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AI-DRIVEN ORGANISATIONAL TRANSFORMATION: A TRANSITION-BASED TYPOLOGY AND COMPETENCY IDENTIFICATION FRAMEWORK

Abstract. The rapid diffusion of artificial intelligence (AI) across contemporary organisations transforms work structures, decision-making processes and the roles of employees. This article develops a theoretical and methodological framework for identifying and classifying organisational models in the context of AI diffusion in work processes. The analysis is situated within the long-term trajectory of technical progress – specifically the transition from skill-biased change to AI-augmented employee creativity – and draws on the dualistic ontology of management science. A typology of four successive models is proposed – traditional, AI-supported, AI collaboration and cognitive organisation – differing in the degree of AI autonomy, the scope of automation and the required employee competency profiles. The author presents a human-function-based identification matrix comprising six competency domains, evaluated against normative model profiles using mean absolute error as a goodness-of-fit measure. The article concludes by identifying three directions for further research: hybrid human-AI team effectiveness, the moderating role of institutional conditions in AI adoption, and the development of composite AI-maturity indices.

Keywords: artificial intelligence; organisational models; employee competencies; AI diffusion; human functions; diagnostic framework

INTRODUCTION

Technological progress, by driving increased production efficiency and labour productivity, constitutes a significant factor in the development of management and quality sciences. As a result of accelerating technical and technological innovation – particularly the widespread diffusion of artificial intelligence

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(AI) in the production of goods and services – AI is exerting an unprecedented impact on organisations and employees (Özkiziltan and Hassel, 2020), resulting in profound structural, functional and process transformations associated with the transition from traditional structures based on human decision-making to complex systems of human-AI collaboration.

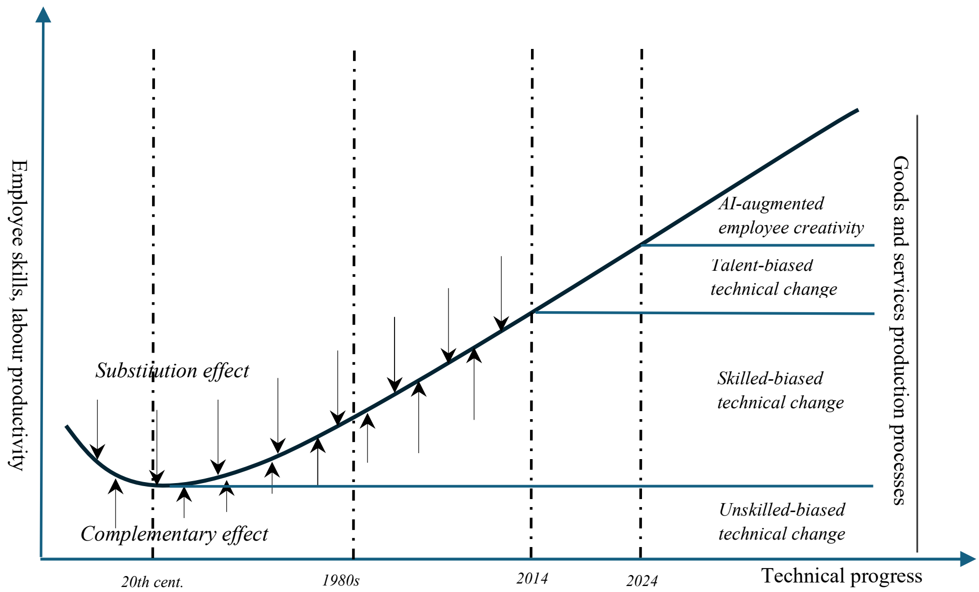
The aim of this article is to develop a theoretical and methodological framework for identifying and specifying organisational models in the context of AI diffusion, with particular emphasis on the trajectory of technical progress as the macro-level driver of change, and on employee competencies as key determinants of the organisational interaction structure. Section 1 traces the history of technical progress up to the current stage of AI-augmented employee creativity, Section 2 presents the four-model typology, Section 3 establishes the theoretical warrant for centring identification on human functions, Section 4 presents the identification methodology and diagnostic matrix, and Section 5 discusses findings and research directions.

1. TECHNICAL PROGRESS AND WORK CONTENT: FROM SUBSTITUTION TO AI AUGMENTATION

Production technologies determine work processes and condition the functions and task scopes of organisational positions. Technical progress modifies social relations in work by making new demands on employees at both executive and managerial levels, expanding the scope of tasks performed by technology and increasing the degree to which humans are replaced by technical means. At the same time, new technologies create new tasks at individual positions – the so-called complementarity effect (Autor et al., 2003). These two effects – substitution and complementarity – always coexist: every technological upgrade replaces certain human tasks and creates new ones, such as monitoring, supervision and coordination of automated systems (Figure 1).

The history of technical progress identifies four characteristic trajectories of change in work content. In the era of early industrialisation, unskilled-biased technical change degraded craft skills, replacing artisans with low-skilled factory operatives (Mokyr, 1990; Bravermann, 1998). From the early twentieth century, skill-biased technical change reversed this trend: electrification, mechanisation and subsequently information and communication technologies raised educational and skill requirements across occupations (Goldin and Katz, 1996; Autor and Acemoglu, 2011). From the second decade of the twenty-first century, talent-biased technical change intensified demand for experts in robotics, AI and data analysis, while simultaneously automating medium-skilled tasks in accounting, administration and production (Brynjolfsson and McAfee, 2014; OECD, 2017).

Figure 1. The impact of technical progress on the content of work (ex-post)



Note. From Jabłoński (2025).

The fourth and currently most relevant trajectory is AI-augmented employee creativity (Davenport and Kirby, 2016; Jia et al., 2024). Unlike the preceding trajectories, which primarily concerned the substitution or upgrading of skills associated with well-codified tasks, this trajectory highlights the complementarity of AI and human creativity. AI systems surpass humans in accuracy, reliability and scalability for repetitive, codified tasks (Balasubramanian et al., 2022), but remain limited in unstructured, novel and creative domains (Wilson and Daugherty, 2018). Empirical research demonstrates this complementarity directly: AI-assisted agents were significantly more effective at resolving novel problems than unassisted colleagues, with the effect being greatest among agents with higher baseline creativity (Jia et al., 2024). Human-AI cooperation thus generates synergy precisely at the boundary of codified and non-routine tasks.

This fourth trajectory is the direct theoretical foundation for the organisational models examined in this article. The growing capacity of AI to handle codified processes reconfigures the entire structure of organisational work: it shifts the human function from execution towards analysis, oversight and creative co-creation, and changes the required competency profile at every level of the organisation. The practical realisation of AI-augmented work at organisational scale is enabled by cloud computing – an architecture providing ubiquitous, on-demand access to configurable computing resources (Mell and Grance, 2011) – and specifically by AI as a service (AIaaS), which embeds machine-learning and generative AI capabilities directly into organisational workflows, modifying human–technology relations by delegating cognitive functions to systems and introducing quasi-social agency into algorithmic processes (Szpunar, 2023; Skalik, 2024; Jabłoński, 2025).

Where the pace of AI-related change outpaces organisations' ability to adapt in real time, normative models serve as theoretical scaffolding for designing desired configurations of human–system interaction under conditions of technological uncertainty (Dahlke and Ebersberger, 2025; Beck and Jahn, 2021; Steiber and Munoz, 2025).

2. ORGANISATIONAL MODELS IN THE CONTEXT OF AI ADOPTION

The dynamic development of AI is driving an expanding body of literature seeking to systematise changes in contemporary organisations. Numerous normative organisational models have emerged – from traditional process-based and hierarchical approaches (Davenport and Kirby, 2016; Shrestha et al., 2019; Susskind and Susskind, 2015) to hybrid organisations (Raisch and Fomina, 2024), cognitive organisations (Berente et al., 2021) and those based on AI agents (Wu and Or, 2025) – all sharing the assumption of growing human–AI collaboration in task execution, process management and decision-making (Łabędzki et al., 2025; Raftopoulos and Hamari, 2023). These contributions, however, share a limitation that deserves attention. They characterise what advanced organisations look like – their governance arrangements, their decision-making architectures, the nature of human–AI interaction at the frontier – but they do not provide a procedure for establishing where a given organisation currently stands. This absence reflects a broader tendency in the AI maturity literature to prioritise aggregate, technology-centred indicators at the expense of the competency dimension of human-AI interaction. Frameworks such as that proposed by Hansen et al. (2024), which maps AI diffusion across five capability stages from awareness to strategic integration, represent a step forward in this direction, as does the systematic review by Sadiq et al. (2021), which synthesises over two dozen maturity models and demonstrates that most are constructed around dimensions of data readiness, technology infrastructure and governance, leaving the human competency side of adoption unoperationalised. Even frameworks that engage with skills – such as Deloitte's five-stage AI Maturity Framework or the PwC AI Capability Maturity Framework – are calibrated for enterprise-level benchmarking and do not offer a position-level diagnostic instrument. The typology proposed here addresses this gap directly: by anchoring model identification in observable competency profiles at the level of individual job positions, it enables both fine-grained in-house diagnosis and longitudinal tracking of transformation progress, neither of which aggregate maturity indices are designed to provide.

Research in this domain indicates a consistent developmental sequence that directly parallels the trajectory of AI-augmented creativity described in Section 1. AI initially supports humans in information gathering and processing; it then takes over selected communication functions; subsequently, it participates in decision-making; and finally – in its most advanced forms – it becomes an innovation initiator, co-creating strategies and solutions. This progressive shift of human function from execution to coordination to creative co-authorship corresponds to successive stages of AI integration. Four organisational models may therefore be distinguished: the traditional model, the AI-supported model, the AI collaboration model and the cognitive organisation model (Jabłoński, 2025, pp. 150-155). The key organisational changes, enabling conditions, shifts in human function and competency thresholds characterising each transition between successive stages are summarised in Table 1.

Table 1. Transformation trajectories and transition conditions across successive AI-integration stages

Transition stage	Key organisational change	Trigger / enabling condition	Shift in human function	Competency threshold and representative technologies
Stage 1: traditional → AI-supported	AI moves from passive data repository to active communication layer: chatbots, virtual assistants and AI-powered CRM systems are deployed to handle structured customers and inter-unit interactions	Availability of affordable cloud-based conversational AI (AIaaS); sufficient volume of repetitive communication tasks to justify automation; basic digital infrastructure in place	From sole executor of communication tasks to informed user and prompt-issuer: the employee sets queries, evaluates AI-generated responses and retains full decision authority	Competency threshold: Level 1–2 (basic digital literacy + functional prompt skills). Technologies: rule-based chatbots, AI-CRM platforms, virtual scheduling assistants, document-processing bots

Stage 2: AI-supported → AI collaboration	AI acquires analytical agency: systems transition from reactive response to proactive generation of forecasts, risk assessments and multi-scenario recommendations; human-AI decision loops are formalised	Availability of large language models with extended contextual memory and reasoning capability (show-thinking); organisational readiness to delegate analytical sub-tasks; development of AI agent oversight protocols	From user to analyst, controller and AI agent manager: the employee interprets AI-generated outputs, audits reasoning chains, manages agent pipelines and bears accountability for AI-augmented decisions	Competency threshold: Level 2–3 (applied AI management, critical thinking, process redesign). Technologies: LLM-based analytical agents, RAG-enhanced decision-support tools, predictive analytics platforms, autonomous RPA+
Stage 3: AI collaboration → cognitive organisation	AI becomes an innovation co-creator: generative systems autonomously produce novel products, strategies and organisational solutions; multi-agent architectures coordinate complex value-creation workflows without continuous human prompting	Maturity of autonomous multi-agent frameworks; institutional readiness for AI governance (accountability, auditability, ethical oversight); leadership capacity to redefine organisational purpose around human–AI collaboration	From manager to curator and meaning-maker: the employee defines strategic intent, frames ethical constraints, evaluates AI-generated options and ensures coherence of purpose within dynamic, goal-driven team structures	Competency threshold: Level 3 (strategic, systemic and ethical AI governance). Technologies: autonomous multi-agent systems (AutoGen, CrewAI, LangGraph), generative AI platforms (GPT-4o, Gemini Ultra, Claude Opus), AI governance frameworks

Note. Own elaboration.

Three observations follow from Table 1. Each transition is driven by a qualitative shift in AI autonomy rather than a quantitative increase in automated tasks: what changes is the nature of AI agency, from reactive to proactive, and to self-directed. The enabling conditions are simultaneously technological and organisational – the availability of sufficiently capable systems on the one hand, the readiness of governance structures and competency profiles on the other. And the shift in human function across the three transitions traces a coherent arc from execution through oversight to meaning-making, directly reflecting the AI-augmented creativity trajectory established in Section 1.

3. HUMAN FUNCTIONS IN WORK PROCESSES AS THE BASIS FOR IDENTIFYING ORGANISATIONAL MODELS

The identification of which of the four models a given organisation instantiates can be grounded in the analysis of the functions performed by employees and the competencies exercised in their fulfilment. This approach exemplifies the classical configurational strand of organisational research, according to which organisational types arise from the relationships between elements of structure, processes and environment (Galbraith, 1973; Mintzberg, 1983), and it finds current application in the analysis of AI-driven organisational systems (Raisch and Fomina, 2024; Raftopoulos and Hamari, 2023).

The theoretical warrant for centring identification on human functions is provided by the foundational assumptions of management science and specifically by its dualistic conception of real being. In the classical tradition, an organisation is understood as a system of consciously coordinated activities (Barnard, 1938) in which human participation – as both executor and decision-maker – is a definitional condition distinguishing an organisation from a mere aggregation of technical resources (Daft, 2016; Mintzberg, 1983). As Zieleniewski (1981, pp. 276-278) asserts unequivocally: “Things organised in which humans are not included as members, even if a human being was their organiser, lie outside the direct scope of the theory of organisation and management.” This understanding, formulated within the praxeological theory of management (Kotarbiński, 1965), retains full validity in the AI era.

In light of the dualistic conception of real being (Krzyżanowski, 1999), an organisation consists of two ontological categories: things (including people, tools, technologies, systems) and interactions (material, energetic and informational) that bind them into an organised whole. AI systems, as products of human activity, belong to the category of things; their interactions with people constitute informational interactions forming a real constituent of organisational existence. Studying the functions performed by humans and the competencies employed in their execution therefore allows direct apprehension of the interaction structure and its transformation as AI usage intensifies. Observable work practices – delegating tasks to AI, supervising agents, interpreting outputs, making decisions – serve as empirical indicators of how the arrangement of relations between “things” and “interactions” is changing.

The differences between the four models stem primarily from the scope of technology application within the structure of job-position functions: the division of roles, the sequencing of activities, the dynamics of decision-making and the channels of information flow. Adopting an employee competency perspective combines a deductive approach (typologies, normative models) with an interpretive approach (meanings attributed to actions by organisational participants), making it both theoretically justified and empirically tractable – and consistent with the two-category ontology of Krzyżanowski (1999), since it is in the competency requirements associated with job positions that the transformations of informational-decisional interactions induced by AI become most directly visible and measurable.

4. METHODOLOGY FOR IDENTIFYING ORGANISATIONAL MODELS IN THE CONTEXT OF AI DIFFUSION

Identifying employee competency levels – which serve as the basis for defining the dominant organisational model – should be closely linked to job function, as job tasks determine the scope and level of competencies necessary to effectively utilise technology in the performance of professional duties. The selection of the six competency domains was guided by a single overriding requirement: each domain had to change in a theoretically meaningful and observable way as AI autonomy increases across the four models. This criterion alone excluded a number of competency areas that, while relevant to organisational performance in general, do not discriminate between the proposed models. General leadership capability, for instance, matters in all four – from the traditional to the cognitive organisation – and therefore adds no diagnostic power. Similarly, communication competency is not excluded because it is unimportant, but because it is already captured within the AI-literacy and decision-making role dimensions; retaining it as a separate domain would introduce redundancy without improving fit.

The six domains that survived this filtering process also satisfy two further conditions. Together, they span the full range of human functions identified in Section 3 – from task execution and data processing at the operational end to systemic design and ethical governance at the strategic end – which means the matrix is anchored in the same ontological framework that motivates the typology itself. And each domain can be assessed independently through structured interview, observation or questionnaire, making the instrument usable across both research and consultancy settings without requiring sector-specific adaptation. Competencies tied to particular industries – clinical judgment in healthcare, regulatory literacy in financial services – were excluded precisely because they would undermine that generality. Building on the human-function identification logic developed in Section 3, the proposed methodology proceeds in five stages:

1) defining a set of competency domains required in individual organisational models (Table 2);

2) linking competency domains to actual job-level tasks within the assessed organisation;

3) assessing the level of individual employee competency domains on a uniform four-point scale (0 = absent, 1 = basic, 2 = applied, 3 = advanced);

4) comparing the empirical competency profiles against the normative model profiles using mean absolute error (MAE) as a goodness-of-fit measure;

5) assigning the assessed unit to the model with the lowest MAE value – i.e., the model whose normative competency profile most closely matches the empirical profile.

The framework's identification matrix (Table 2) operationalises this five-stage procedure, translating the four-model typology into a set of measurable competency indicators. Each of the six rows corresponds to a distinct human-function competency domain – grounded in the AI-augmented creativity trajectory and the substitution/complementarity logic established in Section 1 – while each column corresponds to one of the four organisational models, enabling direct comparison of empirical profiles against normative benchmarks. Mapping observed practices onto the matrix allows an organisation – or any of its sub-units – to be assigned to the appropriate model, competency gaps to be identified and development pathways to be charted.

The six domains in Table 2 were not chosen to make the matrix complete – they were chosen because each one changes in a theoretically predictable direction as AI autonomy increases. The trajectory established in Section 1 runs from codified execution toward oversight, interpretation and creative co-creation, and three domains track this shift directly: *primary task type*, *interaction with AI agents* and *required AI literacy level*. The remaining three draw on the ontological framework of Section 3: since organisations consist of things and interactions, expanding AI capability alters both the cognitive content of roles and the structures through which responsibility is assigned. *Decision-making role* and *dominant competency cluster* capture how cognitive work is redistributed as automation deepens. *Locus of responsibility* captures how accountability shifts as AI agency expands from tool to co-creator.

Table 2. Identification matrix: human functions and competency indicators across the four organisational models

Competency domain	Traditional model	AI-supported model	AI collaboration model	Cognitive organisation model
Primary task type	Execution and data entry	Content generation with AI assistance	Interpretation, oversight, coordination	Strategic design, creative co-creation
Decision-making role	Full human decision-making	Human decides, AI informs	Joint human–AI decision-making	AI proposes, human approves / curates
Dominant competency cluster	Operational (technical, procedural)	Operational + basic digital literacy	Analytical, AI-management, critical thinking	Strategic, ethical, systemic
Interaction with AI agents	None	Occasional, tool-like	Regular, oversight-based	Continuous, co-creative
Locus of responsibility	Exclusively human	Predominantly human	Distributed (human + AI)	Systemic (governance frameworks)
Required AI literacy level	None or basic awareness	Functional (prompt use, output evaluation)	Advanced (agent management, process integration)	Expert (system design, ethical governance)

Note. Own elaboration.

The normative competency profiles reflect the AI-augmented creativity trajectory established in Section 1 (Jia et al., 2024; Davenport and Kirby, 2016). The MAE for model m is defined as $MAE(m) = (1/N) \sum |e_i - p_i(m)|$, where N is the number of competency domains (six here), e_i is the observed score for domain i on the four-point scale (0–3), and $p_i(m)$ is the corresponding normative score under model m. The model with the lowest MAE is assigned as the dominant organisational type. By way of illustration: if an organisation scores [1, 1, 0, 1, 0, 0] across the six domains, its distance from the AI-Supported Model profile [1, 1, 1, 1, 0, 0] is $(0+0+1+0+0+0)/6 \approx 0.17$, and from the AI Collaboration Model profile [2, 2, 2, 2, 1, 1] is $(1+1+2+1+1+1)/6 \approx 1.17$ – the unit is classified as AI-Supported. MAE was preferred over Euclidean distance because its values remain on the same scale as the competency scores, making misfit directly interpretable; and over discriminant analysis because it does not require assumptions about distributional form that cannot be met with small organisational samples. The measure treats deviations linearly, so one poorly scoring domain does not distort the overall result – which is important when data come from self-report or structured observation rather than objective testing. The underlying assumption of equal intervals between scale points is standard in applied competency work and is consistent with the behavioural anchors used here.

The methodology can be applied at the level of the entire enterprise or any sub-unit, is compatible with survey-based and observation-based data collection, and is scalable as AI capabilities evolve.

5. DISCUSSION AND CONCLUSIONS

The theoretical and methodological framework developed in this article makes three principal contributions. First, it situates the typology of AI-driven organisational models within the long-term history of technical progress, demonstrating that the four models are not ad hoc constructs but expressions of a coherent developmental logic rooted in the substitution/complementarity dynamics of technological change. Second, it provides an explicit ontological foundation for the human-function approach to organisational identification, drawing on the classical dualistic tradition of Polish management science (Krzyżanowski, 1999; Zieleniewski, 1981; Kotarbiński, 1965) to establish that human functions are not merely one possible identification criterion but a definitionally privileged one. Third, it operationalises these theoretical insights in a concrete diagnostic instrument – the identification matrix and MAE-based assignment procedure – that is immediately applicable in both research and management practice.

Existing AI maturity frameworks – including the AI capability maturity model of Hansen et al. (2024), Deloitte's five-stage AI Maturity Framework and the PwC AI Capability Maturity Framework – are designed for strategic benchmarking: they assign a single maturity stage based on aggregate indicators such as infrastructure investment, data governance and leadership commitment to AI. This is useful for comparing organisations over time, but it produces no information about variation within an organisation – about which functions are genuinely transformed and which are not. The present framework asks a different question, at a different level of analysis: which model of human-AI work organisation is dominant in this unit, and how far is it from adjacent models? An organisation that has invested heavily in AI infrastructure but whose workforce profiles remain at the traditional stage will score accordingly – a disaggregation that aggregate indices cannot provide. The two approaches are complementary: maturity frameworks for strategic positioning, the present one for operational diagnosis.

The proposed methodology has certain limitations that must be acknowledged. It relies primarily on the assessment of competencies and work practices, which introduces observer bias unless structured observation protocols or validated questionnaires are employed. The boundaries between models are not sharp discontinuities but gradual continua; organisations routinely exhibit mixed profiles across sub-units. Furthermore, the rapid pace of AI development means that the competency profiles associated with each model may require periodic revision as new AI capabilities emerge. A second limitation relates to the model's universality. The four-stage sequence is presented as a normative typology, but organisations do not always move through it in orderly progression. Heavily regulated sectors – healthcare, financial services, critical infrastructure – operate under institutional constraints that may slow or cap AI autonomy expansion regardless of how competent their workforce actually is; the EU AI Act alone introduces compliance obligations that cut across all four model stages in ways the typology does not currently address. Smaller organisations, or those in regions with limited digital infrastructure, may find that the enabling conditions listed in Table 1 are simply unavailable to them, not temporarily but structurally. Cultural factors matter too: where trust in algorithmic outputs is low, or where privacy norms restrict data collection, AI adoption will lag behind what competency profiles alone would predict. None of this invalidates the framework, but it does mean that MAE-based assignments should be read as diagnostic starting points rather than definitive classifications – and that sector, size and cultural context belong in the interpretation alongside the scores themselves.

Three directions for further research appear particularly promising. First, empirical validation of the identification matrix across diverse industries is needed to confirm its discriminant validity and refine the competency indicators. Second, longitudinal studies tracking transitions between models would illuminate the organisational conditions – leadership, culture, institutional inertia – that facilitate or impede AI-driven transformation. Third, integrating the framework with quantitative measures of AI adoption intensity could yield a composite index of organisational AI maturity.

The four-model typology and the identification methodology proposed in this article offer a theoretically grounded and practically applicable framework for diagnosing work organisations in the age of artificial intelligence. By anchoring identification in human competency and function – and situating the typology within the long trajectory of technical progress – the framework treats the advance of AI as an organisational and human phenomenon, not merely a technological one.

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TRANSFORMACJA ORGANIZACYJNA OPARTA NA SZTUCZNEJ INTELIGENCJI: TYPOLOGIA BAZUJĄCA NA TRAJEKTORIACH PRZEJŚCIA I RAMY IDENTYFIKACJI KOMPETENCJI

Streszczenie

Szybkie rozprzestrzenianie się sztucznej inteligencji (AI) we współczesnych organizacjach głęboko ingeruje w struktury pracy, procesy decyzyjne i role pracowników. Niniejszy artykuł przedstawia teoretyczno-metodologiczne ramy identyfikacji i klasyfikacji modeli organizacyjnych w kontekście AI obecnej w procesach pracy. Studium omawia długofalowy postęp techniczny, a konkretnie przejście od przemian, które bazują na umiejętnościach pracowników, do ich działań kreatywnych, które są wspomagane przez sztuczną inteligencję. Zaproponowano cztery modele, tj. tradycyjny, wspierany przez AI, współpracujący z AI oraz organizacji kognitywnej, które różnią się stopniem autonomii AI, zakresem automatyzacji i wymaganymi profilami kompetencji pracowników. Autor przedstawia macierz identyfikacji obejmującą sześć domen kompetencji, ocenianych względem normatywnych profili modeli za pomocą średniego błędu bezwzględnego (*mean absolute error*) jako miary dopasowania. Na koniec artykuł identyfikuje trzy kierunki dalszych badań w zakresie efektywności hybrydowych zespołów ludzko-AI, zmiany roli uwarunkowań instytucjonalnych przy implementacji AI oraz opracowania złożonych wskaźników dojrzałości organizacyjnej w zakresie AI.

Słowa kluczowe: sztuczna inteligencja; modele organizacyjne; kompetencje pracowników; rozprzestrzenianie AI; funkcje ludzkie; ramy diagnostyczne