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A Competency Model of the "Augmented Manager": Requirements for Managers in Hybrid Human-AI Teams

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Abstract. The rapid diffusion of generative artificial intelligence (AI) into managerial work has reshaped the competency requirements imposed on managers across functions and industries. Surveys conducted between 2023 and 2025 show that the share of organisations using AI in at least one function rose from 55% to 88%, and 53% of C-level executives now report regular use of generative AI. In advanced economies, around 60% of jobs are exposed to AI, with high-skill knowledge-intensive occupations showing the highest exposure. These shifts indicate that traditional management competency models, formulated in the era of pre-AI work, no longer capture the full skill profile required of a manager who operates inside hybrid human-AI teams. The purpose of the article is to develop a structured competency model of the "augmented manager" that synthesises classical management competency theory with contemporary research on AI literacy, human-AI collaboration, and the empirical evidence of AI's effect on knowledge work. Methods. The study applies a systematic approach grounded in content analysis of established competency frameworks (McClelland; Boyatzis; DigComp 2.2; OECD AI and the Future of Skills), comparative analysis of empirical productivity studies, and conceptual modelling. The information base comprises 27 verified sources, including peer-reviewed journal articles, working papers of international organisations (IMF, OECD, World Economic Forum), and consulting research (McKinsey, BCG, Accenture). Results. The article proposes a four-cluster competency model encompassing cognitive-analytical, digital-technological, ethical-regulatory and human-relational dimensions, mapped against measurable performance outcomes in hybrid teams. Empirical evidence confirms that AI-augmented work produces productivity gains of 12-40%, with the largest gains accruing to lower-skilled workers, which has direct implications for managerial decisions on team composition and training. Conclusions. The augmented manager is conceptualised not as a replacement for traditional managerial roles, but as their extension into a context where competence in selecting, evaluating, governing and combining AI outputs with human judgement becomes the central performance variable. Directions for further empirical validation of the proposed model are outlined.

Keywords: augmented manager, managerial competencies, human-AI collaboration, hybrid teams, competency model, management upskilling.

АКТУАЛЬНІ ПИТАННЯ ЕКОНОМІЧНИХ НАУК

Компетентнісна модель «аугментованого менеджера»: вимоги до управлінців у гібридних людино-ШІ командах

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Анотація. Швидке поширення генеративного штучного інтелекту (ШІ) в управлінській діяльності трансформує вимоги до компетенцій менеджерів. Опитування 2023-2025 рр. показують, що частка організацій, які використовують ШІ хоча б в одній функції, зросла з 55% до 88%, а 53% керівників вищої ланки регулярно застосовують генеративний ШІ. У країнах з розвиненою економікою близько 60% робочих місць перебувають під впливом ШІ, найвища експозиція - у висококваліфікованих знаннєвомістких професіях. Ці зрушення вказують на те, що традиційні компетентнісні моделі менеджменту, сформовані в епоху до-ШІ роботи, більше не охоплюють повний профіль навичок, необхідних для управлінця в гібридних людино-ШІ командах. Метою статті є розробка структурованої компетентнісної моделі «аугментованого менеджера», що поєднує класичну теорію управлінських компетенцій із сучасними дослідженнями ШІ-грамотності, людино-машинної взаємодії та емпіричними даними про вплив ШІ на знаннєву працю. Методи. Застосовано системний підхід, контент-аналіз усталених компетентнісних рамок (МакКлелланд; Бояціс; DigComp

2.2; OECD AI and the Future of Skills), порівняльний аналіз емпіричних досліджень продуктивності та концептуальне моделювання. Інформаційну базу становлять 28 верифікованих джерел, включаючи статті в рецензованих журналах, документи МВФ, ОЕСР, ВЕФ та консалтингові дослідження (McKinsey, BCG, Accenture). Результати. Запропоновано чотирикластерну компетентнісну модель, що охоплює когнітивно-аналітичний, цифрово-технологічний, етико-регуляторний та людино-реляційний виміри і співвіднесена з показниками результативності в гібридних командах. Емпіричні дані підтверджують приріст продуктивності на рівні 12-40% від ШІ-аугментації, з найбільшими ефектами у менш кваліфікованих працівників. Висновки. Аугментований менеджер концептуалізується не як заміна традиційних управлінських ролей, а як їх розширення в контекст, де компетентність у відборі, оцінюванні, регулюванні та поєднанні ШІ-виходів із людським судженням стає центральною змінною результативності.

Ключові слова: аугментований менеджер, управлінські компетенції, людино-ШІ співпраця, гібридні команди, компетентнісна модель, апскілінг менеджерів,.

Problem statement. The contemporary managerial environment is being reshaped by the rapid integration of generative AI into routine and strategic work. Between 2023 and 2025 the proportion of organisations using AI in at least one business function grew from 55% to 88%, while regular use of generative AI by C-suite executives reached 53% by early 2025 [3; 4; 5]. The World Economic Forum projects that 39% of workers' core skills will change by 2030, and analytical thinking together with AI and big data competencies are identified as the top skills on the rise, with 86% of employers expecting AI and information processing technologies to transform their business by 2030 [1]. The International Monetary Fund estimates that almost 40% of global employment and around 60% of jobs in advanced economies are exposed to AI, with high-skill cognitive occupations - including management - showing the highest exposure [6]. These quantitative shifts indicate that managerial work is no longer the same activity it was a decade ago: the same job title increasingly implies a different daily reality where a portion of cognitive tasks is delegated to or co-performed with intelligent systems.

At the same time, the empirical record on productivity gains from AI assistance is sufficiently developed to require its translation into management theory. Field experiments report a 14-15% increase in resolved chats per hour among customer support agents using generative AI [8], a 12.2% increase in completed tasks and a 25.1% acceleration of work among consultants operating inside the AI capability frontier [9], and time savings of around 40% with a quality improvement of 18% on writing tasks [10]. These gains are not uniform: in customer support and consulting they accrue disproportionately to less experienced workers, indicating that AI assistance levels the performance distribution rather than amplifying existing skill premia [8; 9]. The managerial implications of this empirical pattern - in particular for hiring, training and team composition decisions - have not yet been systematised in a coherent competency model.

The unresolved scientific and practical problem lies in the absence of an integrated competency framework that connects (i) traditional management competency theory developed by McClelland and Boyatzis [2; 7], (ii) the augmented-intelligence and human-machine collaboration perspective developed in consulting and applied research [13; 20], (iii) AI literacy frameworks formulated in education and information science [17; 18], and (iv) institutional digital and AI skill rubrics introduced at the European level through DigComp 2.2 and through OECD's AI and the Future of Skills programme [14; 23]. Without such integration, organisations face uncertainty about which competencies to develop in current managers, which to hire for, and how to design training that prepares managers for hybrid human-AI work rather than for pre-AI managerial routines.

The connection of the study to important scientific and practical tasks lies in the need to formulate a verified, structured competency model that can serve as a basis for upskilling programmes, performance evaluation criteria, and educational curricula in management. The relevance of the topic for Ukraine is additionally underscored by the post-war restoration agenda, in which digital transformation of management functions is recognised as a driver of industrial recovery [25; 28].

Analysis of recent research and publications. The theoretical roots of the competency approach in management trace back to the work of McClelland [2], who argued for testing competence rather than intelligence as a predictor of professional performance. Boyatzis [7] formalised this insight into the first comprehensive competency model of the effective manager, identifying behavioural characteristics that differentiate high performers from average ones. These foundational works established the methodological convention - still dominant today - that managerial effectiveness is best understood as a configuration of observable behavioural competencies anchored in underlying motives, traits, skills and self-image.

The contemporary translation of competency theory into the era of AI was anticipated by Daugherty and Wilson [13], who introduced the concept of the "missing middle" of human-AI collaboration and proposed the MELDS framework (Mindset, Experimentation, Leadership, Data, Skills) for organisations seeking to combine human and machine capabilities. Davenport and

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Mittal [20] extended this perspective to the executive level, describing the management practices of "AI-fueled organisations" and the strategic posture required of leaders who treat AI as core infrastructure rather than as an experimental technology. Together these works define the conceptual space in which the augmented manager operates: not as an automation specialist, and not as a passive user of AI tools, but as an active orchestrator of human and machine work.

The empirical foundation for the augmented-manager perspective has been built since 2023 by a series of rigorous experimental studies. Brynjolfsson, Li and Raymond [8], in a study of 5,179 customer support agents, found that access to a generative AI conversational assistant produced a 15% increase in issues resolved per hour, with a 34% improvement for novice and low-skilled workers and very small effects for the most experienced agents. Dell'Acqua and colleagues [9] conducted a pre-registered field experiment with 758 consultants at Boston Consulting Group, demonstrating a 12.2% increase in successful task completion, a 25.1% acceleration of work and roughly 40% higher output quality on tasks lying inside the AI capability frontier. Crucially, the same study showed that on tasks outside this frontier, AI use degraded performance - a finding that the authors capture in the metaphor of the "jagged technological frontier". Noy and Zhang [10], working with 453 professionals on mid-level writing tasks, observed a 40% reduction in time taken and an 18% improvement in output quality with ChatGPT assistance. Peng and colleagues [21] reported a 55.8% acceleration of coding task completion among developers using GitHub Copilot. The common signal across these studies is that AI assistance is most valuable when integrated with deliberate management of task-AI fit - which is itself a managerial competency.

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The conceptualisation of AI literacy as a distinct competency cluster has been advanced primarily by Long and Magerko [17], whose work on the design of AI literacy education identified seventeen interrelated competencies, and by Ng and colleagues [18], who synthesised the field into a four-dimensional model covering knowing and understanding AI, using and applying AI, evaluating and creating AI, and AI ethics. At the institutional level, the European Commission's Joint Research Centre has elaborated the Digital Competence Framework for Citizens (DigComp 2.2) with extensive examples concerning AI, the Internet of Things and data [14]. The OECD's two-volume programme "AI and the Future of Skills" [23; 24] develops a methodology for assessing AI capabilities against established educational and occupational skill taxonomies, providing the most extensive cross-jurisdictional reference base for skill comparisons in the AI era. Eloundou and colleagues [12] complement this institutional work by quantifying labour market exposure: approximately 80% of the United States workforce could have at least 10% of their work tasks affected by large language models, and 19% of workers could see at least 50% of their tasks impacted. Felten, Raj and Seamans [11] provide the AI Occupational Exposure dataset, which makes managerial occupations visible as a category with high exposure to AI relative to many other occupational groups.

Ukrainian-language research has approached the topic from the broader perspective of digital transformation of management. Sedikova and Sedikov [26] examine new management paradigms in the digital economy and frame the shift from classical to cognitive management. Holovachko, Korolovych and Havrylets [27] document contemporary transformations of accounting, management and marketing under digitalisation. Zabranskyi [28] addresses the transition to enterprise development models based on big data and AI, with implications for strategic management. Trubnikov [25] positions digital transformation of management as a driver of post-war reconstruction of Ukrainian industrial enterprises. Kharchenko, Tkachenko and Mandziuk [15] examine digital platforms as instruments for improving management efficiency. Hrosheleva and colleagues [16] address the cross-cultural dimension of communicative management. These works provide the national context for the study but do not yet operate with the concept of the augmented manager as such; the term itself remains predominantly an English-language construct, and one of the objectives of the present article is to introduce it systematically into the Ukrainian-language management discourse.

Identification of previously unresolved parts of the general problem. Despite the depth of the literature in each of its constituent strands - classical competency theory, augmented-intelligence research, AI literacy frameworks and empirical productivity studies - the integration of these strands into a single competency model of the augmented manager has not been accomplished. Existing competency frameworks for managers are either generalist and developed before the diffusion of generative AI [2; 7], or are technology-oriented and aimed at citizens or learners rather than at managers specifically [14; 17; 18]. The empirical productivity studies report robust effects but stop short of translating them into a managerial competency profile [8; 9; 10]. Consulting frameworks such as Daugherty and Wilson's MELDS [13] capture the organisational level but do not specify the behavioural-competency level required of individual managers. The present article addresses this gap.

Formulation of the article objectives (task statement). The purpose of the article is to develop a competency model of the augmented manager that integrates traditional managerial competency theory with contemporary research on AI literacy, human-AI collaboration and the empirical effects of AI on knowledge work, and to substantiate its applicability to the design of upskilling programmes for managers in hybrid human-AI teams.

To achieve this purpose the following research tasks are formulated:

- to characterise the augmented manager as a concept and to identify its differentiating features relative to the traditional manager and to fully automated decision-making;
- to compare key competency frameworks and to identify the set of competencies that determine managerial effectiveness in hybrid human-AI teams;
- to develop a structured four-cluster competency model of the augmented manager and to map its clusters onto measurable performance outcomes;
- to substantiate practical recommendations for the development of augmented-manager competencies in organisational training and educational programmes.

Research methodology. The study is positioned as a theoretical-analytical inquiry without primary empirical data collection. The research design combines four methods. First, the systematic approach is used to treat managerial competencies as a structured set of interrelated elements rather than as a list of isolated skills. Second, content analysis is applied to four established competency frameworks - Boyatzis's competent manager model [7], DigComp 2.2 [14], OECD AI and the Future of Skills [23; 24] and the AI literacy frameworks of Long and Magerko [17] and Ng and colleagues [18] - in order to identify common competency descriptors and to consolidate them across taxonomies. Third, comparative analysis is applied to empirical productivity studies [8; 9; 10; 21] in order to extract the managerial implications of their findings. Fourth, conceptual modelling is used to integrate the results into a four-cluster competency model with mapped performance outcomes.

The information base consists of 27 verified sources covering 2018-2026, with priority given to publications of 2023-2026 in light of the rapid evolution of generative AI. The base includes peer-reviewed journal articles (including Q1 publications such as Brynjolfsson et al. in the Quarterly Journal of Economics [8] and Noy and Zhang in Science [10]), working papers of international organisations (IMF Staff Discussion Note [6]; OECD reports [23; 24]; WEF Future of Jobs Report [1]), consulting research grounded in survey methodology (McKinsey State of AI reports [3; 4; 5]; BCG research [19]), the foundational monograph on human-machine work by Daugherty and Wilson [13], and Ukrainian-language peer-reviewed articles in category B journals [15; 16; 25; 26; 27; 28]. The selection criterion was the presence of a working DOI or stable institutional URL and adherence to scientific (rather than promotional or journalistic) genre.

The principal limitation of the design is the absence of primary survey or experimental data from managers in hybrid teams. The proposed model is therefore presented as a theoretically substantiated framework that requires further empirical validation through expert surveys, longitudinal observational studies or controlled experiments. The Ukrainian-language source base is also necessarily limited: the construct of the augmented manager is at the moment of writing predominantly anchored in English-language scholarship, and this article contributes to its introduction into the Ukrainian discourse.

Presentation of the main material of the study. The augmented manager is defined here as a manager whose decision-making, communication, analytical and coordination work is systematically extended by intelligent systems - in particular, by generative AI, predictive analytics and decision-support tools - while retaining ultimate accountability for managerial outcomes. The augmented manager is distinct both from the traditional pre-AI manager, whose competencies were developed within a workflow in which machines played a supporting and largely deterministic role, and from a hypothetical fully automated decision-making system in which managerial accountability dissolves. The term "augmented intelligence" was popularised by Daugherty and Wilson [13] as the deliberate alternative to the substitution narrative of "artificial intelligence": the goal is the joint output of human and machine, not the replacement of one by the other.

Scale of the shift in managerial work.

Quantitative evidence on the scale of AI integration into management is provided by McKinsey's annual State of AI surveys. The early-2024 wave reported that 72% of organisations used AI in at least one function and that 65% used generative AI regularly - roughly double the share observed less than a year earlier [3]. The March 2025 wave found 78% organisational AI use and 71% regular generative AI use, with 53% of C-suite executives reporting personal regular use of generative AI versus 44% of mid-level managers [4]. The most recent State of AI survey, conducted in the third quarter of 2025, reports that 88% of organisations use AI in at least one function and that 62% are now experimenting with AI agents [5]. Figure 1 summarises this trajectory; the dashed bar for Q3 2025 generative AI usage is shown as the author's estimate, as the corresponding share was not directly reported in the most recent survey.

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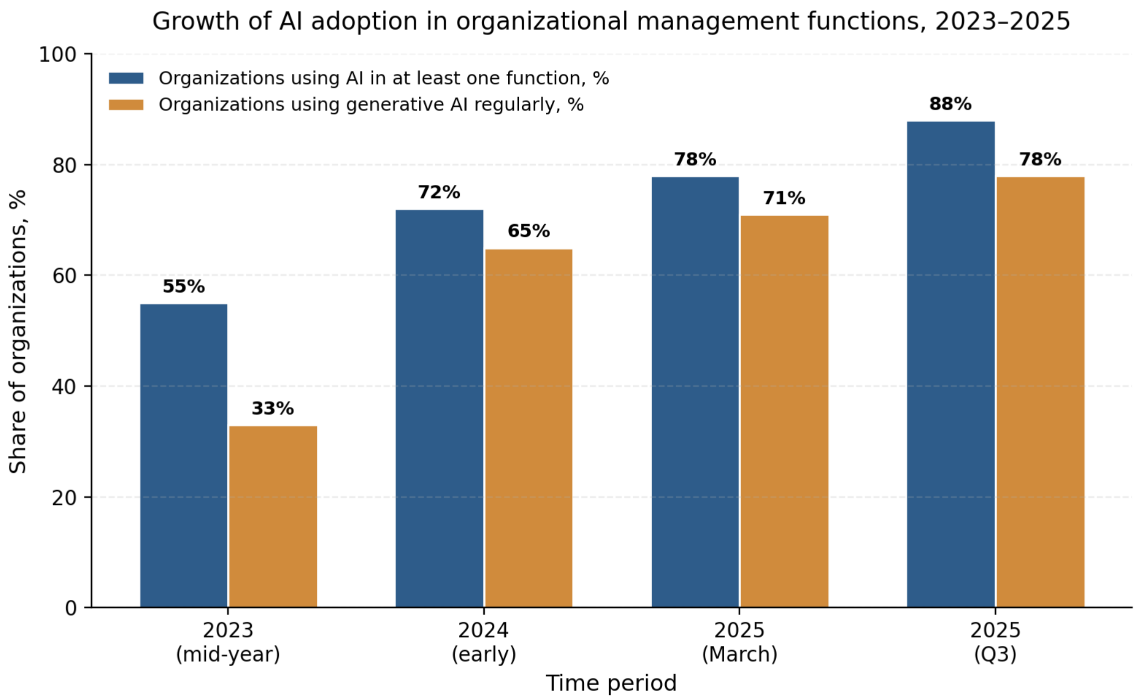

Fig. 1. Growth of AI adoption in organisational management functions, 2023-2025

Source: compiled by the author based on McKinsey Global Survey on AI [3; 4; 5].

The trajectory shown in Figure 1 has two implications for managerial competencies. First, the diffusion is fast enough that competencies presumed adequate two years ago are increasingly insufficient; this puts a premium on the manager's capacity for continuous learning. Second, the gap between executive-level adoption (53%) and mid-level adoption (44%) reported by McKinsey [4] indicates that augmented-manager competencies are still distributed unevenly within the management hierarchy, which is a strategic risk for organisations that depend on coherent decision-making across levels.

The exposure of managerial occupations to AI is further confirmed by macro-level studies. The IMF estimates that approximately 60% of jobs in advanced economies are exposed to AI, with high-skill cognitive occupations - including managerial functions - showing the highest exposure [6]. Eloundou and colleagues [12] estimate that around 80% of the United States workforce could

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have at least 10% of their tasks affected by large language models, with 19% of workers facing impact on at least 50% of their tasks. Felten, Raj and Seamans [11] place several managerial occupational categories among the most AI-exposed jobs in their AI Occupational Exposure index. Figure 2 visualises these exposure levels.

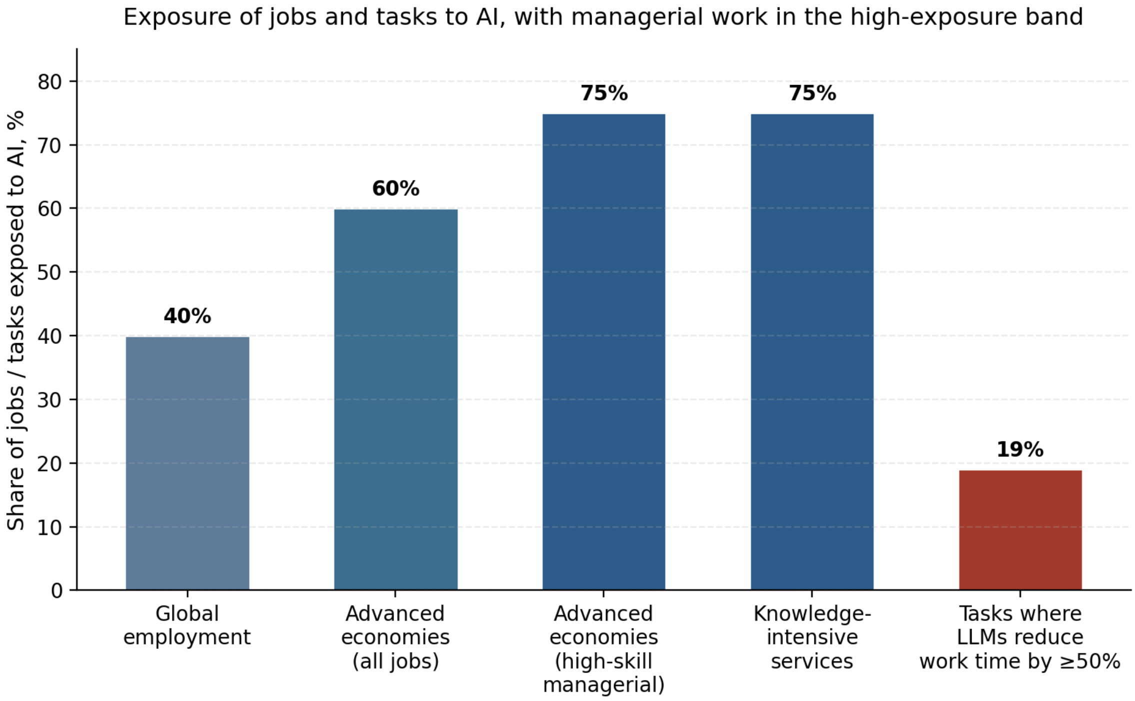

Fig. 2. Exposure of jobs and tasks to AI, with managerial work in the high-exposure band

Source: compiled by the author based on IMF [6] and Eloundou et al. [12].

Empirical productivity effects of AI in knowledge work.

Translating exposure into productivity requires a different evidence base. A series of pre-registered field experiments conducted in 2023 produced converging quantitative estimates of the productivity gains attainable when knowledge workers are paired with generative AI. Brynjolfsson, Li and Raymond [8] worked with 5,179 customer support agents at a large software company and measured a 15% increase in issues resolved per hour among agents with access to a generative

AI assistant. Dell'Acqua and colleagues [9] paired 758 BCG consultants with GPT-4 on a battery of consulting-style tasks and observed a 12.2% increase in successful task completion and a 25.1% acceleration of work on tasks inside the AI capability frontier, with quality scores 40% higher for the assisted group. Noy and Zhang [10] worked with 453 college-educated professionals on mid-level writing tasks and reported a 40% reduction in time taken with an 18% increase in output quality among ChatGPT users. Peng and colleagues [21] documented a 55.8% acceleration of coding task completion by developers using GitHub Copilot. Figure 3 summarises these results.

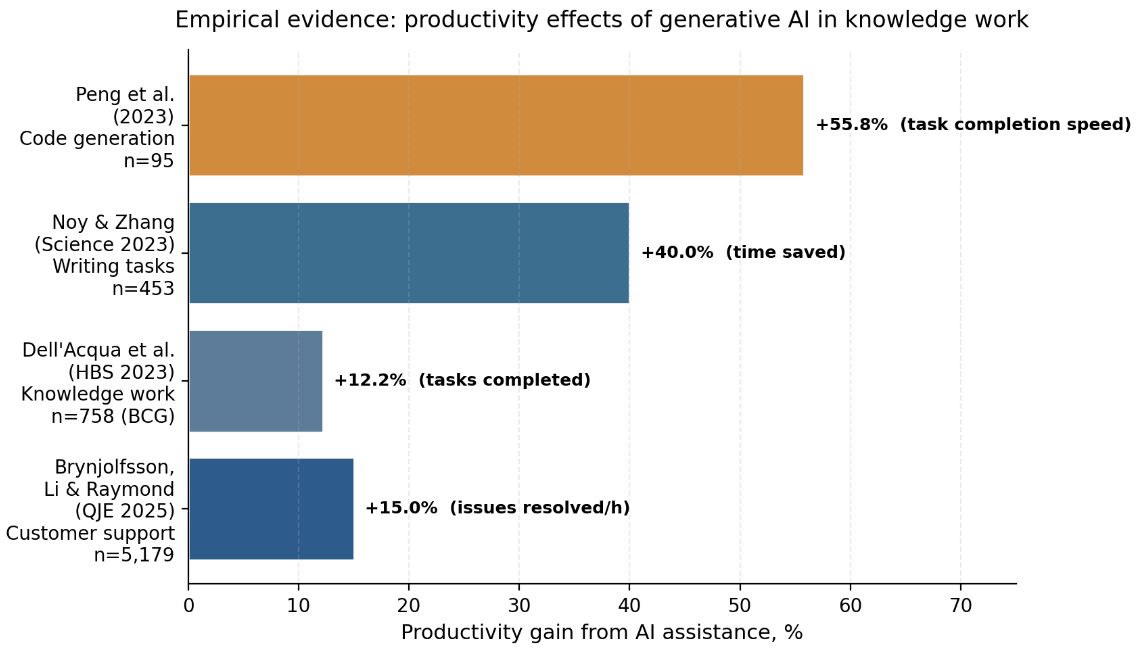

Fig. 3. Empirical evidence on productivity effects of generative AI in knowledge work

Source: compiled by the author based on [8; 9; 10; 21].

Two findings from this literature are of particular consequence for managerial competencies. The first is the distributional pattern of gains. Brynjolfsson, Li and Raymond [8] report a 34% improvement for novice and low-skilled workers and a near-zero effect for the most experienced agents (Figure 4). Noy and Zhang [10] observe a compression of the productivity distribution.

Dell'Acqua et al. [9] report that lower-performing consultants improved disproportionately. The managerial implication is direct: AI assistance functions as a skill-levelling technology that lifts the performance floor more than the ceiling. This reshapes team-composition, training-investment and compensation decisions, and creates a new managerial responsibility - that of deciding when, and for which team members, AI augmentation is the appropriate intervention.

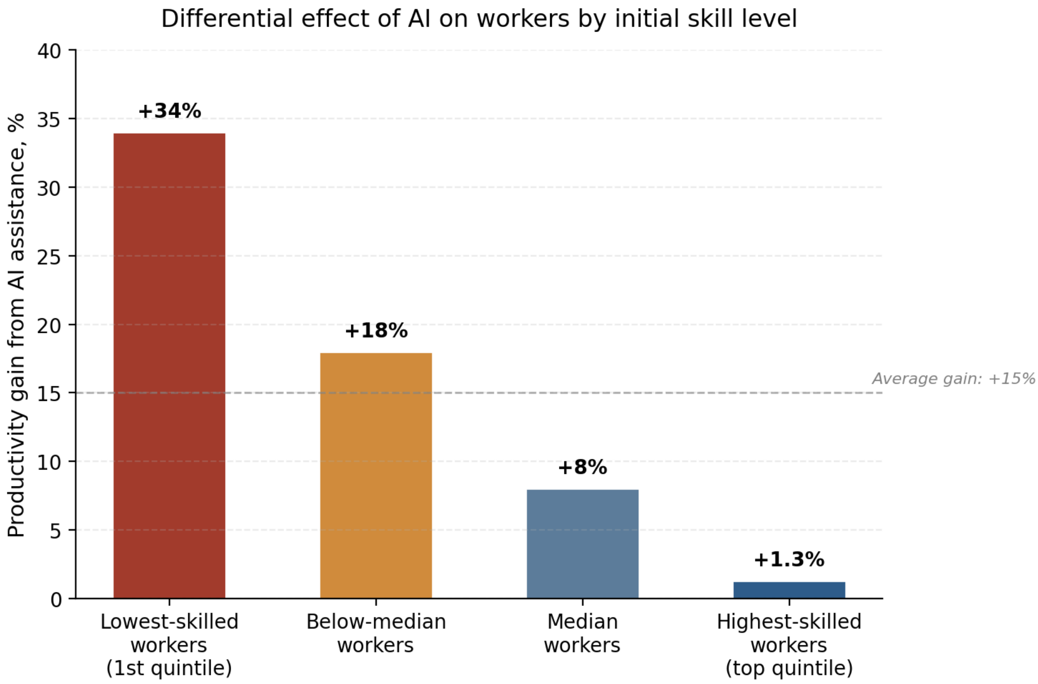

Fig. 4. Differential effect of AI on workers by initial skill level

Source: compiled by the author based on Brynjolfsson, Li, & Raymond [8].

The second consequential finding is the existence of the jagged technological frontier - the irregular boundary between tasks where AI improves human performance and tasks where it degrades it. Dell'Acqua and colleagues [9] demonstrate that consultants using GPT-4 on tasks outside the frontier produced worse outcomes than the control group. This finding makes it impossible to treat AI use as uniformly beneficial: the manager's discriminatory judgement about task-AI fit becomes a critical competency. Two interaction styles emerged in the same study - "centaur" use, where the human and the AI divide work along a strategic boundary, and "cyborg" use, where the two are intertwined within a single task - and both required deliberate managerial reflection about division of labour with the AI [9]. These findings provide the empirical foundation for the cognitive-analytical cluster of the proposed competency model.

Shifting skill priorities in the labour market.

The reordering of skill priorities is documented at scale by the World Economic Forum's Future of Jobs Report 2025, which surveyed over a thousand global employers covering more than 14 million workers. The report identifies AI and big data as the top skill on the rise, followed by networks and cybersecurity and technological literacy. At the same time, analytical thinking, resilience and flexibility, leadership and social influence, and creative thinking are ranked as the top core skills for the 2025-2030 horizon [1]. Figure 5 visualises the relative importance of skills as reported by employers.

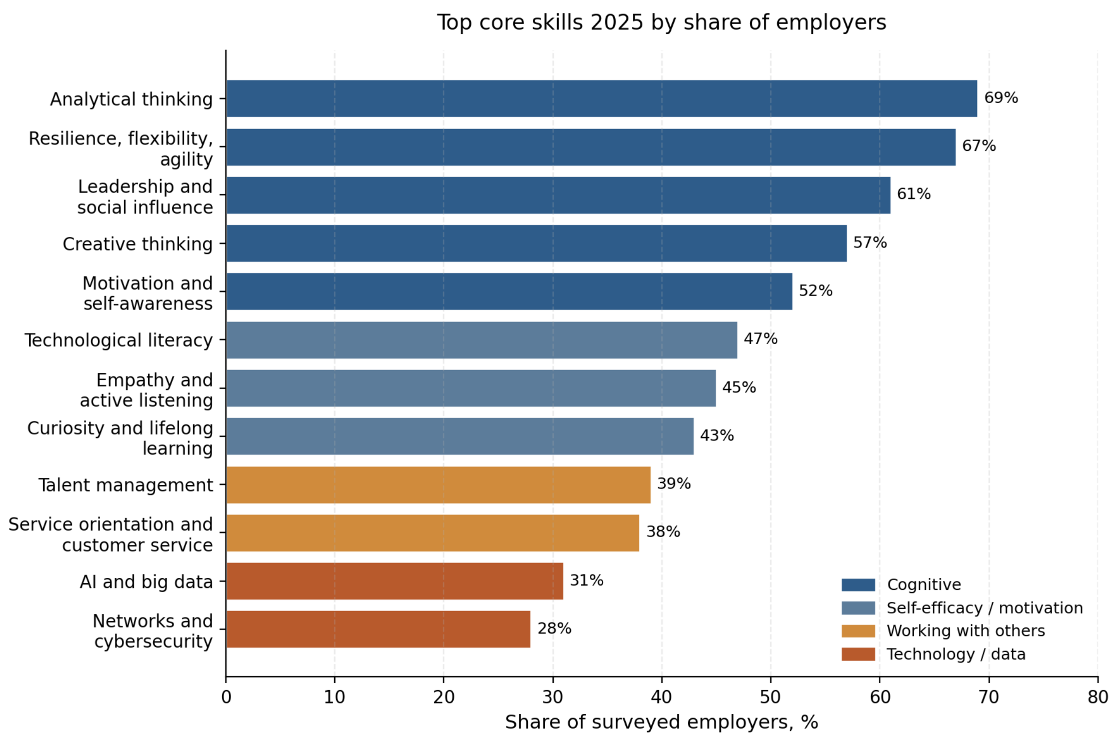

Fig. 5. Top core skills 2025 by share of employers

Source: compiled by the author based on the World Economic Forum, Future of Jobs Report 2025 [1].

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The pattern in Figure 5 is significant for two reasons. First, the highest-ranked skills are cognitive (analytical thinking) and human-relational (leadership, social influence, empathy, motivation) rather than purely technological. Second, AI and big data competence is rising rapidly in priority without displacing these foundational human skills. The augmented manager profile must therefore combine, rather than choose between, technological and human-relational competencies.

A four-cluster competency model of the augmented manager.

Synthesising the foregoing analysis with classical competency theory [2; 7], the augmented-intelligence framework [13; 20], AI literacy taxonomies [17; 18], and the institutional skill rubrics of DigComp 2.2 [14] and OECD AI and the Future of Skills [23; 24], the present article proposes a four-cluster competency model of the augmented manager (Figure 6).

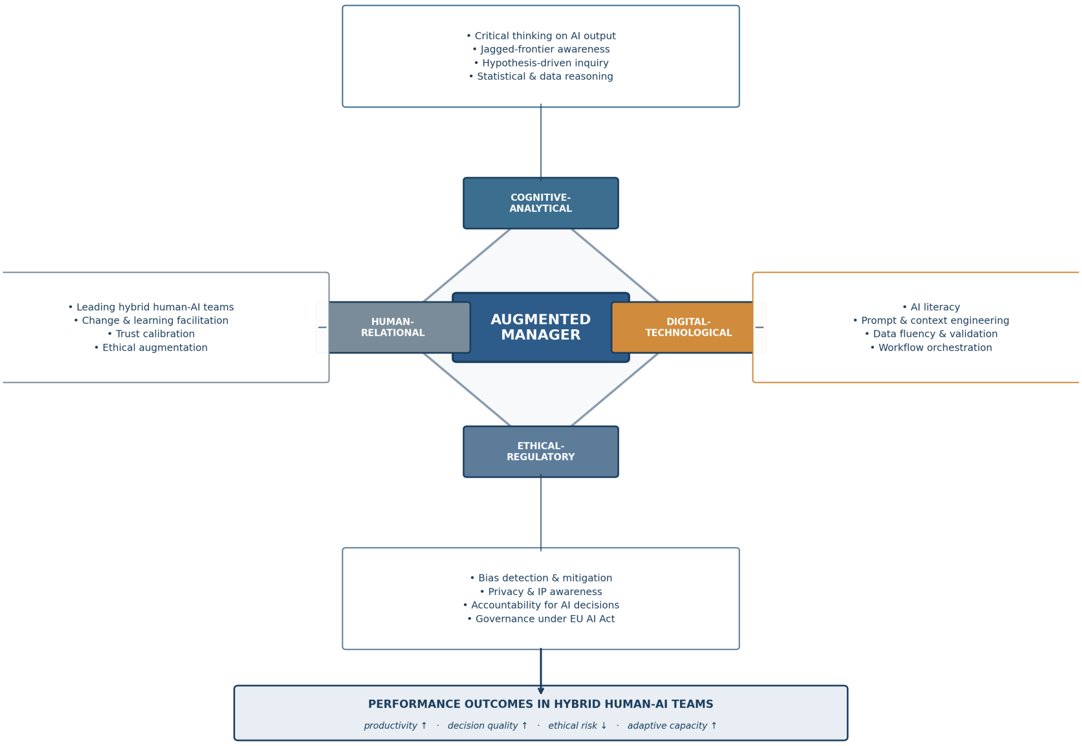

Fig. 6. Four-cluster competency model of the augmented manager

Source: author's own development based on the synthesis of [2; 7; 13; 14; 17; 18; 20; 23; 24].

Table 1 specifies the four clusters by listing their constituent competencies, the empirical or theoretical basis on which each competency rests, and the corresponding behavioural manifestations that distinguish an augmented manager from a traditional manager.

Table 1

Four-cluster competency model of the augmented manager

Cluster	Constituent competencies	Behavioural manifestation	Theoretical / empirical basis
Cognitive-analytical	Critical thinking on AI output; jagged-frontier awareness; hypothesis-driven inquiry; statistical and data reasoning	Verifies AI outputs against independent evidence; identifies tasks where AI use is contraindicated; designs prompts as testable hypotheses	[2; 7; 9; 23]
Digital-technological	AI literacy; prompt and context engineering; data fluency and validation; workflow orchestration of AI tools	Selects appropriate AI tools for tasks; structures prompts and context; validates training-data assumptions; integrates AI into team workflows	[14; 17; 18]
Ethical-regulatory	Bias detection and mitigation; privacy and IP awareness; accountability for AI-assisted decisions; governance under the EU AI Act and equivalent frameworks	Anticipates fairness, bias and IP risks; documents the basis for AI-assisted decisions; complies with applicable AI governance regimes	[13; 14; 23; 24]
Human-relational	Leading hybrid human-AI teams; change and learning facilitation; trust calibration; ethical augmentation rather than replacement	Communicates AI use transparently with team and stakeholders; coaches team members on AI augmentation; calibrates trust between team members and AI tools	[1; 7; 13; 20]

Source: author's own development based on [1; 2; 7; 9; 13; 14; 17; 18; 20; 23; 24].

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The cognitive-analytical cluster operationalises the boundary condition identified in the jagged-frontier literature [9]: managers cannot delegate task-AI fit to the AI itself. The competency that distinguishes the augmented manager here is the disciplined practice of treating an AI output as a hypothesis to be tested, not as a conclusion to be acted upon. This recovers the McClelland-Boyatzis tradition of behavioural competency assessment [2; 7] and applies it to the new condition in which the manager's source of input includes a stochastic generative system.

The digital-technological cluster operationalises the AI literacy frameworks of Long and Magerko [17] and Ng and colleagues [18] and the DigComp 2.2 specification of competencies concerning AI, IoT and data [14]. In the model proposed here, prompt and context engineering is treated as a specific subcompetency that distinguishes managers who can extract value from AI tools from those who cannot, and workflow orchestration captures the managerial dimension that is absent from generic AI literacy: not only using AI, but designing how a team uses AI.

The ethical-regulatory cluster is grounded in the OECD AI and the Future of Skills work [23; 24], in the EU AI Act regulatory regime (which DigComp 2.2 partially reflects [14]), and in the responsibility framework set out by Daugherty and Wilson [13]. It captures both the prudential dimension - anticipating risk - and the accountability dimension, in which managers remain answerable for AI-assisted decisions and must document the basis for them.

The human-relational cluster is the dimension most continuous with classical management competency theory. The augmented manager retains the leadership, social influence, communication and learning-facilitation competencies that have always defined effective managers [7]. Two modifications are introduced. First, leadership of hybrid teams adds a dimension absent from the classical model: explaining to team members why and how AI is being used, and what the boundaries of its use are. Second, trust calibration becomes a managerial competency in its own right - both calibrating one's own trust in AI systems and calibrating the team's trust in their AI-augmented colleagues.

Mapping the model onto performance outcomes.

The empirical literature reviewed above permits a tentative mapping of the four clusters onto measurable performance outcomes in hybrid teams. Productivity gains - the dimension most directly documented by Brynjolfsson, Li and Raymond [8], Dell'Acqua and colleagues [9], and Noy and Zhang [10] - are most strongly conditioned on the digital-technological cluster (whether the manager and team know how to use the tool) and on the cognitive-analytical cluster (whether they apply the tool to tasks where it improves rather than degrades performance). Decision quality is most strongly conditioned on the cognitive-analytical cluster, given that the jagged-frontier mechanism operates through differential reliability of AI outputs across tasks [9]. Ethical-regulatory risk - exposure to bias, privacy violations, IP infringement and compliance breaches - is conditioned by the ethical-regulatory cluster. Adaptive capacity, defined as the team's ability to absorb the rapid evolution of AI capabilities, is most strongly conditioned by the human-relational cluster, since adaptation requires sustained team-level learning. Table 2 summarises this mapping.

Table 2

Mapping of competency clusters onto performance outcomes in hybrid human-AI teams

Competency cluster	Productivity gains	Decision quality	Ethical-regulatory risk	Adaptive capacity
Cognitive-analytical	High influence	Decisive influence	Moderate influence	Moderate influence

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Competency cluster	Productivity gains	Decision quality	Ethical-regulatory risk	Adaptive capacity
Digital-technological	Decisive influence	Moderate influence	Moderate influence	High influence
Ethical-regulatory	Indirect influence	High influence	Decisive influence	Moderate influence
Human-relational	Moderate influence	Moderate influence	High influence	Decisive influence

Source: author's own development based on [8; 9; 10; 13; 14; 23].

Practical recommendations for the development of augmented-manager competencies.

Translating the model into actionable interventions requires attention to three levels. At the organisational level, training programmes should treat the four clusters as parallel learning tracks rather than as a single curriculum. The empirical pattern of skill-levelling reported by Brynjolfsson, Li and Raymond [8] suggests that organisations realise the largest near-term productivity gains by investing first in the digital-technological cluster for less experienced staff, since this cluster is most directly responsible for capturing the immediate productivity benefits documented in field experiments [8; 9; 10; 21]. The cognitive-analytical and ethical-regulatory clusters require a longer development horizon and are particularly relevant for managers in senior positions whose decisions have systemic consequences.

At the team level, the model implies a redesign of role descriptions to make explicit the augmented-manager dimension. Daugherty and Wilson [13] identify six new categories of human-AI hybrid roles, of which trainer, explainer and sustainer roles are most directly under managerial responsibility. Davenport and Mittal [20] argue that AI-fueled organisations require executives who treat AI as a core operational concern rather than as a special project. Translating these arguments into role descriptions means that managerial job specifications should explicitly include responsibility for the four clusters identified in Table 1, with measurable criteria attached to each.

At the educational level, the model has implications for the design of management curricula. The findings of the Future of Jobs Report 2025 [1] - in which AI and big data is the top rising skill while analytical thinking remains the top core skill - support a curriculum design in which AI literacy is integrated as a cross-cutting competence rather than offered as a separate module. The OECD AI and the Future of Skills programme [23; 24] provides a methodological reference for designing assessment instruments. In the Ukrainian context, the digital transformation of management curricula is supported by recent national research [25; 26; 27; 28] and by emerging journal-based discussion of digital platforms in management [15] and of cross-cultural communicative management [16].

Conclusions. The study has integrated four bodies of literature - classical management competency theory, augmented-intelligence and human-machine collaboration research, AI literacy frameworks, and empirical productivity studies - into a single competency model of the augmented manager. The model consists of four interrelated clusters: cognitive-analytical, digital-technological, ethical-regulatory and human-relational. Each cluster is grounded in established theoretical or empirical sources and is operationalised through specific behavioural manifestations. The clusters are mapped onto four performance outcomes in hybrid human-AI teams: productivity gains, decision quality, ethical-regulatory risk and adaptive capacity.

The substantive contribution of the model is threefold. First, it positions the augmented manager not as a replacement for the traditional manager but as the same role operating under altered conditions, in which a portion of the cognitive workload is delegated to or co-performed with intelligent systems while accountability remains human. Second, it makes the jagged-frontier mechanism documented by Dell'Acqua and colleagues [9] managerially actionable: the cognitive-analytical cluster captures the judgement required to distinguish tasks where AI use improves performance from tasks where it degrades it. Third, it integrates the skill-levelling pattern documented by Brynjolfsson, Li and Raymond [8] and Noy and Zhang [10] into managerial decisions about team composition and training investment.

Directions for further research follow from the limitations of the present design. Primary survey data on the relative weighting of the four clusters in different industries and organisational levels are required to refine the model. A panel design comparing competency development trajectories of managers in organisations that have adopted structured augmented-manager training with those that have not would provide a stronger empirical basis for the recommendations in the previous section. The Ukrainian context, in which the post-war restoration of industry coincides with the global diffusion of generative AI, offers a particularly valuable setting for such empirical work [25; 28]. Finally, the model should be tested against the evolving capabilities of AI agents [5], since the agent-based regime in which AI systems initiate and execute multi-step actions imposes additional governance and trust-calibration demands on managers.

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