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DOI: <https://doi.org/10.20535/2307-5651.36.2026.360548>**Derhachova Victoriia**Doctor of Economic Sciences, Professor
(corresponding author)

ORCID ID: 0000-0003-0317-8675

Kavun Fedir

PhD student

ORCID ID: 0009-0004-2749-743X

National Technical University of Ukraine
“Igor Sikorsky Kyiv Polytechnic Institute”

ORGANIZATIONAL MECHANISMS OF HUMAN–ARTIFICIAL INTELLIGENCE INTERACTION IN THE ENTERPRISE MANAGEMENT SYSTEM

This article examines how structured process workflows for human–artificial intelligence interaction can improve organizational management outcomes, and how leadership interventions causally shape the effectiveness of such teams. Drawing primarily on a large-scale survey of 3,613 employees and 238 senior executives conducted across six countries in October–November 2024, the article documents a persistent and significant gap: employees already use generative AI far more intensively than their leaders realize – specifically, the actual share of active AI users is three times higher than current top-management estimates – yet only one percent of organizations report having achieved full AI maturity, defined as its complete integration into daily workflows with measurable impact on business outcomes. The article argues that this maturity gap is not a technological problem but a problem of leadership and purposeful workflow design. Using sociotechnical systems theory and principal–agent theory as complementary analytical lenses, the article proposes a five-phase workflow architecture that delineates roles, decision-making authority, task handoff points, escalation triggers, and feedback loops for human–AI teams. Two causal identification strategies – difference-in-differences and regression discontinuity – are examined as empirical tools for estimating the effect of leadership interventions on team performance; key identification assumptions and threats to internal and external validity in organizational settings are discussed, including parallel trends, participant selection, and spillover effects. The findings are translated into six concrete managerial recommendations. The conclusions align closely with the report's position that leadership alignment, structured role-targeted personnel development, and human-centric governance are the primary levers available to organizations seeking to achieve maturity in the field of AI.

Keywords: enterprise management, digital transformation of management, artificial intelligence in management, human–AI interaction, organizational decision-making processes, leadership interventions, knowledge management, effectiveness of managerial decisions, innovative development of enterprises.

Дергачова В. В., Кавун Ф. Д.Національний технічний університет України
«Київський політехнічний інститут імені Ігоря Сікорського»

ОРГАНІЗАЦІЙНІ МЕХАНІЗМИ ВЗАЄМОДІЇ ЛЮДИНИ ТА ШТУЧНОГО ІНТЕЛЕКТУ В СИСТЕМІ УПРАВЛІННЯ ПІДПРИЄМСТВОМ

У статті досліджується, як структуровані процесні робочі потоки для взаємодії людини та штучного інтелекту можуть покращити результати організаційного управління, а також те, як лідерські інтервенції причинно-наслідковим чином формують ефективність таких команд. Спираючись передусім на масштабне опитування 3 613 співробітників і 238 керівників вищої ланки, проведене у шести країнах у жовтні–листопаді 2024 року, стаття фіксує стійкий і значущий розрив: співробітники вже використовують генеративний ШІ набагато інтенсивніше, ніж усвідомлюють їхні керівники, – зокрема, реальна частка активних користувачів ШІ втричі перевищує поточні оцінки топменеджменту, – проте лише один відсоток організації повідомляє про досягнення повної зрілості у впровадженні ШІ, тобто про його цілковиту інтеграцію у щоденні робочі процеси із вимірним впливом на бізнес-результати. У статті обстоюється думка, що цей розрив у зрілості є не технологічною проблемою, а проблемою лідерства та цілеспрямованого проєктування робочих процесів. Використовуючи теорію соціотехнічних систем і теорію «принципал–агент» як взаємодоповнювальні аналітичні лінзи, стаття пропонує п'ятифазну архітектуру робочих процесів, яка окреслює ролі, повноваження щодо прийняття рішень, точки передачі завдань, тригери ескалації та петлі зворотного зв'язку для команд людина–ШІ. Дві стратегії каузальної ідентифікації – різниця різниць і регресія розривів – розглядаються як емпіричні інструменти оцінювання впливу лідерських інтервенцій на ефективність команди; обговорюються ключові припущення щодо ідентифікації та загрози внутрішній і зовнішній валідності в організаційних умовах, зокрема паралельні тренди, відбір учасників і ефекти переливання. Результати дослідження перекладено у шість конкретних управлінських рекомендацій. Отримані висновки тісно узгоджуються з положенням звіту про те, що узгодженість у діях керівництва, структурована рольова підготовка персоналу та людиноцентроване врядування є основними важелями, доступними організаціям, що прагнуть досягти зрілості у сфері ШІ.

Ключові слова: управління підприємством, цифрова трансформація управління, штучний інтелект у менеджменті, взаємодія людини та штучного інтелекту, організаційні процеси прийняття рішень, лідерські інтервенції, управління знаннями, ефективність управлінських рішень, інноваційний розвиток підприємств.



Problem statement. Organizations invest heavily in generative AI, yet a 2024 McKinsey survey found that while 92 percent of companies planned to increase AI spending, only one percent of leaders described their deployments as mature – fully integrated into workflows and driving substantial business outcomes [1]. This gap points to structural deficits in workflow design and leadership governance ([7]; [29]). Compounding this, C-suite respondents estimated only four percent of employees use AI for at least 30 percent of daily work, while the actual employee-reported figure was three times higher [1]. This perception gap produces misallocated interventions and insufficient training. Neither the process-level architecture of human–AI workflows nor the causal mechanisms through which leadership interventions improve human–AI team performance has been adequately addressed in the literature – gaps this article addresses.

Analysis of recent research and publications. The McKinsey “Superagency in the Workplace” report [1] surveys over 3,600 employees and nearly 240 C-suite executives across six countries, providing the primary empirical foundation for this article. Three findings are central: employees are more AI-ready than their leaders recognize (nearly all report generative AI familiarity, and most anticipate AI reshaping at least 30 percent of their work within two years); leadership is the primary adoption barrier (C-suite executives are 2.4 times more likely to cite employee readiness as a constraint than their own alignment failures); and training is the intervention employees most desire (48 percent rank it most important, yet more than a fifth receive minimal organizational support).

In the broader academic literature, Wilson and Daugherty (2018) argued that AI value depends on structured human–AI collaboration rather than replacement. Seeber et al. (2020) proposed a taxonomy distinguishing AI as a tool, assistant, or autonomous agent – a framework directly relevant to workflow role-assignment decisions. Jarrahi (2018) demonstrated complementarity between human contextual reasoning and AI pattern recognition, supporting the case for differentiated role design. On leadership specifically, Avolio et al. (2021) found consistent evidence that transformational leadership behaviors – particularly vision clarity and psychological safety – mediate team performance in digital-work contexts. Edmondson (2019) showed that psychological safety is a prerequisite for effective escalation of AI errors. A persistent gap across both the practitioner and academic literatures is the near-absence of causal identification: most available evidence on leadership effects in AI-augmented teams is correlational, limiting managerial conclusions about what interventions actually work ([21]; [15]).

Formulating the purposes of the article. This section provides a plain-language guide to the article’s purpose and structure.

Purpose – This article studies how organizations can deploy AI more effectively through structured human–AI teamwork architectures and appropriate leadership actions.

Who this is for – This article is for managers, executives, and anyone curious about how AI fits into the workplace – no technical background in AI is required.

What the reader will learn – You will learn why most organizations have not yet made full use of AI, even though the technology is available. You will see how to design a clear five-step process for human and AI collaboration

at work. You will understand which actions leaders can take – such as providing training, setting clear rules, and building a culture of openness – to improve results. You will also learn about research methods that can tell us whether a leadership action truly caused a performance improvement, rather than just coinciding with one. Finally, you will receive six practical recommendations that a leader can act on immediately.

Why it matters – Despite enormous investment in AI, a major global study found that only one percent of organizations have fully integrated AI into their work. This article argues that the solution is not more technology – it is better leadership and better-designed teamwork.

How the article is organized – The article moves from theoretical framework and workflow design through causal analysis to managerial recommendations, drawing on a survey of 3,600+ employees and 240 senior executives.

Presentation of the main research material. The primary empirical source for this article is Mayer et al. (2025), “Superagency in the Workplace: Empowering People to Unlock AI’s Full Potential” (McKinsey & Company), which reports findings from a survey of 3,613 employees and 238 C-level executives conducted in October and November 2024 across six countries, supplemented by executive interviews and a database of 250+ AI use cases. Peer-reviewed articles, edited volumes, and institutional reports from 2015–2025 provide the secondary literature base. Causal analysis draws on difference-in-differences [2], regression discontinuity design [16], and structural causal models [24] to structure counterfactual reasoning about the leadership interventions documented in Mayer et al. (2025).

Background. Generative AI is widely compared to transformative innovations of prior eras, yet organizational adoption has stalled well short of its potential ([1]; [7]). The McKinsey survey reveals a stark maturity gap: despite 92 percent of companies planning increased AI investment and near-universal generative AI familiarity, only one percent of C-suite leaders describe their organizations as having reached AI maturity – defined as AI fully integrated into workflows and driving substantial outcomes [1]. The barriers are organizational: leadership alignment, workflow design, and employee support.

A further finding concerns systematic leadership misperception: C-suite respondents estimated only four percent of employees use AI for at least 30 percent of daily work, while the employee-reported figure was three times higher [1]. Leaders who underestimate employee AI use tend to underinvest in training, under-design governance, and fail to leverage AI-proficient employees – particularly millennial managers already functioning as informal AI advocates.

Theoretical Framework. Sociotechnical systems (STS) theory ([28]; [13]) holds that performance emerges from joint optimization of social and technical subsystems. Applied to human–AI teaming, STS theory predicts that workflow outcomes depend not only on AI capability but on the fit between AI functionality and the surrounding social structures – roles, norms, and authority relationships. This prediction is supported by the McKinsey report’s finding that companies experiencing the highest AI value are those that have integrated AI into workflows, not merely deployed it as a standalone tool [1]. Boudreau (2019) confirmed this empirically: AI adoption effects

on productivity were moderated by organizational design choices, not AI quality alone.

Principal-agent theory [12] offers a complementary lens: the leader acts as principal, with human employees and AI systems as agents governed under information asymmetry. The McKinsey report confirms this asymmetry – only 39 percent of C-suite respondents used benchmarking standards to evaluate AI tools, and of those, only 17 percent prioritized ethical over operational metrics [1]. The framing clarifies why workflow design and leadership behavior are theoretically inseparable: the workflow operationalizes governance at the task level.

Causal inference methodology – specifically the potential outcomes framework [26] and structural causal models [24] – provides the epistemological basis for evaluating whether leadership interventions actually drive AI team performance improvements, rather than merely correlating with them. The McKinsey report's findings are inherently correlational, making the methodological contribution of causal identification strategies especially relevant for translating the report's descriptive evidence into actionable organizational science.

Workflow Architecture for Human – AI Teaming. The report identifies “seamless integration into existing workflows” as the second most desired enabler of AI adoption among employees (45 percent), trailing only formal training at 48 percent [1]. Drawing on the report's frameworks and supplementary organizational science literature, a five-phase workflow architecture is proposed here.

Phase 1 – Role and Capability Assignment: Roles should be assigned on comparative advantage: AI handles high-volume pattern recognition, real-time data synthesis, and repetitive decisions; humans retain contextual judgment, ethical reasoning, stakeholder communication, and exception handling ([17]; [29]).

Phase 2 – Decision Authority Rules: Authority rules should reflect decision stakes and reversibility: low-stakes reversible decisions may be fully AI-delegated; high-stakes irreversible decisions require human sign-off; intermediate decisions use hybrid protocols where AI recommends, the human reviews and may override, and overrides are logged. Poorly specified rules produce automation bias and automation disuse, both degrading decision quality ([23]; [18]).

Phase 3 – Handoff Protocols: Task-state transfers must minimize information loss and cognitive load. Effective handoffs present AI outputs with confidence estimates and supporting evidence; presenting conclusions without context drives the automation bias that 50 percent of survey respondents cite as their primary AI concern ([1]; [14]).

Phase 4 – Escalation Triggers: Escalation protocols specify when workflows deviate to a higher authority or review queue: triggers may be rule-based (AI confidence below threshold), exception-based (input outside training distribution), or feedback-based (override rate exceeds threshold). Crucially, escalation fails without psychological safety – employees must trust that flagging AI errors carries no punitive consequences [11].

Phase 5 – Monitoring and Feedback Loops: The report advocates federated governance: central oversight of high-risk issues with delegated monitoring to business units [1]. Feedback loops must close at three levels: AI system (model retraining from override logs), human (skill development from accuracy data), and organizational (policy revision from compliance data).

Causal Impact of Leadership Interventions. The report argues that leadership, not technology, is the barrier to AI scale [1]. Executives who cite employee readiness are misdiagnosing the problem: employees already use AI extensively, desire more training, and trust their employers on AI governance more than universities or technology companies – 71 percent [1]. Establishing causal claims requires moving beyond the cross-sectional evidence dominating both the McKinsey report and the broader literature. Two identification strategies are examined.

Difference-in-Differences (DiD). The DiD estimator compares pre-to-post outcome changes for a treated group against a comparable untreated control [2]. The McKinsey report's staggered rollout across organizational units at different maturity stages provides a natural DiD setting – 39 percent of C-suite respondents describe their organizations as still “emerging” or “nascent” [1]. The critical assumption is parallel trends: absent intervention, treated and control groups would have followed the same trajectory. Validity threats include differential selection of high-performers into early cohorts, Hawthorne effects, and spillovers. With staggered timing, heterogeneity-robust estimators [8] are advisable to avoid aggregation bias [15].

Regression Discontinuity (RD). The RD design identifies causal effects when treatment follows a threshold rule: units above a cutoff receive treatment, units below do not [16]. Natural RD settings arise when AI deployment is mandated above a minimum unit size or when teams below a performance threshold are assigned to coaching programs. The identification assumption is continuity near the cutoff; estimates are local, limiting external validity. Validity threats include sorting, measurement error at the threshold, and SUTVA violations – the McCrary (2008) density test is the standard sorting diagnostic.

Table 1

Illustrative Human-AI Team Workflow – Customer Inquiry Resolution

Step	Actor	Trigger	Action	Metric
1	AI Agent	Customer contact received	Conversation, data synthesis, intent detection	Resolution rate; CSAT score
2	AI Agent	Intent classified	Autonomous action (payment, shipping, etc.)	Model confidence (%); task completion time
3	Human Representative	Confidence < 80% OR customer escalation request	Review AI output, apply contextual judgment	Override rate; escalation accuracy
4	Human Manager	Policy exception OR complaint flag	Final authority decision	Decision quality (ex-post review)
5	Feedback Loop (AI + Human + Leader)	Weekly review cycle	Override log analyzed; model retrained; norms revised if needed	Accuracy drift; policy compliance rate; fairness score

Discussion. The report's findings, workflow architecture, and causal analysis converge on one conclusion: leadership interventions are most consequential when targeting specific workflow mechanisms – training, escalation norms, role clarity, and feedback design – rather than pursuing diffuse cultural change without structural reinforcement.

That 48 percent of employees rank formal training as the most important adoption factor, yet more than a fifth receive minimal support, is the most actionable gap in the empirical record [1]. Role-targeted training – technical bootcamps for engineers, prompt engineering for functional professionals – improves trust calibration, reduces automation bias, and raises error-detection capacity [18].

Employee trust in employer AI governance – 71 percent, higher than trust in universities or technology companies [1] – is an underutilized leadership asset. This trust creates the psychological safety substrate effective escalation requires: employees secure in their employers' intentions report AI failures more candidly, generating override data that feeds model retraining and policy improvement [11]. Leaders who erode this trust undermine the foundation on which workflow quality depends.

Managerial Implications. Six actionable recommendations emerge from the report's frameworks and findings.

First, close the perception gap through structured listening. C-suite leaders underestimate employee AI use by a factor of three [1]. Regular structured audits of actual employee AI use, informal workflow integrations, and encountered challenges are essential to close this gap.

Second, invest in role-targeted training at scale. Formal training is employees' most desired intervention [1]. Programs should be role-differentiated: model evaluation and integration for technical staff; prompt engineering and output verification for functional professionals.

Third, publish a decision-authority matrix before deployment. Before deploying any AI system, leaders should publish an explicit decision-authority matrix specifying AI-delegated decisions, those requiring human review, and those requiring managerial authorization.

Fourth, design escalation without stigma. Leaders should convert baseline trust into operational psychological safety: remove metrics penalizing escalation, create low-friction error-flagging channels, and model override acknowledgment publicly ([11]; [1]).

Fifth, instrument feedback loops from deployment day one. Override logs, confidence score distributions, decision accuracy reviews, and compliance data should be operational from workflow launch – essential inputs for model retraining, policy revision, and organizational learning.

Sixth, phase rollouts deliberately to enable causal learning. Stagger AI deployment across business units intentionally to create quasi-experimental variation, converting a logistical necessity into an organizational learning asset.

Limitations. Four limitations apply. First, the workflow architecture is conceptual and has not been tested as an integrated system. Second, causal identification strategies

require natural experiments or phased rollouts that may not be universally available. Third, the McKinsey report is cross-sectional and self-reported, preventing full causal identification [1]. Fourth, the sample skews toward large enterprises (75 percent of US respondents from organizations with revenues exceeding \$100 million), limiting SME generalizability.

AI in Ukraine – Wartime Examples. The following examples illustrate how AI has been applied in Ukraine during the ongoing war with Russia (since February 2022). All items are drawn from official government sources, NATO bodies, and established policy research institutions.

Ukraine's Delta battlefield management system, developed from 2016 onward and formally adopted by the Ukrainian Ministry of Defence in August 2024, integrates satellite imagery, drone feeds, sensor data, and civilian reports into a real-time digital map accessible to frontline units, with AI and machine-learning capabilities for video and text processing of enemy positions added in 2024. [31]

In April 2023, the Ukrainian government launched Brave1, a state-backed platform coordinated by the Ministry of Digital Transformation and the Ministry of Defence to fund and accelerate dual-use AI and military technology startups; as of September 2024 the platform had awarded 299 grants totalling USD 6.5 million.

Ukraine's AI platform Avengers, presented at NATO Edge 24 in December 2024 by the Ukrainian Centre of Innovations and Defence Technologies, detects approximately 12,000 targets daily, reducing routine analysis workload for frontline warfighters. [32]

In December 2024, Ukrainian forces conducted the first fully unmanned ground operation near Lyptsi, north of Kharkiv, deploying dozens of AI-enabled uncrewed ground vehicles and first-person-view drones with no infantry participation, successfully destroying Russian positions.

Ukraine's acoustic drone-detection system Zvook, developed with AI algorithms from the Ukrainian tech startup Respeecher, can detect incoming drones up to 4.8 km away and relay location data to the Delta system within 12 seconds, with a false-positive rate of just 1.6 percent. [33]

Conclusions. The McKinsey report presents an actionable paradox: the technology has arrived, employees are ready, yet organizations remain far from AI maturity. Resolving it requires two complementary investments: structural (a workflow architecture specifying roles, decision authority, handoffs, escalation triggers, and feedback loops) and epistemological (evaluating leadership interventions with difference-in-differences and regression discontinuity rigor). The report's core finding – that leadership, not technology, is the barrier – is both diagnosis and mandate. Leaders who close perception gaps, invest in role-differentiated training, and design workflows that make escalation safe and governance transparent will be best positioned to convert AI investments into sustained competitive advantage.

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