of the task statement. This changed the practice of use: the worker was able not only to “ask questions,” but also to consistently adjust the result by specifying requirements, adding context, examples, and quality criteria, turning the query into a guided process. The academic literature has recorded this change as a separate paradigm – prompt-based learning and prompt programming. In a systematic review [14], prompt is described as a mechanism for converting input data into a text form with a template that allows the model to perform tasks through gap filling or generation according to instructions. The review also systematizes the types of prompts and their configuration strategies. The study [15] emphasizes that the results can significantly depend on the structure of the null query, narrative frameworks, context “anchors” and metaprompts that set the model’s way of reasoning and the format of the response. In applied terms, these findings mean that the ability to “set the task correctly” ceases to be an informal experience and acquires the features of a reproducible technology of work.

On this basis, prompt engineering is being formed as a separate applied skill, as the need for standardized quality of results, predictability and manageability is growing in the corporate environment. The practice of using GenAI in organizations demonstrates that employees use it not only for information search, but also for preparing texts, summarizing documents, analysing, preparing solutions and assisting in routine operations, which increases the dependence of productivity on the quality of instructions. The Microsoft and LinkedIn Work Trend Index 2023 report [16] records that a significant proportion of knowledge workers are already using GenAI in their work, and also provides indicators of the rapid growth of AI skills in profiles and training trajectories. In parallel, international analytical documents on the labour market indicate the transformation of skills under the influence of technologies, including GenAI, which increases the importance of new competencies for the adaptation of employees and organizations.

The separation of prompt engineering from general digital literacy is explained by the fact that this skill has its own structure of actions and quality criteria that directly affect the work result. First, the employee performs the task formalization in natural language: defines the goal, roles, context, input data, constraints, and output format. Second, he or she decomposes complex tasks into subtasks and manages the sequence of requests: they actually design the process of obtaining an answer in a dialogue. Third, the employee must assess the quality and risks of the response, as generative models can produce errors, incomplete or incorrectly generalized conclusions, which requires verification, comparison with

sources, and control of sensitive data. In this context, framework documents on AI risk management are an additional prerequisite for the institutionalization of the competence: they emphasize the need to take into account the context of application, impacts and risks when using AI systems in organizations [17].

So, the evolution of employee interaction with GenAI has gone from working with a tool with fixed commands to managing the result through textual formulation of the task, its iterative refinement, and quality control. The prerequisites for the formation of prompt engineering as a separate applied skill are the technical shift to models capable of executing instructions; standardization of the dialog format as a working interface; empirically confirmed dependence of the result on the prompt structure in scientific works; scaling the use of GenAI in companies, where reproducibility and controllability are becoming a management requirement; and increasing the importance of a risk-oriented approach to the use of AI, which requires the employee not only to “know how to ask”, but also to be able to ensure correctness, compliance with policies, and control over consequences.

The transition from the Prompt Engineer model as a separate role to the integration of embedded AI skills into the functional responsibilities of employees in different departments necessitates a rethinking of the content of the prompt engineering skills in the HR system. Unlike the initial stage of the implementation of GenAI, when organizations experimented with separate specialized positions, modern practice demonstrates the integration of AI skills into the profiles of Product, Operations, Marketing, Legal, Data, and HR. The World Economic Forum’s The Future of Jobs Report 2023 [17] states that technological changes, in particular AI, are causing a revision of the skill structure in most professions, and analytical and technological competencies are integrated into functional roles.

McKinsey’s analytical report The State of AI in 2023: Generative AI’s breakout year [18] confirms that GenAI is most often implemented as a tool to improve productivity in existing roles, rather than through the creation of a large number of new specialized positions. A similar trend is reflected in the Deloitte study State of Generative AI in the Enterprise (2024) [19], which emphasizes that organizations are moving to a model of operationalizing AI through functional units. Under these conditions, prompt engineering acquires clear substantive characteristics as an applied skill that has structural elements, levels of complexity, and functional manifestations.

Structurally, this skill includes several interrelated components. The first is task formalization: the ability to transform a business problem into a clearly structured textual instruction with a definition of the goal, role of the model, context of application,

limitations, and format of the expected result. This component actually performs the function of cognitive design of the query and determines the quality of the initial interaction with the system. The second element is contextualization, which involves integrating relevant data, industry norms, internal policies, or business process specifics directly into the query structure. The lack of context significantly reduces the accuracy of results, as confirmed by analytical studies on the use of GenAI in the corporate environment [19].

The third component is iterative refinement, i.e. the ability to manage multi-stage interaction, adjust the formulation, detail the criteria and gradually achieve the required accuracy. The fourth element is validation and risk control, which involves checking logical consistency, factual reliability, lack of bias and compliance with corporate security standards. The National Institute of Standards and Technology document entitled AI Risk Management Framework 1.0 emphasizes the need to implement quality assessment and risk management procedures when using AI systems in business processes, which is directly related to the employee’s competence in controlling the generation results [20].

Given the complexity of professional tasks, it is appropriate to distinguish the levels of development of this competence. The basic level is characterized by the use of standard instructions for typical operations, such as preparing short texts or generalizations. At this stage, the employee is able to obtain correct results within the framework of simple tasks, but does not yet deeply adapt the request to the business context. The intermediate level involves the decomposition of complex problems, the use of examples, the use of structured templates, and taking into account the company’s internal data. The advanced level is characterized by the systematic integration of prompts into business processes, the creation of standardized libraries of instructions, interaction with retrieval-augmented generation (RAG) mechanisms and corporate restrictions (guardrails). Deloitte’s analytical materials on the implementation of GenAI in enterprises confirm that organizations that move from individual experimentation to standardized integration into processes create the maximum value [19].

The functional manifestations of prompt engineering directly depend on the industry specifics. In Product departments, this competence is used to form product requirements, describe user stories, and analyse the competitive environment. In Operations, it helps to optimize processes, prepare reports, and model efficiency scenarios. In Marketing, it is used to generate content, segment audiences, and test communication strategies. In Legal departments, it is used to prepare draft contracts, conduct primary analysis of regulatory provisions, and structure legal

opinions. In Data functions, it helps to formalize requests to analytical systems and interpret results. In HR, prompt engineering is used to form competency profiles, describe job openings, develop assessment scenarios, and analyse personnel data. LinkedIn Economic Graph 2024 data [21; 22] indicate an increase in demand for AI competencies across a wide range of professions, confirming the trend toward role hybridization and embedding AI skills into standard functional profiles.

So, prompt engineering should be considered as a multi-level applied competence, which has a clearly defined internal structure and functional manifestations in different professional contexts. Its development entails the transformation of competency models, changes in performance assessment criteria, and the need to standardize training and quality control procedures within the company's HR strategy (Table 1).

The practice of using GenAI in organizations shows that without clearly defined procedures for responsibility, information security and knowledge management, the integration of AI tools can lead to erroneous management decisions, data leakage or blurring of the boundaries of professional

responsibility. The AI Risk Management Framework 1.0 [20] emphasizes that organizations should identify, assess and minimize risks associated with the reliability, bias, confidentiality and security of the use of AI systems (Table 2).

The risks of implementing prompt engineering are multidimensional and go beyond purely technological issues. They cover legal, organizational, informational, and cognitive aspects. A key limitation is that the skill itself does not guarantee the safe use of GenAI; a necessary condition is its institutionalization through internal policies, verification standards, control mechanisms, and knowledge management. So, the implementation of prompt engineering in corporate practice should be accompanied by the formation of a comprehensive risk management system that combines liability regulation, information protection, quality standards, and the development of internal competencies.

**Conclusions.** The study substantiates that prompt engineering cannot be considered as a narrowly technical skill or a separate temporary role in the structure of the organization. It is transformed into an applied competence integrated into the functional profiles of employees of various departments, which

**Table 1 – Integration of prompt engineering into the company's HR architecture**

HRM dimension	Traditional work organization model	Model with integrated AI competence	Expected management result
Job Architecture	Positions are formed according to the functional principle; digital tools are of an auxiliary nature	The competence of working with GenAI is integrated into the job descriptions of functional units (product development, marketing, legal support, analytics, HRM)	Hybridization of professional roles; increased flexibility of structure; reduced need for highly specialized positions
Competency Profile	Dominance of industry knowledge and professional experience	Combining industry expertise with the ability to formalize tasks for AI, contextualize the request and check the quality of the result	Increased intellectual productivity and speed of decision-making
Recruitment Approach	Evaluation of previous experience, technical and professional skills	Assessing the candidate's ability to adapt in a digital environment, the ability to structure requests, critically evaluate the results of generation	Shortened period of entry into office; increased efficiency of initial adaptation
Training and Development System	Periodic professional development programmes	Continuous learning; retraining and digital competence improvement programmes; creation of internal libraries of verified query templates; development of internal mobility	Increasing the use of AI tools in everyday activities; reducing the skills gap
Performance Assessment	Evaluation of the final product or achievement of planned indicators	Evaluation of the result taking into account the stability of the quality of interaction with AI, compliance with verification standards and data security	Increasing the reproducibility of results, reducing the risk of erroneous management decisions
Quality and Risk Management	Control is carried out mainly at the level of human verification	Implementation of verification standards for generation results, bias control procedures and compliance with internal policies	Reducing operational and reputational risks, increasing trust in digital processes
Cost Effectiveness	Productivity depends mainly on the individual qualifications of the employee	Productivity is determined by a combination of professional expertise and effective use of AI	Reducing task completion time; increasing added value; increasing process profitability

Source: compiled by the authors based on [8; 9; 16–19; 21]

**Table 2 – Risks and organizational limitations of implementing prompt engineering in corporate practice**

Risk category	Risk content	Potential consequences for the organization	Management mechanisms for minimization
Professional Responsibility	Uncertainty about the distribution of responsibility between the employee and the AI system for an erroneous result	Legal disputes, reduced trust in decisions, reputational losses	Enforcing the principle of personal responsibility for the final decision; internal regulations for checking results
Information Security	Use of confidential or personal data in queries to external models	Data leaks, violations of data protection legislation	Access restriction policies; use of corporate environments; automatic filtering of sensitive data
Quality and Reliability of Results	Generation of inaccurate, incomplete or biased answers	Faulty management decisions, financial losses	Mandatory validation; multi-level verification; quality standards
Knowledge Management	Dispersion of created prompts and lack of centralized storage of practices	Duplication of errors, loss of hard-earned decisions, uneven quality	Creating internal libraries of verified templates; systematization of best practices
Organizational Competency Mismatch	Uneven level of skill formation among employees	Performance gaps, internal imbalances	System training programmes; assessing the level of digital readiness

Source: compiled by the authors based on [20]

causes a change in the architecture of positions, approaches to the competency models and the logic of human capital management.

Analysis of the evolution of employee interaction with generative models showed a transition from the use of digital tools as an auxiliary resource to a model in which the textual formulation of the task becomes a key mechanism for managing the result. This means that the quality of professional functions increasingly depends on the employee's ability to formalize the task, contextualize it, iteratively refine the request and validate the result. Accordingly, prompt engineering acquires the status of a structured competence with clearly defined elements and levels of formation.

It is proven that the integration of this competence changes the HR system in several dimensions. First, there is a hybridization of professional roles and the integration of the AI component into the functional responsibilities of employees. Second, the approach to hiring is transformed, where, along with industry knowledge, the candidate's ability to interact with

algorithmic systems in a structured way is assessed. Third, the training system is changing, which becomes continuous and focuses on developing skills for working with generative tools. Fourth, the performance assessment system is modified, where, along with the final result, the stability of the quality of AI interaction and compliance with verification standards are taken into account.

Therefore, prompt engineering should be considered as an element of the company's long-term HR strategy, which affects the value-added creation model, the structure of professions and the competitiveness of the organization. Its effectiveness is determined not only by the individual abilities of the employee, but also by the systemic mechanisms for training, standardization, and control. Further research should be focused on the development of quantitative models for assessing the economic efficiency of integrating this competence and a comparative analysis of industry approaches to its operationalization.

### References:

1. Kots, O., Stoiko, M., & Kots, O. (2025). Intehratsiia shtuchnoho intelektu v stratehii upravlinnia personalom pidpriemstva: priorytety ta perevahy v umovakh hlobalizatsii rynku pratsi [Integration of artificial intelligence into enterprise human resource management strategy: Priorities and advantages in the context of labor market globalization]. *Ekonomika ta suspilstvo*, no. 78. DOI: <https://doi.org/10.32782/2524-0072/2025-78-120> (in Ukrainian)
2. Vaskiv, O. M., & Borshchuk, I. V. (2024). Rol ChatGPT v avtomatyzatsii zavdan HR-industrii [The role of ChatGPT in automating HR industry tasks]. *Biznes Inform*, no. 1, pp. 418–425. DOI: <https://doi.org/10.32983/2222-4459-2024-1-418-425> (in Ukrainian)
3. Parkhomenko-Kutsevil, O. (2024). Obgruntuvannia vykorystannia tekhnolohii shtuchnoho intelektu u systemi upravlinnia personalom publichnoi sluzhby Ukrainy [Justification of the use of artificial intelligence technologies in the HR management system of the public service of Ukraine]. *Publichne upravlinnia: kontseptsii, paradyhma, rozvytok, udoskonalennia*, no. 8, pp. 98–106. DOI: <https://doi.org/10.31470/2786-6246-2024-8-98-106> (in Ukrainian)
4. Chernenko, N. I. (2022). Shtuchnyi intelekt v upravlinni personalom [Artificial intelligence in human resource management]. *Tavriiskyi naukovyi visnyk. Serii: Ekonomika*, no. 12, pp. 76–83. Available at: <http://hdl.handle.net/123456789/7983> (in Ukrainian)

5. Obikhod, S. V. (2024). Innovatsiini pidkhody do upravlinnia personalom yak faktor konkurentospromozhnosti u konteksti hlobalnoi nestabilnosti [Innovative approaches to human resource management as a factor of competitiveness in the context of global instability]. *Ekonomika, upravlinnia ta administruvannia*, vol. 1, no. 107, pp. 48–54. Available at: <https://ema.ztu.edu.ua/article/view/300250/292606> (in Ukrainian)
6. Strohmeier, S. (2020). Smart HRM – A Delphi study on the application and consequences of the Internet of Things in human resource management. *The International Journal of Human Resource Management*, vol. 31, is. 18, pp. 2289–2318. DOI: <https://doi.org/10.1080/09585192.2018.1443963>
7. Duggan, J., Sherman, U., Carbery, R., & McDonnell, A. (2020). Algorithmic management and app-work in the gig economy: A research agenda for employment relations and HRM. *Human Resource Management Journal*, vol. 30, is. 1, pp. 114–132. DOI: <https://doi.org/10.1111/1748-8583.12258>
8. Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., et al. (2023). Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. *Human Resource Management Journal*, vol. 33, is. 3, pp. 606–659. DOI: <https://doi.org/10.1111/1748-8583.12524>
9. Aguinis, H., Beltran, J. R., & Cope, A. (2024). How to use generative AI as a human resource management assistant. *Organizational Dynamics*, vol. 53, is. 1, Article 101029. DOI: <https://doi.org/10.1016/j.orgdyn.2024.101029>
10. Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. *The Quarterly Journal of Economics*, vol. 140, is. 2, pp. 889–942. DOI: <https://doi.org/10.1093/qje/qjae044>
11. Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., et al. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems*, vol. 33. Available at: <https://proceedings.neurips.cc/paper/2020/file/1457c0d6bfc4967418bfb8ac142f64a-Paper.pdf>
12. Ouyang, L., Wu, J., Jiang, X., Almeida, D., Wainwright, C., Mishkin, P., et al. (2022). Training language models to follow instructions with human feedback. Available at: [https://cdn.openai.com/papers/Training\\_language\\_models\\_to\\_follow\\_instructions\\_with\\_human\\_feedback.pdf](https://cdn.openai.com/papers/Training_language_models_to_follow_instructions_with_human_feedback.pdf)
13. OpenAI. (2026). *ChatGPT: Optimizing language models for dialogue*. Available at: <https://chatgpt.com/uk-UA/>
14. Liu, P., Yuan, W., Fu, J., Jiang, Z., Hayashi, H., & Neubig, G. (2023). Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. *ACM Computing Surveys*, vol. 55, no. 9. Available at: <https://arxiv.org/abs/2107.13586>
15. Reynolds, L., & McDonnell, K. (2021). Prompt programming for large language models: Beyond the few-shot paradigm. Available at: <https://arxiv.org/abs/2102.07350>
16. Microsoft & LinkedIn. (2024). *2024 work trend index annual report: AI at work is here. Now comes the hard part*. Available at: <https://www.microsoft.com/en-us/worklab/work-trend-index/ai-at-work-is-here-now-comes-the-hard-part>
17. World Economic Forum. (2023). *The future of jobs report 2023*. Available at: [https://www3.weforum.org/docs/WEF\\_Future\\_of\\_Jobs\\_2023.pdf](https://www3.weforum.org/docs/WEF_Future_of_Jobs_2023.pdf)
18. McKinsey & Company. (2023). *The state of AI in 2023: Generative AI's breakout year*. Available at: <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year>
19. Deloitte. (2024). *State of generative AI in the enterprise: Now decides next*. Available at: <https://www2.deloitte.com/us/en/insights/focus/tech-trends/state-of-generative-ai-enterprise.html>
20. National Institute of Standards and Technology. (2023). *Artificial intelligence risk management framework (AI RMF 1.0)* (NIST AI 100-1). Available at: <https://nvlpubs.nist.gov/nistpubs/ai/nist.ai.100-1.pdf>
21. LinkedIn Economic Graph. (2024). *AI skills and the future of work*. Available at: <https://economicgraph.linkedin.com>
22. Harvard Business Review. (2026). *AI doesn't reduce work – it intensifies it*. Available at: <https://hbr.org/2026/02/ai-doesnt-reduce-work-it-intensifies-it>

### Список використаних джерел:

1. Коць О., Стойко М., Коць О. Інтеграція штучного інтелекту в стратегію управління персоналом підприємства: пріоритети та переваги в умовах глобалізації ринку праці. *Економіка та суспільство*. 2025. Вип. 78. DOI: <https://doi.org/10.32782/2524-0072/2025-78-120>
2. Васків О. М., Боршук І. В. Роль ChatGPT в автоматизації завдань HR-індустрії. *Бізнес Інформ*. 2024. Вип. 1. С. 418–425. DOI: <https://doi.org/10.32983/2222-4459-2024-1-418-425>
3. Пархоменко-Куцевіл О. Обґрунтування використання технологій штучного інтелекту у системі управління персоналом публічної служби України. *Публічне управління: концепції, парадигма, розвиток, удосконалення*. 2024. Вип. 8. С. 98–106. DOI: <https://doi.org/10.31470/2786-6246-2024-8-98-106>
4. Черненко Н. І. Штучний інтелект в управлінні персоналом. *Таврійський науковий вісник. Серія: Економіка*. 2022. Вип. 12. С. 76–83. URL: <http://hdl.handle.net/123456789/7983> (дата звернення: 27.02.2026).
5. Обіход С. В. Інноваційні підходи до управління персоналом як фактор конкурентоспроможності у контексті глобальної нестабільності. *Економіка, управління та адміністрування*. 2024. Вип. 1 (107). С. 48–54. URL: <https://ema.ztu.edu.ua/article/view/300250/292606> (дата звернення: 27.02.2026).
6. Strohmeier S. Smart HRM – a Delphi study on the application and consequences of the Internet of Things in Human Resource Management. *The International Journal of Human Resource Management*. 2020. Vol. 31, Issue 18. P. 2289–2318. DOI: <https://doi.org/10.1080/09585192.2018.1443963>
7. Duggan J., Sherman U., Carbery R., McDonnell A. Algorithmic management and app-work in the gig economy: A research agenda for employment relations and HRM. *Human Resource Management Journal*. 2020. Vol. 30, Issue 1. P. 114–132. DOI: <https://doi.org/10.1111/1748-8583.12258>

8. Budhwar P., Chowdhury S., Wood G., Aguinis H., Bamber G. J., Beltran J. R. et al. Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. *Human Resource Management Journal*. 2023. Vol. 33, Issue 3. P. 606–659. DOI: <https://doi.org/10.1111/1748-8583.12524>
9. Aguinis H., Beltran J. R., Cope A. How to use generative AI as a human resource management assistant. *Organizational Dynamics*. 2024. Vol. 53, Issue 1. Article 101029. DOI: <https://doi.org/10.1016/j.orgdyn.2024.101029>
10. Brynjolfsson E., Li D., Raymond L. Generative AI at Work. *The Quarterly Journal of Economics*. 2025. Vol. 140, Issue 2. P. 889–942. DOI: <https://doi.org/10.1093/qje/qjae044>
11. Brown T. B., Mann B., Ryder N., Subbiah M., Kaplan J., Dhariwal P. et al. Language Models are Few-Shot Learners. *Advances in Neural Information Processing Systems*. 2020. Vol. 33. URL: <https://proceedings.neurips.cc/paper/2020/file/1457c0d6bfc4967418bfb8ac142f64a-Paper.pdf> (дата звернення: 27.02.2026).
12. Ouyang L., Wu J., Jiang X., Almeida D., Wainwright C., Mishkin P. et al. Training language models to follow instructions with human feedback. 2022. URL: [https://cdn.openai.com/papers/Training\\_language\\_models\\_to\\_follow\\_instructions\\_with\\_human\\_feedback.pdf](https://cdn.openai.com/papers/Training_language_models_to_follow_instructions_with_human_feedback.pdf) (дата звернення: 27.02.2026).
13. OpenAI. *ChatGPT: Optimizing Language Models for Dialogue*. 2026. URL: <https://chatgpt.com/uk-UA/> (дата звернення: 27.02.2026).
14. Liu P., Yuan W., Fu J., Jiang Z., Hayashi H., Neubig G. Pre-train, Prompt, and Predict: A Systematic Survey of Prompting Methods in Natural Language Processing. *ACM Computing Surveys*. 2023. Vol. 55, № 9. URL: <https://arxiv.org/abs/2107.13586> (дата звернення: 27.02.2026).
15. Reynolds L., McDonell K. Prompt Programming for Large Language Models: Beyond the Few-Shot Paradigm. 2021. URL: <https://arxiv.org/abs/2102.07350> (дата звернення: 27.02.2026).
16. Microsoft & LinkedIn. *2024 Work Trend Index Annual Report: AI at Work Is Here. Now Comes the Hard Part*. 2024. URL: <https://www.microsoft.com/en-us/worklab/work-trend-index/ai-at-work-is-here-now-comes-the-hard-part> (дата звернення: 27.02.2026).
17. World Economic Forum. *The Future of Jobs Report 2023*. Geneva: World Economic Forum, 2023. URL: [https://www3.weforum.org/docs/WEF\\_Future\\_of\\_Jobs\\_2023.pdf](https://www3.weforum.org/docs/WEF_Future_of_Jobs_2023.pdf) (дата звернення: 27.02.2026).
18. McKinsey & Company. *The state of AI in 2023: Generative AI's breakout year*. 2023. URL: <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year> (дата звернення: 27.02.2026).
19. Deloitte. *State of Generative AI in the Enterprise: Now decides next*. 2024. URL: <https://www2.deloitte.com/us/en/insights/focus/tech-trends/state-of-generative-ai-enterprise.html> (дата звернення: 27.02.2026).
20. National Institute of Standards and Technology. *Artificial Intelligence Risk Management Framework (AI RMF 1.0)*. NIST AI 100-1. 2023. URL: <https://nvlpubs.nist.gov/nistpubs/ai/nist.ai.100-1.pdf> (дата звернення: 27.02.2026).
21. LinkedIn Economic Graph. *AI Skills and the Future of Work*. 2024. URL: <https://economicgraph.linkedin.com> (дата звернення: 27.02.2026).
22. *AI doesn't reduce work – it intensifies it*. Harvard Business Review. 2026. URL: <https://hbr.org/2026/02/ai-doesnt-reduce-work-it-intensifies-it> (дата звернення: 27.02.2026).

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