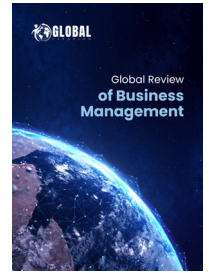




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Human–AI Collaboration and Workforce Productivity: Managerial Strategies for High–Performance Organizations

Mathilde Sabouné^{1*} **Jorien Nyobe²**

1. Excelia Business School, Laboratoire CERIIM, La Rochelle, France

2. Excelia Business School, CERIIM – Research Center in Managerial Intelligence and Innovation, France

Corresponding Author:

Mathilde Sabouné

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Abstract

Background:

Human-AI collaboration had been elevated to management concerns as they wanted to gain productivity without diminishing judgment, trust or capability of their workforce.

Objective:

This secondary analysis explored how managers set up the roles, workflows, skills and governance to put artificial intelligence to the test and make it delivering sustainable performance.

Methods:

Empirical and conceptual evidence published in the area was checked and was narratively synthesized from decision support, knowledge work, operations, human resources and innovation.

Results:

Results indicated that AI took care of scalable pattern recognition, routine-drafting, monitoring and forecasting of activities, employees kept their abilities in contextual interpretation, exception management, relationship work and accountability. Lack of good data, division of tasks, overconfidence or increased surveillance, or a combination of these, led to a decline in gains when automation was introduced or implemented. High performing organizations reinforced task-level redesign through just the right types of controls, ongoing learning, psychological safety, and outcome-based measurement, and just the right level of trust.

Conclusion:

The study designed an integrated managerial framework, for strategic alignment, work design, capability development, responsible governance and adaptive performance evaluation. Human–AI collaboration was consequently viewed more as a systems organization, and a technology deployment project was viewed as a subcase of a human–AI collaboration transition.

Keywords

Human–AI Collaboration; Workforce Productivity; Work Design; Managerial Strategy; Responsible Governance; Organizational Performance

1. Introduction

Previously, AI was an ‘industry specialist’ analytical tool; now, it’s a ‘general purpose’ organizational technology being used more and more to search, create, predict, consider options, co-ordinate and service customers in the workplace. The Automation vs employment debate is unbalanced. AI can’t create value on its own and humans can’t create value on their own, it is their design that creates value in most organizations. Managers are thus left with a question of practicality: how to decide which tasks to automate and which to leave human, which roles will take ownership, who will learn most and how to control and regulate the processes between the man and the machine (Arslan et al., 2022).

Productivity is more than mere replaces labor or faster. A system can increase in productivity in task completion, but produce rework, poor decisions, employee resistance, compliance risk, and/or the loss of the talent. On the other hand, a collaborative design might need training and evaluation at first and result in higher throughput, innovation, responsiveness to customers and resilience in the organization over time. Performance, quality, flexibility, and personal efficiency and staff capacity, including risks adjusted to the value of the performance should therefore be considered as important criteria of sustainable productivity. In high-performance organizations (HPOs) it is really important because knowledge work

doesn’t lend itself easily to output count (Budhwar et al., 2023).

Recurring benefits that have been identified in the managerial literature with respect to human-AI collaboration. Data analysis is not only the ability to process massive amounts of data without concurring errors, but also to uncover patterns, draft content and automate ongoing operational changes, as well as help maintain consistent decision-making processes. Workers bring context knowledge, decision, tacit knowledge, creativity, empathy and responsibility. When aligned and used well, they can help teams to extend analytical reach, without sacrificing “sense making” by humans. However, all of the above technologies can form failure modes. Good scaling of bad data. An automation bias can result from confident outputs. Monitoring tools may lead to more work, and a loss of trust. Fragmented implementation can re-priorities efforts from production to verification without decreasing the overall amount of work done (Chang & Ke, 2024).

Managers need to line up use cases with strategy, break down jobs at the level of tasks, create a proper level of oversight of humans, build employee capability, promote psychological safety and measure things more than an adoption. They also need to be able to differentiate between assistive configuration, augmentative configuration and autonomous configuration. An assistant proposes and/or drafts; an augmentative system provides a role in analysis and recommending; an independent system performs within limits. Each configuration is associated with different needs for transparency, review, and escalation and accountability (Chowdhury et al., 2024).

The present study focused on the managerial approach towards high performance by working with humans and AI. It was built upon using a secondary analysis approach to combine rigorous empirical and conceptual evidence from a number of studies concerned with managerial decision-making, knowledge work, operations, innovation and HRM. The analysis was based on three questions.

- **RQ1:** Which task workflow configurations were most likely to positively impact productivity?
- **RQ2:** How did the managerial skills translate into the organization?

- **RQ3:** What risks and boundary conditions prevented gains?

The study has created an integrated framework that includes strategic alignment, work design, capability development, responsible governance and adaptive measurement. Essentially it proposed that productivity was not just a by-product of the deployment of technology but of a managed socio-technical system.

2. Conceptual Foundations

The concept of human–AI collaboration can be thought of as cooperative interdependence between humans and computational systems for performing organizational tasks. The idea is not just ‘tool use’ as both are involved in the process and the outcomes. Artificial Intelligence can organize or format information, produce alternative information, prioritize, suggest action or even implement decisions. Humans have the ability to frame problems, provide context, validate output, answer exceptions, reach out for negotiation and stay responsible. Task allocation, information exchange, feedback and authority, are therefore crucial aspects of effectiveness of collaboration (Chukwuka & Dibie, 2024).

The first conceptual basis is the complementarity. Humans and/or machines don’t always excel in everything they do. The thing is, artificial intelligence works really bang for the buck when patterns are learnable from large and relevant datasets, and objectives can be defined. Human performance has value in the face of absence, because it has to be determined through moral judgment, due to social interpretation, and because of opposing goals. Complementarity is the design of rolls around these comparative strengths, as well as the ability of one role to be aware of the other’s weaknesses, or make them up for. Having a human next to an algorithm isn’t enough to ensure a better performance (Gong et al., 2025).

A second base of the job-demand and resource – perspective. Artificial intelligence can serve as a tool to decrease repetitive tasks, to enhance the speed of information retrieval, to assist learning and to enhance the idea of competence. It can also set up demands by constantly monitoring, doing work in

hurry modes, more verification and skill insecurity, and also setting up the expectation of always being on call. Well-being and productivity of employees depend on. Demands and if the individual has adequate autonomy to embark on intelligent use of the technology. This same use can stimulate veteran staff members and undermine members who are uneducated or don’t have decision making power (Jabeen et al., 2025).

The collaborative systems work better if an organization is able to report back errors, overrides, user feedback and changes in context. It has various levels of learning. Prompting and verification skills as well as domain integrating skills are developed by the employees. Teams optimize work flows, escalation. Update of data, models, policies and performance standards in organisations. Wherever there are no feedbacks, automation can solidify erroneous expectations. To be able to share what local staff have learned and understand across the organization thus, mechanisms for sharing local experience to creation of institutional knowledge is needed (Joseph et al., 2024).

A fourth foundation, trust calibration, is provided. Good users don’t come to a conclusion on accepting or rejecting AI automatically (Khan et al., 2024). They learn to take a justified reliance on system competence, situation, uncertainty and consequences. Transparency might help with calibration with understandable explanations that are relevant to students; too much technical detail may add to the cognitive load. It’s important for managers to design trust, which is achieved by establishing clear performance boundaries, providing a source of confidence information, making comparisons with alternatives, and displaying accountability. Its aim is not to achieve as much trust as possible, but to be justifiably trusted.

These visions all indicate that humans & AI productivity is conditional. It is based on capability fit, work characteristics, learning systems and calibrated control. These must be taken into the managerial strategy and cannot be addressed as merely implementation issues.

3. Methodology

The study was a secondary analysis of literature data,

which is designed by critical and narrative synthesis. The approach was chosen due to the diversity of literature on human–AI collaboration that ranged throughout organizational behavior, information systems, operations management, human resource management, innovation, and human–computer interaction. The methods, tasks, sectors and productivity indicators of the respective studies examined were very diverse and could not simply be bundled together in a statistical pool to fulfill the needs of this paper.

Empirically published articles, systematic review, conceptual papers, field-experiments, organisational case analyses and practitioner oriented research were purposefully reviewed. The evidence base was directed towards the use of AI in the workplace in scenarios related to decision making, knowledge creation, customer service, human resource management, forecasting, quality control and innovation. Studies that focused only on the technical benchmark of performance were not considered adequate unless they related to human performance outcomes or work design and organizational outcomes.

The organizational context, purpose of AI, role of human, characteristics of the task, workforce configuration, and performance result were extracted using a structured matrix. Productivity outcomes were measured on five categories of task efficiency,

decision quality, innovation, service/operational performance and workforce sustainability. Workforce sustainability comprised skill development, engagement, psychological safety, fatigue, autonomy and employability.

The analysis has been done in three stages. Open coding resulted in identification of the repeating benefits, risks, and design efforts. Second, evidence was focally coded under the following themes: strategic alignment, task allocation, workflow integration, skills, trust, leadership, governance and measurement. Third, integrative interpretation explored how these themes interacted and were supportive or undermining to each other in performance cycles. Finding with opposite results were not “averaged” out, but kept; they showed important boundary conditions.

The methodological transparency was interpreted along with the realism of the task and the relevance of the performance measure with the quality of evidence understood as per the claims and evidence possessed. Studies involving multiple sources of evidence, repeated observations, collaborative versus each alone were given more weight. An attempt has been made here to exclude no parts of the review, but it is not claimed that everyone is covered. It was designed to build up into an analytically coherent ‘managerial framework’, based on a variety of secondary materials, that would not indulge in unsupported causal generalization.

Table 1. Secondary-analysis design and analytical boundaries

Element	Specification	Analytical purpose
Review design	Critical narrative secondary analysis	Integrated heterogeneous workplace evidence without implying pooled causal effects.
Evidence domains	Decision support, knowledge work, operations, human resources, innovation, and service	Captured productivity mechanisms and workforce consequences across organizational functions.

Included evidence	Empirical studies, field experiments, organizational cases, systematic reviews, and conceptual frameworks	Technical benchmarks were considered only when connected to work or organizational outcomes.
Analytical categories	Efficiency, decision quality, innovation, service performance, and workforce sustainability	Enabled a balanced interpretation of productivity rather than speed alone.
Core lenses	Complementarity, job demands-resources, organizational learning, and trust calibration	Explained why identical technologies produced different outcomes under different designs.
Quality interpretation	Task realism, transparency, comparative conditions, outcome relevance, and claim-evidence alignment	Contradictory evidence was retained to identify boundary conditions and implementation risks.

4. Findings

4.1 Strategic alignment and use-case selection

The most successful instances of higher productivity involved a specific area of business being addressed, as opposed to a big goal of implementing AI. For high value use cases, decision makers were identified, performance baselines were established and available, and the impact of a task on the organization was tied to improving the performance of the task. This included minimizing forecast mistakes, speeding up the document review process, enhancing ‘first time right’ and identifying quality difference and providing quicker scenario analysis. Often, processes have been weakly implemented because they sought to achieve end-to-end automation, but failed to address process ‘choke points’ or lack of clarity regarding who would be responsible for taking action based on the information gained.

Managers had to define the objective function in order to make possible the strategic alignment.

Undoubtedly, an optimized service can compromise about speed, and an optimized cost-pressure can compromise about the service or fairness. High performing organizations then transformed their strategic priorities into a number of acceptance criteria (La Torre et al., 2021). They took into account the accuracy, the cycle time, the consequences for the customer, the workload for the employees, the compliance and the recoupability. This stopped the technical teams being their own measure of success that of good performance of the model and not their actual measure of success that of the business.

Organizations delivered more value with a few use cases that could scale up in the future than with a single or disjointed pilots. Shared data standards and governance, training and infrastructure among related applications. Comparable coordinated portfolios were also possible to evaluate value, risk and the impact on the workforce. Work not meeting thresholds were modified or discontinued.

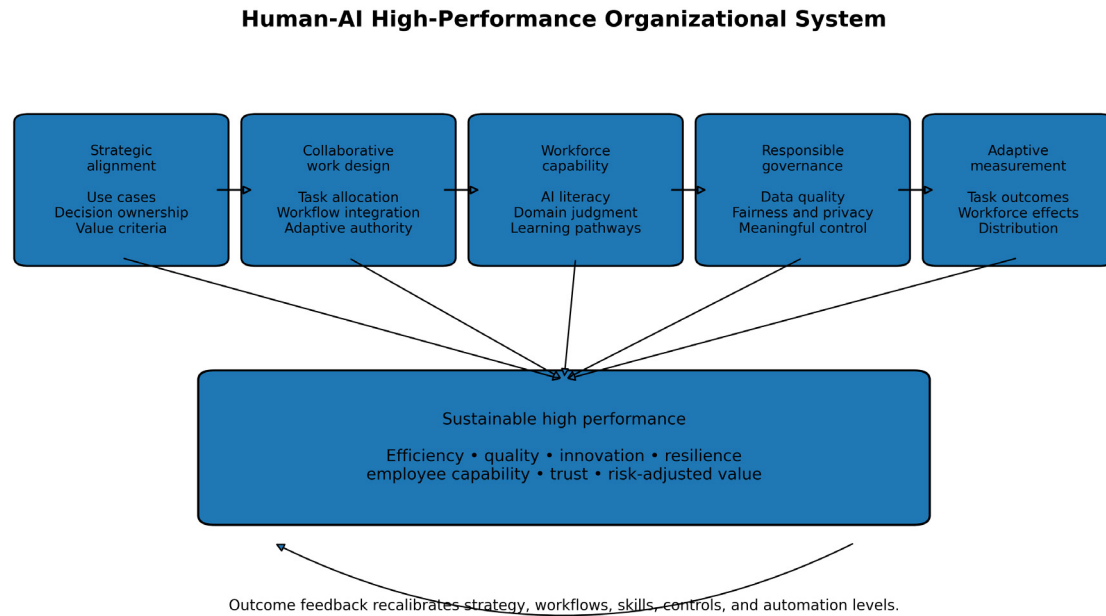


Figure 1. Integrated human-AI high-performance organizational system

4.2 Task decomposition and role allocation

Job-level automation often yielded poor results, as occupations have heterogeneous tasks to be performed. In the category ‘effective managers’, work was broken down into a set of activities involving searching, classification, prediction, generation, interaction, judgement and execution. Attempts were made to hand-over repetitive work to AI that was high-volume and had testable outputs with high information volume and a repetitive structure. Humans needed to be responsible for ambiguous framing, exception handling, stakeholder communication, for making ethical compromises and to be accountable when consequences were significant.

This task-level approach facilitated some of the following configurations of collaboration. The individual(s) responsible for sequential assistance prepped information that would not have been available for human review. Concurrent augmentation provided assistance to staff for task accomplishment. The method of operation was “people monitored exception cases and supervisory automation handled routine cases”. Delegated autonomy was given within the scope of preset limits and an audit trail would be created. High-performing organisations were aligning configuration, with risk, reversibility, and uncertainty instead of using the same configuration for all work

(Martini et al., 2024).

Less duplication and burden on verification with role clarity. Staff had to be familiar with when it was acceptable to challenge the system, what constitutes accepted evidence that supports an override and procedure for resolving disagreement. Some staff members were simply accepting the result of any work, some were rechecking everything as they couldn’t tell if it was their responsibility to do so or not. These two behaviors led to a fall in productivity. Employees’ focus was concentrated where human judgment has the most to offer thanks to clear authority.

4.3 Workflow integration and process redesign

The value of Artificial Intelligence in inefficient processes, without process re-engineering is low. Poorly integrated workflows included employees copying information between systems, copying/replicating information, making redundant decisions already made by the model, and reconciling conflicting information. High-performing organizations mapped the end-to-end process, and got rid of unnecessary handoffs before scaling up collaborations. They linked outputs to the outcomes that would take place further downstream and they included escalation mechanisms and ensured that data produced through

the work helped to enhance work going forward. Changes were also made in relation to timing as a result of the process redesign. Organizations did not only use AI at the point of decision making, also integrated it across the workflow. The early going systems found relevant information, the middle systems worked on providing alternatives and the later systems worked on monitoring implementation and outcomes. This distributed support relieved cognitive overload, and would allow for a continuous correction process. But decision pauses were provided by managers to cases of high consequence – to ensure there was no

reflection lost by speed (Olan et al., 2022). Normalization and discretion was kept in balance. While formal routines enhanced standardization and transparency, the use of standardized formats might stifle expert knowledge and new ideas. Eighty percent of the designs were effective, enabling employees to add context, even to reject recommendations, and experiment without going out of control. The workflow took the place of an automated script and turned into a learning structure.

4.4 Productivity mechanisms

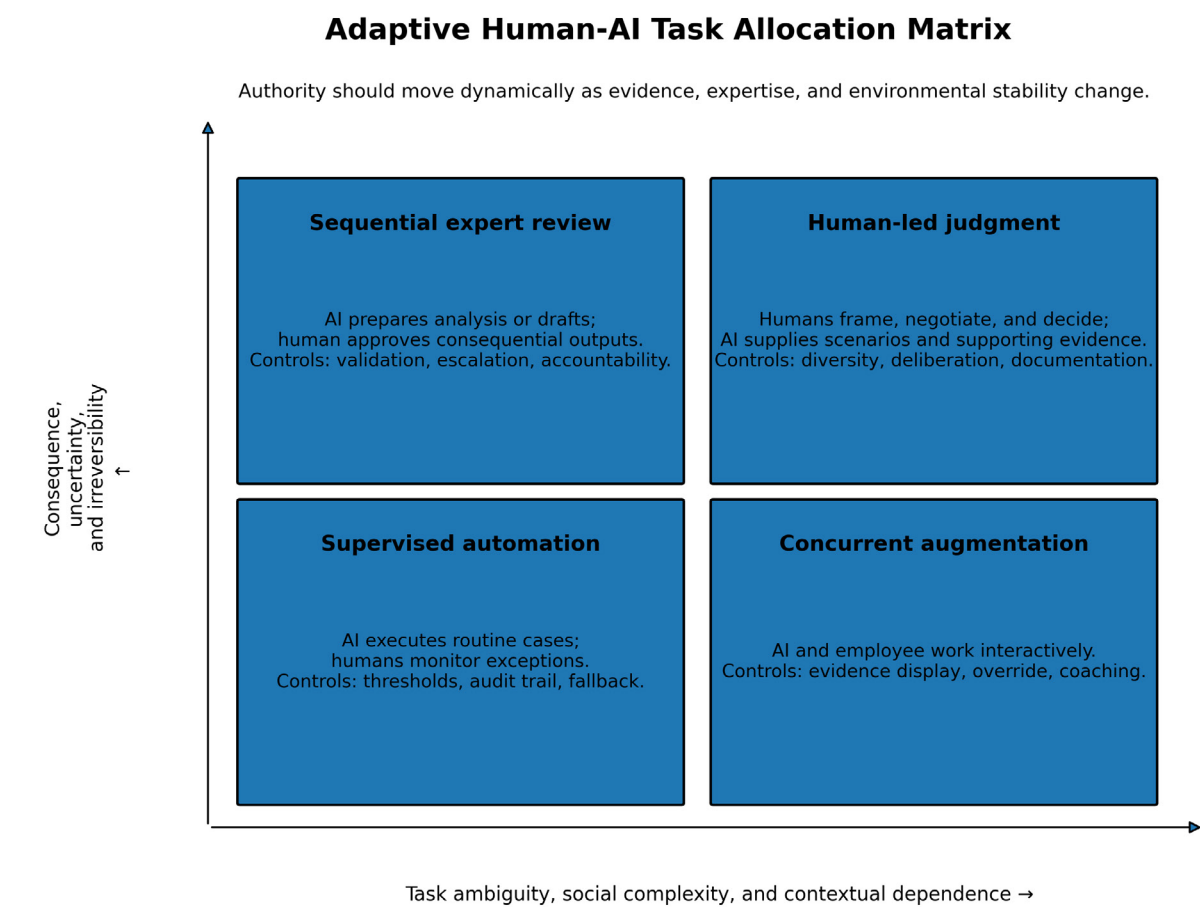


Figure 2. Adaptive allocation of human and AI authority across task conditions

Five main mechanisms for productivity have been shown from the evidence. First, because of compression, we needed less time to search, summaries, write and do our daily analysis. Second, the number of alternatives, scenarios or cases that employees could assess was larger as if they'd been amplified. Thirdly, consistency lessened the

variations of avoidable decision. The fourth element was anticipation, which aided in forecasting, and also in early detection. Fifth, accessibility helped to introduce support of analysis or communication, for less experienced staff members. The results of these mechanisms vary. The benefit of compression was a better cycle time, however

at the risk of quality not being looked at. As long as it was amplified, innovation flourished; however, too many choices meant too much delay in making the decisions. They became more consistent and reliable but there was repetition of bias. Planning increased, based upon data that included the present conditions, as the seal-caught population exceeded the set-caught one. Accessibility to learning but may support dependency. This meant that the overall performance 'pathway' was assessed and not simply a technical 'mechanism' which resulted in a net benefit (Rulandari & Silalahi, 2025).

Combination was the most frequent way the largest gains could be seen. This enabled employee to devote more time in the service process to the customer or trouble shooting. Improved Forecasts resulted in better inventory and staffing decisions. The use of drafting support boosted throughput and quality assured through peer review. Redistribution of man power was often more valuable than man power saving.

4.5 Skills, learning, and workforce development

The skill mix of work changed due to the integration of humans and AI. Staff needed fundamental communication skills in AI, such as an awareness of the probabilistic nature and limitations of AI systems, how AI reliance is often linked to data and the susceptibility to failure modes. They also had to possess domain expertise to assess relevance, some communication skills to be able to explain decisions made with the aid of AI and some metacognitive skills to identify when further checks were required. Just prompting wasn't enough of a capability.

High performance organizations were the ones that were utilizing "Role Based Learning" not "generic awareness training". Managers were educated about governance, investment evaluation and redesign of work forces. The domain awareness and the communication were studied by technical specialists. Realistic scenarios were used to practice with the front line employee's interpretation, verification and escalation. Training was complemented with coaching, communities of practice and examples of successful/failed outputs (outcome artifacts).

The impact of whether AI enhanced or undermined expertise was dependent on learning design. If only

final recommendations were given to the employees, their diagnostic skills could be lost. Learners were provided with comparison opportunities when the systems presented evidence, alternative and uncertainty. Because of this manager played with different levels of automation to a developmental context. Structured explanation could be provided for new employees and more compact GUI could be used by the experts. Practice at various points of time maintained critical skills in event of failure (Shah, 2024). Where the jobs were also made a difference. Workers were more inclined to participate if the supervisors told them about the changes in the jobs that would occur and offered viable options and opportunities for access to better-paying jobs. Many people had fears of displacement which were not negated by vague promises of augmentation. Workforce planning was connected with investment in reskilling based on the anticipated evolution in role needs, number of roles and promotion criteria.

4.6 Leadership, participation, and psychological safety

Leveraging leadership behavior on adoption and performance. AI programs were translated by the employees through the medium of communication, the allocation of resources, and responses to errors. Leaders who framed technology as flawless were less likely to raise challenges and made bolstering automation bias. Leaders with constraints, providing opportunity to challenge and view errors as learning experiences encouraged calibrated use.

Processes were poorly documented and frontline workers helped to make up for that by participating in the work design, promoting an understanding of exceptions, informal worker processes and customer consequences. There were hidden tasks identified during the co-design workshops, and review points were identified, agreed to, and decided upon by teams in the co-design workshops. In addition, participation improved procedural fairness, especially as related to issues of scheduling, evaluation, or the availability of employment opportunities that involved technology (Sowa et al., 2021).

Thus, psychological safety was paramount to reporting modelers' failure and disagreeing with modeler's recommendations. Employees had to

feel comfortable that there were not repercussions for admitting that they weren't as consistent, with responsible overrides. This was supported by organisations by providing non-retaliation policies, incident review and baskets of leadership. Challenge in turn entailed discipline. Reasons for override were recorded to be analyzed for patterns which led to the updating of models and policies. Workload was also safeguarded by managers. Sometimes expectations were raised and old duties weren't lifted with the introduction of productivity tools. With sustainable implementation, the tasks were eliminated and transition targets were adjusted and fatigue monitored. Provided overtime was unpaid, it indicated failure in implementation.

4.7 Trust, transparency, and responsible governance

Trust grew as more was experienced in terms of ability of the system, consistency, and reaction of the organization (how it handled things when they went wrong). Managers facilitated calibration by letting people know what the data was for, its known limitations, associated confidence levels and data boundaries. Interfaces did not show generic explanations for things, but did show evidence of the decisions. Users were able to examine sources, gather some alternatives, and locate uncertainty.

The governance was in direct ratio to impact. For drafting in low risk, essential data checking and review was needed. These had to be validated, provided with access controls and audit trails, and subjected to bias testing and to objective supervision by a third party in systems dealing with consequential decisions. Only reviewers who took the time to learn the material, specialized knowledge and had the authority gave human approval a real meaning. The responsibility that was created was without a control as it was a ceremonial sign-off.

Data governance continued as the fundamentality. No matter how sophisticated, collaboration was hampered by inaccurate and incomplete or historically biased data. High-performing organizations also had data quality team owners, documented data lineage, ensured sensitive data is restricted, and data retention rules in place. They also kept track of fluctuations in model drift and business conditions.

There had to be explicit parameters on the pains of

surveillance. While AI could help find out bottlenecks, may undermine trust if used on a continuous basis and may lead to gaming. The majority of managers preferred process indicator when there was no need to track individuals. Organizations were transparent about the purpose, access and holding time, as well as the rights of appeal when using employee data. Performance was ensured by maintaining good governance (based on legitimacy and co-optimism).

4.8 Measurement and performance management

No productivity was shown with adoption metrics. Use but not value was described by number of prompts or frequency of logins. Measuring was effective and linked to task outcomes, organizational results and workforce sustainability. Pre- and comparison periods included the costs and benefits of learning and transition.

The metrics used for the tasks were: cycle time, accuracy, rework, exception rate, and throughput. Organizational metrics ranged from revenue, to service quality, to innovation, to cost, to risk exposure and to resilience. The workforce indicators were: cognitive load, engagement, skill development, autonomy, fatigue and turnover intention. Balanced scorecard put an end to local efficiency at the expense of the next part of the chain or the personnel.

Distribution also described was measured by managers. It would be possible to have increases in average productivity with gains for only experienced employees or certain groups. Thus, analysis was conducted on patterns of role, skill level, location and demographic. Tool, trainings and/or decision-making access asymmetries might exacerbate performance gaps. Some corrective measures undertaken were interface redesign, specific coaching, and process re-allocation.

Measurement supported experimentation. Ensures that organizations tried different styles of collaboration, reviewed thresholds for reviews, and tweaked automation levels. With the short cycle evaluation, they were able to improve without having to commit the organization to one configuration. Productivity was seen as the interplay of technology, tasks, people and context and was central to systems performing at a high level.

Table 2. Human-AI collaboration configurations and managerial controls

Configuration	Role design	Suitable applications	Required controls	Primary risk
Sequential assistance	AI searches, summarizes, or drafts before human review	Document analysis, reporting, initial diagnosis	Review standards; source inspection; accountable approval	Fast output may anchor reviewers or hide weak evidence.
Concurrent augmentation	Employee and AI interact throughout the task	Planning, design, customer support, coding	Visible uncertainty; editable recommendations; coaching	Cognitive overload or excessive option generation.
Supervisory automation	AI handles routine cases while people monitor exceptions	Quality control, triage, scheduling, transaction review	Thresholds; exception queues; fallback procedures	Rare failures may be missed as attention declines.
Delegated autonomy	AI executes reversible actions within defined limits	Inventory actions, routine communications, low-risk routing	Action limits; audit trail; rollback; monitoring	Scope creep can create unapproved authority.
Human-led judgment	Humans frame and decide; AI supplies evidence and scenarios	High-impact people, safety, strategy, and ethical decisions	Diverse review; documented reasoning; appeal mechanisms	AI may still shape framing and narrow considered alternatives.

5. Discussion

The secondary evidence suggested that the Organizational conversion was the driver of productivity by human-AI partnership than direct technological substitutions. Managerial systems decided how AI's supplies of computational capacity contributed to work; whether and how it helped. Using strategic alignment valuable problems were selected. Complementary roles were provided by some form of task decomposition. Working in the workflow, ideas linked to action. Capability development – employees to interpret and challenge outputs. Governance helped to manage risk and experience was translated through measurement into learning (Xu & Cho, 2025). The following is a sequence exculpatory of the reason why similar technologies resulted in various success or failure across organizations. Those that thought of AI as a software install experienced biased pilots, lack

of trust, embedded verification expenses, and scaling limitations. Companies who considered collaboration to be operating-model redesign were more likely to also gain better quality and adaptability, in addition to speed. Their secret was challenging-to-replicate procedures that combined skill, data, procedures and responsibility (Tinguely et al., 2023).

The results also validated the concept under exploration of augmentation. Augmentation doesn't necessarily put employees first. We could expand output within a system, make it less autonomous, or monitor more. Sustainable augmentation is where the employee is enhanced in the contingencies to understand, decide, learn and contribute. Managers thus have to wonder if and how collaboration enhances meaningful discretion or if it is simply a form of delegating control to an interface of algorithms. Hybrid systems can be hidden by looking at traditional labor productivity analyses. These are actually

inputs: AI infrastructure, data maintenance, review time, risk controls and rework. Similarly, outputs of value are quality, learning and resilience, employee retention. Businesses that truly want to maximize their productivity need a more expansive productivity model that incorporates total system resources, as well as delayed impacts.

Differentiated automation had evidence of. Don't expect a set balance of human and AI in any organization. Mature feedback of tasks, reliability of models, employees' know-how and environments' stability determine appropriate allocation. A workflow can start off with a lot of scrutiny, gradually progress to conditions of supervised automation, and again transition back to human control if conditions change. This is because adaptive authority is more effective than yields from permanent automation levels.

The work done by management also undergoes a transformation due to human–AI collaboration. The manager's role is no longer as simply an assigner of tasks, but now as a designer of situations that are suitable for decision making. They should carry enough technical knowledge so that they can challenge assertions made by the systems, enough of organizational understanding so they can predict effects of behavior, and enough moral sense so they can control the consequences. Middle managers are especially significant as they interpret enterprise strategy and turn the meanings into 'team' action and see discrepancies between what is formally designed and what is practicing 'on the ground' (Vrontis et al., 2023).

Lastly, the competitive advantage may begin to get closer and closer to the quality of collaboration developed between the models instead of their mere ownership. But organisations will differentiate themselves based on their proprietary context, trusted data, skilled employees, the integration of processes and their responsible relationships with the customer and worker, as foundation technologies become prevalent. Another robust capacity that is not necessarily about AI, per se, is the capacity to redesign work on an iterative basis, with changing mixes of what the human and machine can do (Xu & Cho, 2025).

Collective intelligence can the organization's

collaboration help to coordinate the team or understanding or cross-functional problem solving or just output from each? It is these relational gains that can make the difference in the productivity that ensues in uncertain situations (Xu & Cho, 2025).

6. Integrated Managerial

The design thinking actives were grouped into 5 intertwined domains. Strategic alignment related AI efforts with enterprise issues, customer value, and identifiable business challenges. Managers set up portfolios, decision ownership and stop criteria. This domain kept experimentation from getting out of hand, or away from having an operational value.

The second domain, collaborative work design, broke down the jobs, determined the right human–AI configurations and integrated review, escalation and learning. Managers took into account risk, reversibility, uncertainty, and they had to be empathetic. They also eliminated redundant tasks and revised the workload, instead of superimposing technology onto a lot of existing tasks.

The skills of AI Literacy, domain judgment, communication and verification in the third domain, workforce capability, were developed. These were a set of pieces that included role based training, communities of practice, developmental interfaces, career pathways. Staff were considered partners and assets, and actively utilized their skills for system performance.

The fourth domain, responsible governance, postulated data quality, privacy, transparency, auditability, fairness, security and the meaningful human control. The more one governed, the more one had to fear and the more he feared, the more he governed. There were avenues for staff, affected persons to question deliverables and challenge decisions.

Adaptive performance management (fifth domain) measured task, organizational and employee outcomes. It involved baselines, controlled experimentation, distributing analysis and redesigning periodically. Feedback to strategy, workflow, training and governance.

A cycle of reinforcement took place among these domains. Clear strategy led to good choice of tasks. Promoting good work design resulted in productive

data and experience. Capability through development – enhanced interpretation and challenge. Governance enhanced legitimacy and holds back against detrimental shortcuts. Balance measurements help in determining the value added or lost through collaboration. Failure in any of these areas may help to disrupt the cycle. For instance, strong governance could not save a use case that lacks a strategic level value and many more examples exist.

This can be done in 4 stages: Assess, analysed and diagnosed mapped tasks, data, pain points, risks and staff readiness. Develop specific jobs, controls, measures and learning. Deploy tested the workflow by deploying it with sample users and simulated

exceptions. There was scale-up only after evidence indicated that they were associated with sustained improvements and that they had an acceptable impact on the workforce. Two governance gates and 2 decisions for continuation, redesign, or stop were accomplished for each stage.

The framework put managers in the role of stewards for complementarity. They had to develop mechanisms in which Artificial Intelligence enhanced the human effort and the employees ensured the judgment, values and adaptability of the company. Deliberate, transparent and revisable collaboration brought out high performance.

Table 3. Balanced performance scorecard for human-AI collaboration

Dimension	Indicative measures	Desired signal	Failure signal	Managerial response
Task performance	Cycle time; throughput; accuracy; rework; exception rate	Faster output with stable or improved quality	Hidden verification effort; error propagation	Compare total process time and downstream rework.
Decision performance	Calibration; consistency; forecast value; override quality	Better choices under uncertainty	Automation bias; unjustified rejection	Review accepted, rejected, and missed recommendations.
Organizational value	Revenue; cost; service; innovation; resilience	Sustained risk-adjusted improvement	Local optimization; delayed costs	Link task gains to enterprise outcomes and baselines.
Workforce capability	Skill growth; autonomy; engagement; internal mobility	Employees move toward higher-value contributions	Deskilling; dependency; exclusion	Use role-based training and independent practice.
Workforce sustainability	Cognitive load; fatigue; psychological safety; turnover intention	Productivity without work intensification	Surveillance; hidden overtime; accelerated targets	Remove obsolete work and monitor workload distribution.
Responsible performance	Fairness; privacy incidents; appeals; audit findings	Legitimate and controllable collaboration	Bias; data misuse; ceremonial oversight	Apply consequence-proportional governance and appeal rights.

7. Limitations and Future Research

The use of secondary analysis left this study susceptible to the heterogeneities of different

technologies, tasks, industries and productivity metrics. Reviewed evidence was often in relation to short-term task performance, controlled situations or to early adoption of the technology. There were still some doubts as to the longitudinal impact on

expertise, career, organizational structure and well being. Also, positive publication bias or influence of vendors might have overemphasized the benefits. Future studies may involve investigating other collaboration scenarios for realistic work and its outcome, as well as total system costs. Further studies have to be conducted longitudinally to determine the enhancing or decaying effect of multiple applications of AI to expertise. These are areas which require increased focus: namely small organisations, non-Western environments, front-line roles and limited digital experience. The studies should also measure the managerial interventions such as participation, adaptive authority and workload protection. Lastly, the financial, operational, ethical, and workforce outcomes should be measured within common structures within productivity research.

8. Conclusion

Human–AI collaboration can enhance the productivity of workers, but it is dependent on management design and not technology alone. Evidence indicated that AI was beneficial when managing scalable analysis, routine generation, monitoring, and forecasting, but employees managed the remainder of these functions which included contextual judgment, exception management, relationships and accountability.

High performance organizations related use cases with strategy, tasked off complementary strengths, redesigned their workflows, created capability in the workforce, scaled their level of trust, and responsibly governed their data and decisions. They focused on productivity, which involved efficiency, quality, adaptability, risk and employee sustainability – not just adoption or speed alone. They also made adjustments to automate processes based on changes of tasks, models, and conditions.

The main decision point for management is thus not which to select — humans or robots. Is developing a learning system where each enhances the effectiveness of another. Organizations that develop this capacity can leverage the ready technology into unique performance, while maintaining judgment, legitimacy and long-lasting value of their workforce.

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Mathilde Sabouné:

Conceptualization, Methodology, Investigation, Data Curation, Formal Analysis, Visualization, Writing – Original Draft, and Project Administration.

Jorien Nyobe:

Validation, Interpretation, Writing – Review and Editing, and Supervision.

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