

Generative Change Management

A Pedagogical Proposal for Human-AI Hybrid Productivity and Competitiveness

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Abstract

The integration of generative artificial intelligence (AI) into work raises three interdependent questions for people who lead teams and processes: how professional contribution is redefined when cognitive capabilities are shared with AI; how production is reorganized when parts of a workflow are delegated to AI with different degrees of autonomy; and how AI-generated outputs participate in organizational decisions, knowledge, and relationships.

Generative Change Management (GChM) addresses these questions through three pedagogical dimensions that correspond to the framework's core capabilities: professional value develops expanded professional capability; productive agility develops hybrid production architecture; and organizational relationships develop hybrid organizational intelligence. Their deliberate articulation supports hybrid productivity. Algorithmic language operates as a cross-cutting professional competency, while symbolic-algorithmic linkage describes the organizational process through which AI-generated outputs acquire meaning, legitimacy, and practical authority.

The proposal works with situations drawn from participants' professional practice. Through analysis, design, application, reflection, and redesign, participants learn to configure digital production units, distinguish delegation of execution from delegation of judgment and criteria, define verification and process reconstruction, preserve accountability, and integrate human and AI capabilities without weakening professional judgment or collective learning. Hybrid competitiveness is treated as a downstream strategic effect that may emerge when hybrid productivity becomes an organization-specific and difficult-to-replicate capability.

Keywords: *Generative Change Management; hybrid productivity; hybrid competitiveness; expanded professional capability; hybrid production architecture; digital production unit; hybrid organizational intelligence; symbolic-algorithmic linkage; algorithmic language; professional learning.*

1. Organizational Context

Generative AI has spread rapidly and unevenly across organizations, reaching activities such as analysis, creation, programming, synthesis, and knowledge production. The Artificial Intelligence Index Report 2026 indicates that 70% of surveyed organizations use generative AI in at least one function. Work redesign is proceeding at a different pace: approximately 15% report a fundamental transformation of their processes based on these technologies (Sajadieh et al., 2026; World Economic Forum, 2026). Technological availability has advanced faster than organizations' capability to transform work with it.

Research on combinations of human and AI capabilities shows that integration does not produce uniform improvements. Outcomes vary by task and by the way functions are distributed between people and AI systems (Gonzalez et al., 2026; Kellogg et al., 2020; Simón et al., 2024; Vaccaro et al., 2024). The potential advantage therefore depends on determining which capabilities contribute to each segment of work and how they are combined. When that design does not occur, technology enters practice without clear rules of integration. An organization may produce results faster while leaving its underlying productivity unchanged.

The challenge is particularly significant for middle managers, functional managers, and process owners. They translate strategic direction into work practices, distribute responsibilities, sustain quality criteria, and answer for results to other units and third parties. At this level, organizations determine which professional contributions receive recognition, how capabilities are sequenced within a workflow, what evidence supports an AI-generated output, and who can intervene before that output guides a decision.

GChM provides a methodological framework for three interdependent transformations: the redefinition of professional contribution, the design of hybrid production architectures, and organizational coexistence with algorithmic intelligence (Manucci, 2026c). The pedagogical proposal translates these transformations into learning experiences that enable participants to analyze current practice, design new configurations of people and digital production units, apply them in situated work, evaluate the results, and convert experience into organizational learning.

The proposal is designed for work with complex and contested problems, where the definition of the problem changes as perspectives, constraints, and consequences become visible (Alford & Head, 2017; Head & Alford, 2015; Rittel & Webber, 1973). It does not present AI integration as a universal technical solution. It develops the capacity to frame situations, identify relevant knowledge, distribute capabilities, test assumptions, and redesign arrangements in response to evidence.

2. Dimensions of the Approach

The pedagogical proposal develops the capability to analyze, design, and apply new configurations of people, digital production units, and organizational strategy. Participants work with situations drawn from their own professional practice and make explicit the knowledge, assumptions, and criteria that guide action. This reflective orientation treats professional knowledge as situated and often tacit, and turns experience into material for inquiry and redesign (Kinsella, 2010; Ravanal Moreno et al., 2021; Schön, 1983).

Learning is organized as a recursive sequence. Participants diagnose how work is currently produced, examine the attributions and criteria embedded in that practice, design an alternative configuration, apply it to a real situation, and review both the result and the process that produced it. Reflection can become transformative when it changes not only a technique but also the frames through which people define a problem, understand their contribution, and interpret their professional identity (Carter & Nicolaides, 2023; Illeris, 2014; Laros, 2017; Mezirow, 2000).

Pedagogical dimension	Core question	Transformation focus	Capability developed
Professional value	Which contributions generate value when certain cognitive capabilities become widely available?	Relationship among people, AI, and the actual recognition base of professional contribution	Expanded professional capability
Productive agility	How is work reorganized when part of production is executed with different degrees of autonomy?	Workflow architecture, delegation, verification, process reconstruction, responsibility, and accountability	Hybrid production architecture
Organizational relationships	How do AI-generated outputs enter organizational knowledge, deliberation, and decisions?	Trust, legitimacy, recognition, authorship, and symbolic-algorithmic linkage	Hybrid organizational intelligence
Integrated result	How can the three transformations be learned, evaluated, and redesigned together?	Organizational learning and the deliberate articulation of human and AI capabilities	Hybrid productivity

Note. The pedagogical labels name the learning entry points. The fourth column establishes their direct correspondence with the canonical capabilities of GChM.

The term generative describes this learning and change process rather than the technology. The experience is generative when it produces capabilities, criteria, practices, and relationships that were previously unavailable in the organization. Technology expands the possibilities for analysis and execution; the pedagogical process develops the human and organizational capability required to use those possibilities deliberately.

2.1. Professional Value

This dimension addresses the interaction of human and AI capabilities in the production of results. It examines the subjective and professional effects that arise when capabilities associated with expertise become more widely available, the way generative models participate in reasoning and production, and the expanded professional capability that can emerge from deliberate collaboration.

Generative AI immediately expands the possibilities of individual production, but the criteria for governing that productive dialogue develop more slowly. This asymmetry invites a review of professional identity and of the parameters that distinguish an expert contribution. It also increases the importance of capabilities that often remained implicit: formulating problems, interpreting contexts, integrating perspectives, sustaining relationships, exercising judgment, and taking responsibility for results (Nelson & Irwin, 2014; Petriglieri, 2011).

The interaction involves an attributional relationship. People attribute properties such as competence, understanding, reliability, judgment, or authority to a digital production unit. These attributions influence what they consult, what they verify, what they accept without verification, and what they treat as sufficient to settle a decision (Manucci, 2026a). The pedagogical task is to make those attributions observable and open them to examination rather than allowing the fluency of a result to determine its authority.

Generative models produce language, analysis, and alternatives from probabilistic patterns and the context they receive. They do not possess situated knowledge of the organization, membership in the group affected by the decision, or responsibility for its consequences. Their uniformly fluent form offers no reliable indication of relevance or adequacy. The scope of what a model can produce is shaped by problem formulation, context, instructions, sources, tools, and rules. Professional knowledge enters the process through those operations.

The recognition base of a professional practice is the set of contributions through which value is actually recognized, evaluated, and rewarded. It must be distinguished from the criteria formally stated in job descriptions or competency models. Participants examine which contributions receive recognition in practice, which have become more abundant through AI, which remain distinctive, and which new contributions are required. This analysis supports a redefinition of professional value without reducing it to output volume or technological fluency.

Expanded professional capability is the ability to formulate problems, decide, create, learn, and respond with a broader range of possibilities than would be available without AI assistance. Expansion requires an active position toward the problem, the criteria guiding action, the interpretation of results, and the professional and ethical consequences of decisions. It can enable people to address greater complexity and explore a wider space of alternatives, while preserving the judgment through which those alternatives acquire situated value.

Learning activities in this dimension compare assisted and unassisted approaches, reconstruct the assumptions embedded in prompts and outputs, identify changes in the recognition base, and examine when AI expands reasoning or replaces it. Evidence suggests that sustained use can support or weaken critical engagement depending on how interaction is structured (Gerlich, 2025a, 2025b; Sarkar et al., 2024).

The objective is to design a relationship that makes professional reasoning more explicit, testable, and capable of development.

2.2. Productive Agility

This dimension addresses the delegation of productive activity to AI systems with different degrees of autonomy. It examines what happens to a workflow when part of production is executed without direct human intervention, how verification and accountability change as execution shifts, and what hybrid production architecture emerges from the new distribution of capabilities.

Delegation of execution defines which parts of production an AI system can perform. Delegation of judgment defines the extent to which an AI system can participate in evaluating, selecting, prioritizing, or validating alternatives and results. The distinction is essential because transferring an action does not necessarily transfer the judgment that governs it.

Delegation of criterion is a specific and consequential form of delegation of judgment. It occurs when the standard used to assess adequacy is transferred, explicitly or implicitly, to the AI system. An output may then be accepted because it is fluent, structured, confident, or formally consistent, even though those properties do not establish that it is appropriate for the situation. Participants learn to identify where criteria originate, who can challenge them, and what independent evidence is required before a result can advance through the workflow.

The combination of execution and judgment determines the effective degree of autonomy of each segment. Process improvement depends on AI contributions forming articulated sequences rather than isolated accelerations (Demirer et al., 2026). Agentic AI expands this participation because a digital production unit can interpret objectives, use tools, connect operations, execute sequences, monitor conditions, and adjust its intervention. Each degree of autonomy therefore requires explicit rules for data access, evidence, intervention, escalation, legal obligations, and ethical consequences.

Verification and process reconstruction are separate but complementary requirements. Verification determines whether a result satisfies independent criteria and must have the authority and capacity to change the result. Process reconstruction preserves the evidence needed to explain how the result was produced, which sources and rules were used, what was delegated, and where human intervention occurred. Together, they sustain traceability and make learning possible (Manucci, 2026b).

Responsibility identifies who performs or owns a task. Accountability identifies who answers for the result before third parties. These roles must remain aligned with the effective capacity to understand, evaluate, interrupt, modify, or reject the production process. A person should not be held accountable for an output that they had no meaningful ability to review or change (Elish, 2019).

A knowledge map identifies where relevant experience, expertise, judgment, and verification capacity reside in the organization. Participants examine how a new workflow changes consultation routes and whether repeated use of AI weakens knowledge of who knows what. Preserving the knowledge map is not a symbolic defense of human participation. It supports escalation, peer challenge, institutional memory, collective learning, and resilience (Lewis, 2003).

A hybrid production architecture is the way an organization deliberately combines human capabilities and digital production units to generate results that it issues under its own name and for which it remains accountable. The architecture includes functions, dependencies, intervention points, degrees of autonomy, delegation rules, evidence requirements, verification practices, records, and the distribution of responsibility and accountability.

Participants design the architecture in relation to the distinctive core of the practice: the human and organizational capabilities that sustain identity, legitimacy, quality, learning, and competitive differentiation. Decisions about what to transfer, what to expand, and what to preserve are strategic decisions about the organization's future capability, not merely technical decisions about task automation (Prahalad & Hamel, 1990; Teece et al., 1997).

2.3. Organizational Relationships

This dimension addresses the transformation of organizational culture when AI systems contribute to cognitive work. It examines shared meaning, belonging, trust, leadership, and recognition; the place of AI-generated outputs in organizational deliberation; and the collective intelligence that can emerge from coexistence among different forms of cognition.

Organizational culture develops among people who share histories, membership, relationships, and the consequences of what they decide. This shared foundation sustains meaning, belonging, trust, and leadership. AI systems contribute language, analyses, classifications, alternatives, and recommendations without having lived the experience to which that language refers, belonging to the group that receives it, or assuming what happens afterward. Yet their outputs circulate in formats similar to a colleague's contribution and can affect who is heard, which arguments acquire authority, how discussions close, and which contributions receive recognition.

Strategic alignment therefore proceeds through two related but distinct paths. People align through cultural processes in which purpose is interpreted, deliberated, and internalized as a guide for action. Digital production units align through configuration: the instructions, rules, sources, tools, memory, and context they receive. Treating these paths as equivalent obscures the difference between human commitment and technical conformity.

Hybrid organizational intelligence is the collective capability to combine the cognitive sophistication of AI with situated knowledge, interpretation, relationships, institutional memory, and human meaning-making. Its development requires conditions in which disagreement, explanation, contextualization, and reconstruction can change outcomes. Psychological safety and collective reflection are important because people must be able to question a technically fluent result, disclose uncertainty, and revise a shared course of action (Edmondson, 1999; Segal, 2024).

Symbolic-algorithmic linkage is the organizational process through which AI-generated language, analyses, classifications, alternatives, recommendations, and actions are integrated with human processes of interpretation, legitimization, relationship-building, memory, and meaning-making. The linkage defines how algorithmic productions enter deliberation, what authority they receive, how assistance is disclosed, which contributions they displace or expand, and how the organization turns what it receives from AI into something with situated meaning.

This organizational process is distinct from algorithmic language, which is a professional competency. Algorithmic language concerns how a person works with generative models on the knowledge of a domain. Symbolic-algorithmic linkage concerns how the organization receives, validates, recognizes, circulates, and remembers the resulting productions. The distinction prevents an individual interaction technique from being mistaken for the cultural architecture required to integrate AI into organizational life.

3. Algorithmic Language as a Cross-Cutting Competency

Algorithmic language is the professional capability to work with generative models on the knowledge of a domain. It cuts across the three pedagogical dimensions because it is the route through which professional experience enters the digital production process and becomes production. The competency is broader than prompt writing. It combines problem formulation, context building, interrogation regimes, knowledge integration, evidence verification, and responsible authorship and circulation (Annapureddy et al., 2024; Liu et al., 2025; Yan et al., 2024).

Participants develop algorithmic language through repeated cycles of formulation, production, contrast, reconstruction, and revision. The purpose is not to memorize interface-specific techniques. It is to learn how professional criteria can be translated into configurations and interactions that remain explicit, testable, and accountable as models and tools change.

Professional value. Problem formulation defines objectives, constraints, stakeholders, consequences, and criteria for discrimination. Context building makes situated knowledge, prior decisions, exceptions, and relevant conditions available to the model. Interrogation regimes organize sequences of exploration, comparison, refutation, and synthesis. These operations allow professional experience to shape the space of possible production and help participants observe where their own judgment enters the process.

Productive agility. Knowledge integration combines data, sources, perspectives, and domains into a production that can enter a workflow. Evidence verification evaluates outputs against facts, metrics, sources, and explicit criteria. These operations provide the basis for configuring digital production units, defining degrees of autonomy, and establishing verification and process reconstruction. They also make visible whether a workflow preserves the capability to challenge and change an AI-generated result.

Organizational relationships. Authorship and circulation integrate assisted work into the team's processes of validation, recognition, and accountability. Participants make explicit what was generated with assistance, what sources were used, what was verified, what was changed, and who accepts responsibility for circulation (He et al., 2025). This information makes AI-generated production available for organizational scrutiny and supports symbolic-algorithmic linkage.

The competency is developed through situated tasks rather than detached exercises. Participants select a professional problem, specify the knowledge and criteria required to address it, configure an interaction or digital production unit, compare results across different formulations and evidence regimes, and document the choices that changed the result. This design supports transfer because learning is connected to the conditions, relationships, and tools of the work in which it will be used (Blackburne, 2024; Brion, 2022; Coleman et al., 2025; Kauffeld et al., 2025; Mehner et al., 2025; Sala et al., 2019).

The design also protects against passive cognitive offloading. Participants are required to produce independent criteria, identify disconfirming evidence, explain why a result is adequate for the situation, and reconstruct the path from problem formulation to final decision. The aim is a form of AI literacy that improves job performance while preserving the reflective and critical capabilities on which professional learning depends (Gerlich, 2025b; Liu et al., 2025; Woods et al., 2026).

4. Hybrid Productivity and Competitiveness

Hybrid productivity is the capability of an organization to generate results through the deliberate articulation of human and AI capabilities within its work systems. It includes efficiency gains but is not defined by speed

or volume alone. It emerges when expanded professional capability, hybrid production architecture, and hybrid organizational intelligence reinforce one another through practice, evaluation, learning, and redesign. The pedagogical proposal evaluates hybrid productivity through five distinctive outcomes. Each outcome requires attention to both the result and the process that produced it.

Cognitive breadth. The work incorporates a wider range of relevant alternatives, sources, interpretations, and perspectives without confusing abundance with relevance.

Decision quality. Decisions integrate evidence, context, independent criteria, situated judgment, and explicit responsibility for consequences.

Adaptive fluidity. Roles, capabilities, workflows, and degrees of autonomy can be reconfigured as conditions, knowledge, and technologies change.

Cumulative learning. Experience, verification, exceptions, and reviews are converted into improved criteria, configurations, practices, and organizational knowledge.

Responsible scalability. The scope and speed of production expand while the organization preserves understanding, traceability, intervention capacity, verification, process reconstruction, and accountability.

These outcomes provide criteria for comparing an existing configuration with a redesigned one. A pedagogical exercise is successful when participants can explain which capability changed, what evidence supports the change, what new risks appeared, and what should be redesigned. Transfer to organizational practice requires social support, opportunities for application, and mechanisms for sharing what is learned beyond the individual participant (Kauffeld et al., 2025; Mehner et al., 2025).

Hybrid competitiveness is the strategic effect that may emerge when hybrid productivity becomes an organization-specific and difficult-to-replicate capability. It is not a fourth core GChM capability and does not follow automatically from access to AI. Differentiation develops through situated knowledge, professional judgment, organizational relationships, verification practices, learning processes, and production configurations that competitors cannot reproduce merely by using the same technology.

The pedagogical proposal therefore connects individual learning with organizational design. It develops professionals who can work with generative models, teams that can configure and govern hybrid production, and organizations that can integrate AI-generated outputs into their cultural and decision-making processes. The intended result is not a fixed model of human-AI work, but a continuing capability to analyze, design, evaluate, learn, and redesign as technologies and organizational conditions evolve.

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