Chapter 5:

The Impact of Artificial Intelligence on Organizational Change Processes: A New Change Management Paradigm?

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Abstract

Artificial intelligence (AI) is no longer merely used as a new technological tool in organizations; it is becoming one of the constitutive elements of decision-making, coordination, control, knowledge production, work design, and employee experience. This development raises the question of whether AI, beyond being an object of organizational change, is transforming how change emerges, by whom it is directed, and over what time horizon it is managed. The aim of this chapter is to critically evaluate the explanatory power of established change management approaches in the age of AI and to develop an integrated conceptual framework for explaining AI-mediated organizational change. Lewin's planned change approach, Kotter's model, organizational development, continuous change, organizational learning, dynamic capabilities, socio-technical systems, and technology acceptance approaches are compared in the context of AI's learnability, partial autonomy, opacity, and scalability. The conceptual synthesis indicates that the mechanisms of leadership, participation, communication, trust, and institutionalization emphasized by established approaches remain valid; however, assumptions of linear processes, a clearly defined end state, exclusively human agency, and one-off implementation are inadequate. The "double-loop AI change governance" model proposed in this chapter integrates the redesign of organizational task and decision architectures with monitoring the AI system throughout its life cycle in terms of performance, errors, fairness, and employee impacts. In conclusion, it is argued that it is premature to declare that AI constitutes an entirely new paradigm; nevertheless, it necessitates a substantial paradigm extension that reconceptualizes change management as a continuous, distributed, data-informed, and socio-technical governance capability.

Keywords: artificial intelligence, organizational change, change management, algorithmic management, human–AI collaboration, digital transformation, socio-technical systems

1. Introduction

Organizations' turn toward artificial intelligence is creating a transformation dynamic that differs from traditional information technology applications. Earlier digital systems, such as enterprise resource planning or process automation, also altered organizational structures and routines; however, contemporary AI systems enter directly into cognitive work through classification, prediction, recommendation, and content generation, participate in decision processes under certain conditions, and can be updated with new data during use. Generative AI's capacity to produce text, code, images, and analyses has transformed technology from a tool that merely executes predefined instructions into an active component of knowledge production. The impact of AI in organizations is therefore more extensive than the expression "transition to a new technology" can convey.

The fundamental distinction is between change carried out with AI and a change in the nature of change because of AI. In the first case, the organization selects and implements a particular technology and manages employees' adaptation to it. In the second case, AI participates in defining change-related problems, generating alternatives, monitoring employee behavior, and adapting interventions. Technology thereby becomes not only an object of change but also an element that shapes the change process. Redistributing decision rights between humans and algorithms does not eliminate the role of managers, but it changes where and how managerial judgment is exercised (Shrestha et al., 2019). Algorithmic management practices likewise transfer managerial functions such as performance measurement, task allocation, ranking, and rewarding to data-driven systems, thereby transforming both the manifestation of control and the way employees experience it (Kellogg et al., 2020).

The contemporary organizational effects of AI are not unidirectional. Brynjolfsson et al.'s (2025) field study in customer service shows that generative AI support can increase productivity and that the gains are concentrated particularly among less experienced employees. This finding suggests that AI can diffuse expert knowledge. At the same

time, the standardization of knowledge may render the distinctive contributions of experienced employees less visible, while excessive dependence on system recommendations may lead to skill erosion in the long term. Similarly, field evidence showing that individuals working with AI can approach team-level performance in certain tasks indicates that the technology can stretch expertise boundaries, but does not demonstrate that the social and emotional dimensions of collaboration have been entirely substituted (Dell'Acqua et al., 2026). Productivity gains alone are therefore not a sufficient criterion for explaining the success of organizational change.

This study adopts a conceptual review approach, conducted as a narrative (non-systematic) review of the literature through a socio-technical systems lens, to examine how artificial intelligence reshapes organizational change processes and the governance mechanisms through which these processes are managed. It draws on relevant literature on organizational change, change management, artificial intelligence, human–AI collaboration, and socio-technical systems. Rather than reporting an original empirical investigation or a systematic literature review, the chapter critically synthesizes these bodies of literature to compare established change management perspectives, identify their explanatory boundaries in the context of AI, and develop an integrated conceptual framework. The analysis is organized around the implications of AI for the temporality and agency of change, organizational decision-making, work design, governance, and the human experience of change. This conceptual synthesis provides the basis for the proposed Double-Loop AI Change Governance Model.

2. Conceptual and Theoretical Foundations

2.1. Artificial Intelligence, Generative Artificial Intelligence, and Algorithmic Management

Artificial intelligence can be defined as the set of computational systems that collect data from their environment and process these data

for purposes such as classification, prediction, recommendation, optimization, or content generation. This definition treats AI not as a holistic replica of human intelligence but as technical arrangements that perform specific cognitive functions to varying degrees. In an organizational context, defining AI solely in terms of its technical capacity is insufficient; the tasks undertaken by the system, how it affects decisions, and how it relates to the judgment of human actors must also be considered. Organizational AI should therefore be conceptualized not as an independent agent replacing human decision makers, but as a socio-technical arrangement in which managerial tasks and decision processes are redistributed between humans and algorithms (Benbya et al., 2020; Hillebrand et al., 2025).

Generative AI encompasses models that produce new text, code, images, audio, or similar content on the basis of patterns in existing data. In relation to generative AI, the capacity to "generate new content" must be distinguished from the capacity to "produce accurate and reliable information." A system's ability to generate fluent text, code, or recommendations does not mean that the content it produces has been verified. This distinction demonstrates that human oversight in organizations is not merely a technical safeguard but a design principle that protects decision quality and organizational accountability (Dwivedi et al., 2023; Jarrahi, 2018).

Algorithmic management refers to the use of data and algorithms in managerial functions such as task allocation, performance evaluation, scheduling, compensation, and discipline. Management does not disappear in this arrangement; rather, it becomes embedded in code, metrics, data-collection arrangements, and exception rules. Kellogg et al.'s (2020) discussion of "algorithmic control" shows that algorithms' capacities to direct, evaluate, and discipline also reshape employee contestation and accommodation strategies. Algorithmic management should therefore be understood not merely as an instrument of technical efficiency, but as an arrangement of power, visibility, and accountability.

2.2. Organizational Change, Change Management, and Digital Transformation

Organizational change is the differentiation that emerges over a given period in an organization's structure, processes, membership relations, goals, routines, or distribution of power. Change does not occur only in the form of projects planned by top management; it may also emerge through responses to environmental pressures, employees' everyday adaptations, organizational learning, and the accumulation of small adjustments. Organizational change is therefore a multilevel process that may be both planned and emergent, and both episodic and continuous (Huber ve Bartunek, 2016; Weick & Quinn, 1999).

Change management is not identical to change itself. Change refers to differentiation in the state of the organization, whereas change management refers to the managerial and participatory interventions used to direct, make sense of, implement, and institutionalize that differentiation. This distinction makes it possible to include in the analysis changes that are not directly planned by managers but arise through employee practices, technology updates, or environmental conditions (Burnes, 2004).

Digital transformation refers to comprehensive change through which digital technologies reshape an organization's value-creation logic, processes, and stakeholder relationships (Verhoef et al., 2021; Vial, 2019). Although AI transformation is a subset of digital transformation, it should be analytically distinguished because of three characteristics. First, AI generates outputs and influences decisions; it does not merely transmit information. Second, its performance depends on data quality and the context of use. Third, model behavior can change through updates, new inputs, and user interactions. These characteristics render the statement "implementation is complete" problematic. Even when an AI system has technically been deployed, organizational roles, oversight thresholds, and norms of use continue to evolve.

2.3. Human–AI Collaboration and Socio-Technical Formation

Human–AI collaboration refers to the complementary participation of a human and a computational system in a shared task or decision process. This relationship is not a simple division of labor; it is a reciprocal arrangement in which actors evaluate one another's outputs, are affected by one another's errors, and alter their usage strategies over time. The human–AI symbiosis emphasized by Jarrahi (2018) is based on the potential to combine human intuition and contextual judgment with the machine's pattern-recognition capacity. Complementarity, however, does not emerge automatically. Unless task boundaries, forms of explanation, channels for contestation, and responsibility for the final decision are designed, the hybrid system may amplify errors rather than combine the strengths of both parties.

The socio-technical systems approach is of central importance for understanding this issue. Since the work of Trist and Bamforth (1951), the core argument has been that technical and social subsystems should be jointly optimized. The effects of AI are not reducible to model accuracy; they emerge together with performance indicators, incentive systems, managerial behavior, employees' professional norms, and organizational culture. Orlikowski's (1992) approach to the structuration of technology likewise demonstrates that technology both shapes organizational action and is reshaped within practices of use. From this perspective, AI is not an independent variable that "acts upon" the organization from the outside, but a socio-technical component that acquires meaning and power within organizational practices.

3. A Critique of Established Change Management Approaches in the Age of AI

3.1. Lewin: Equilibrium, Process, and Participation

Lewin's (1947) approach to change is commonly presented as a linear model consisting of unfreezing, changing, and refreezing. This reading assumes that the organization is moved from an existing equilibrium to a new equilibrium. From the perspective of learning and frequently updated AI systems, the idea of "refreezing" initially appears inadequate because model performance, data distributions, and usage practices continue to change. Lewin's approach, however, should be considered not merely as a three-stage linear prescription but together with group dynamics and action research. Burnes (2004) demonstrates that, when read in conjunction with Lewin's group dynamics, field theory, and action research, the approach offers a participatory and iterative understanding of change.

What should be retained from Lewin in the age of AI is not the idea of "freezing the end state," but the logic of making the existing force field visible and enabling collective learning. When an algorithmic performance system is implemented, technical accuracy should be examined alongside employees' perceptions of fairness, how managers invoke the system, and the channels through which objections are addressed. Refreezing can be reinterpreted as a temporary governance settlement rather than permanent stability: which decisions may be automated, at which thresholds human review is required, and which data may not be used are tied to institutional rules that are periodically reconsidered.

3.2. Kotter and ADKAR: The Tension Between Managerial Mobilization and Linear Implementation

Kotter's eight-stage model offers practical mechanisms such as creating a sense of urgency, building a guiding coalition, developing a vision, communicating, removing obstacles, generating short-term wins, and embedding change in culture (Kotter, 1995). Top-management support, a shared vision, and early wins remain important in AI transformations. Particularly in projects characterized by high uncertainty, visible pilot results can translate abstract AI discourse into concrete organizational benefit. The problem arises when the model is read as a program initiated by management and progressing through sequential stages. Employees may begin using generative AI spontaneously before a formal strategy exists in many organizations. A model update by the technology provider may alter capabilities and risks even during the project's "implementation" stage. Under these conditions, top-down communication of a single vision is insufficient; a two-way process is required in which feedback from usage practices can modify strategy.

Jeffrey Hiatt proposed the ADKAR model to minimize resistance that may arise in organizational change and to enable change to proceed with an appropriate strategy. The model consists of five main components: Awareness, Desire, Knowledge, Ability, and Reinforcement. Awareness and Desire concern moving the individual out of the current state by recognizing that change is needed even though it has not yet begun. Knowledge and Ability relate to the change process itself, whereas Reinforcement focuses on the future after the change (Hiatt, 2006).

ADKAR's dimensions of awareness, desire, knowledge, ability, and reinforcement are useful for monitoring individual adaptation. Nevertheless, explaining adaptation to AI solely through individual motivation and skill may obscure system errors, organizational injustice, and the intensity of surveillance. An employee's objection to algorithmic evaluation is not always "resistance to change"; it may sometimes be a

valid governance signal concerning data quality, a breach of professional ethics, or inexplicable decisions. In such a case, the target of intervention should not be to change the employee's attitude, but to correct the system and the decision process.

3.3. Organizational Development, Continuous Change, and Sensemaking

The organizational development approach provides a strong foundation for AI transformation in terms of participation, feedback, group processes, and humanistic values. The diagnosis–intervention–evaluation cycle of action research is compatible with piloting AI applications and evaluating their outcomes together with employees. However, when conventional organizational development practices leave technology design to specialists and address social adaptation only afterward, socio-technical integrity is lost. AI teams, human resources, legal, risk, operations, and employee representatives should participate in the same design cycle.

Weick and Quinn's (1999) distinction between episodic and continuous change is particularly useful for explaining the temporality of AI. Episodic change refers to interventions with a defined beginning and end, whereas continuous change describes the cumulative transformation of the organization through everyday adaptations. AI transformation embodies both logics. Model selection, infrastructure investment, and workflow redesign can be conducted as episodic programs, whereas users' prompting practices, exception management, and levels of trust in the system change continuously. AI change management should therefore combine project management with a sensemaking capacity that monitors the continual re-formation of practices.

3.4. Organizational Learning, Dynamic Capabilities, and Technology Acceptance

The organizational learning perspective makes visible AI's bidirectional effects on knowledge production and organizational memory. AI can disseminate the knowledge of experienced employees to a broader group; yet when it obscures the source and context of that knowledge, it may create superficial standardization. Argyris and Schön's (1978) distinction between single-loop and double-loop learning is important here. Single-loop learning involves correcting errors while preserving existing goals. Double-loop learning questions the goals, assumptions, and decision rules themselves. Improving the accuracy of an AI system is single-loop learning; questioning why a particular decision has been automated and whether the performance criterion is fair is double-loop learning.

The dynamic capabilities approach focuses on an organization's capacity to sense opportunities, seize them, and reconfigure its resource base (Teece, 2007). In the AI context, sensing requires distinguishing a technological possibility from a business problem; seizing requires combining investments in data and capabilities with appropriate governance; and reconfiguring requires transforming tasks, decision rights, and competencies. Nevertheless, when the dynamic capabilities approach is not complemented by employee experience and power inequality, it risks reducing change to the strategic capacity of top management alone.

The Technology Acceptance Model and UTAUT explain the role of perceived usefulness, ease of use, social influence, and facilitating conditions in adoption (Davis, 1989; Venkatesh et al., 2003). These variables are important in AI use, but remain incomplete unless trust, explainability, professional identity, and fairness concerns are incorporated. An employee may find a system useful and easy to use yet refuse to use it because of the risk of harm to customers or ambiguity

regarding accountability. Acceptance is therefore not a behavioral outcome independent of ethics and organizational legitimacy.

4. The Impact of Artificial Intelligence on the Nature of Organizational Change

4.1. The speed and continuity of change

AI can increase the speed of organizational change through different mechanisms. First, by reducing the time spent on knowledge-intensive activities such as analysis, content generation, and problem solving, it enables change-related activities to be carried out more rapidly. Second, feedback from user interactions and operational data makes it possible to adjust processes at frequent intervals (Dell'Acqua et al., 2026). Speed, however, is not synonymous with change capacity. An organization may deploy a technical system rapidly, while employees' sensemaking regarding new responsibilities, the assessment of legal risks, and the development of trust relationships may take longer. The asymmetry between technical speed and social adaptation is one of the fundamental tensions of AI transformation.

Continuity does not arise solely from the model's learnability. Updates by AI providers, shifts in data patterns, users' development of new use cases, and changing regulatory expectations continuously redraw the boundaries of implementation (Te'eni et al., 2026). The aim of change management should therefore be to produce safe adaptability rather than to reach a fixed "future state." Continuous change should not mean continuous intervention; otherwise, employees may experience change fatigue. Effective governance clearly distinguishes which elements are experimental and changeable from which principles are stable. Model selection may change, for example, while the principles of non-discrimination, the right to contest decisions, and human responsibility remain stable.

4.2. Agency and Decision Architecture

In established narratives of change, top management initiates change, change leaders implement it, and employees adopt or resist it. In AI-mediated change, agency is more distributed. Data scientists shape the model's technical boundaries, vendors determine update schedules, legal units define limits of use, employees shape actual practices, and algorithms shape the options that become visible. An algorithm is not a morally or legally responsible agent; however, by ranking options, altering the distribution of attention, and rewarding particular behaviors, it produces agent-like effects on organizational action.

Shrestha et al. (2019) show that human and AI decisions can be arranged sequentially, in an integrated manner, or through delegation. What matters is to establish a more detailed decision architecture than simply asking, "Is the human in the loop?" At what stage does the human intervene? Does the person have sufficient information and time to evaluate the system's recommendation? Must the person justify a decision not to follow the recommendation? Who is responsible for the outcomes? If human approval is merely symbolic, the actual decision has been delegated to the algorithm despite the apparent presence of human oversight. Change management should therefore examine the actual distribution of decision rights rather than merely the labels attached to roles.

4.3. Work Design, Structure, and Coordination

AI's impact on work design cannot be reduced to an automation–augmentation dichotomy. Raisch and Krakowski's (2021) automation–augmentation paradox demonstrates that organizations simultaneously seek to delegate tasks to machines and enhance human capacity. Automating a task may make the remaining human work more meaningful, or it may reduce human work to exception and error management. Requiring people to deal continuously with difficult cases about which the system is uncertain can increase cognitive and emotional load. Conversely, reducing routine workload may create space for

judgment and customer relationships. The outcome depends less on the characteristics of the technology itself than on how work is repackaged.

When generative AI lowers the cost of accessing knowledge, functional boundaries may become more permeable. A marketing specialist may generate basic code, while a software developer may draft customer communications. Dell'Acqua et al.'s (2026) field study demonstrates that AI can contribute to the integration of expertise and enable individuals to obtain some of the benefits associated with teams. The organizational implication is not that teams become unnecessary, but that the reasons for forming teams change. While some coordination ties established for access to knowledge may weaken, new ties become necessary for ethical evaluation, critical judgment, and social support.

4.4. Power, Control, and Accountability

AI systems can increase organizational visibility: behaviors that were previously unrecorded can be measured, compared, and predicted. This visibility may improve resource allocation while simultaneously intensifying surveillance. Although algorithmic control may create the impression that rules are neutral, decisions about which data are collected, how objectives are defined, and who bears the cost of errors are managerial choices. As Pachidi et al. (2021) demonstrate, working with algorithmic systems creates new forms of negotiation between professional knowledge and data-driven recommendations. Rather than simply accepting or rejecting the system, employees interpret its outputs, sometimes work around it, and reposition their own expertise.

Attributing accountability to the technical system is a significant risk. The statement "the algorithm recommended it" can diffuse responsibility for a decision; yet it is the organization that selected the model, authorized data use, and defined oversight thresholds. AI governance should therefore include mechanisms for decision traceability, explanation, contestation, correction, and responsibility beyond performance accuracy. Particularly in hiring, promotion, compensation,

and disciplinary decisions that affect employees, explainability is not merely a technical feature but a condition of organizational justice.

4.5. The Transformation of Leadership and Change Agency

Leadership in the age of AI entails responsibilities broader than articulating a technology vision or encouraging employees to use a new tool. Leaders need to establish the connection between technical possibilities and organizational purpose, communicate uncertainties openly, and prevent performance pressures from exceeding ethical boundaries (Deb Biswas & Sengupta, 2026). A leadership discourse that acknowledges that AI can make errors does not necessarily create distrust of technology; on the contrary, it helps employees understand when the system can be trusted. Claims of certainty, by contrast, may damage organizational trust when the first visible error occurs.

Change agency in the age of AI cannot be conceived as the responsibility of a single manager or project team. Identifying risks arising from the development, implementation, and use of AI systems requires technical, organizational, legal, and societal dimensions to be assessed together and actors from different areas of expertise to participate in the process. Indeed, the use of teams representing different disciplines, experiences, and areas of expertise in AI risk management is important for making existing and emerging risks visible (National Institute of Standards and Technology [NIST], 2023). Similarly, organizational AI governance is regarded as a multidimensional governance problem requiring technical requirements to be considered together with organizational goals and values, stakeholder expectations, ethical principles, and legal obligations (Mäntymäki et al., 2022). Although this multi-actor structure necessitates strong coordination mechanisms, it can reduce the limitations associated with assessing AI's heterogeneous effects through a single domain of expertise. Nevertheless, distributing responsibility across numerous actors should not mean that accountability becomes ambiguous. Effective AI governance requires roles, responsibilities, decision authorities, and lines

of communication to be clearly defined. It is particularly important that top management retain responsibility for decisions concerning risks associated with the development and use of AI systems (NIST, 2023). Thus, while change agency in the age of AI becomes distributed and multidisciplinary, ultimate accountability must remain with clearly defined decision-making authorities.

4.6. Organizational Culture and Sensemaking

Organizational culture should be regarded as an important contextual factor affecting how AI systems are used within the organization beyond formal policies and procedures. Formally defining human oversight does not mean that employees will effectively question algorithmic recommendations. Particularly in organizational environments where employees avoid challenging managerial decisions, error reporting is not encouraged, or performance pressure displaces critical evaluation, the practical effectiveness of human oversight may weaken. This situation requires automation bias-the tendency for people to place excessive trust in the recommendations of automated systems and disregard their own judgment or conflicting information—to be evaluated not only as an individual cognitive tendency but also in conjunction with the organizational context in which AI is used.

Sensemaking processes become even more important when AI reshapes employees' tasks, responsibilities, and professional roles. When AI systems assume tasks or decision-making responsibilities that previously fell within employees' domains of expertise, they can affect employees' professional role identities and their assessments of the value of their expertise within the organization (Mirbabaie et al., 2022; Strich et al., 2021). Employees' concerns about whether AI will replace them, which aspects of their expertise will retain value, or which competencies will be expected of them in the future should therefore be addressed not merely as communication deficits, but as questions related to the professional identity and meaning dimensions of change. Given that AI's effect on employee identity may differ depending on whether the technology is used to complement or substitute human tasks (Selenko et al., 2022), it is

insufficient for change management to focus only on explaining the efficiency gains that AI may provide. Organizations should more clearly specify which tasks will be automated, in which areas human judgment and expertise will retain a central position, and the mechanisms that will support employees in adapting to changing roles, tasks, and skill requirements (Zhao et al., 2026).

The aim of cultural transformation is not to make everyone optimistic about AI. Critical curiosity is the appropriate cultural objective: employees should be able to experiment with the technology, question its outputs, report errors, and propose alternative work designs. In such a culture, skepticism is not equated with opposition to innovation. Organizational memory concerning the limitations of AI is developed; failed experiments are transformed into learning resources for subsequent applications rather than concealed.

5. The Human Dimension of Change

5.1. Trust, Justice, and Psychological Safety

Trust in AI does not mean accepting every system output as correct. Appropriate trust means using the system in proportion to its capabilities and limitations. Glikson and Woolley (2020) show that perceptions of tangibility, transparency, reliability, and technical capability affect trust in human–AI interaction. Low trust may lead to the non-use of a useful system, whereas excessive trust may result in automation bias. The aim of change management is not to maximize trust, but to calibrate it.

Distributive, procedural, and interactional justice should be considered together in AI applications. Who receives the benefits and bears the costs generated by the system? Is the decision process consistent and open to contestation? Are employees provided with respectful and comprehensible explanations? Even when a model's average accuracy is high, the implementation may lose legitimacy if the costs of errors are concentrated among particular groups. Psychological safety also requires employees to be able to voice AI errors, ethical concerns, and their own learning difficulties without fear of punishment. A culture that labels an

employee who reports an error as "anti-technology" renders system risks invisible.

5.2. Professional Identity, Autonomy, and Resistance

AI affects not only employees' tasks but also their understandings of "good work" and "expertise." The imitation within seconds by a model of judgment that an expert has developed over years may create a sense of status loss and devaluation. Conversely, reducing routine work through AI may strengthen the contextual and relational dimensions of expertise. The difference between these two outcomes is associated with employees' participation in the design process and their genuine autonomy over final decisions.

The concept of resistance should be reconsidered in this context. In the change literature, resistance has sometimes been presented as an irrational obstacle to be overcome. Employee objections, however, may reveal deficiencies in system data, potential customer harm, or invisible dimensions of work. In line with Ford et al. (2008), resistance is not independent of the discourse and actions of change agents. A productive approach in AI transformation is to investigate what risk information an objection carries rather than suppress it. Not every objection is necessarily valid; however, its validity should be tested empirically and ethically before the objective becomes persuading the employee.

5.3. Skill Transformation and Organizational Learning

AI literacy cannot be limited to the ability to use AI tools or interact effectively with these systems. AI literacy is a multidimensional domain of competence requiring individuals to understand the capabilities and limitations of AI systems, critically evaluate the outputs they generate, and consider the ethical and societal consequences arising from the use of these technologies (Long & Magerko, 2020). Reskilling and development

programs for employees that focus only on technical tool use may therefore be insufficient for developing the critical evaluation and ethical reasoning competencies required by AI literacy. Employees' ability to assess the reliability and limitations of AI outputs, recognize appropriate boundaries of use, and understand risks such as privacy, bias, and accountability should also be regarded as important components of AI literacy. Nevertheless, not every employee in an organization needs the same level of technical AI expertise. AI literacy requirements differ according to employees' organizational roles and the task and decision responsibilities they assume. Differentiating AI-related competencies by considering how senior managers, middle managers, and other employees interact with AI systems and the responsibilities they bear therefore offers a more appropriate approach to developing organizational AI literacy (Benlian & Pinski, 2025).

From an organizational learning perspective, the most critical risk is that short-term productivity gains may conceal long-term capability loss. Less experienced employees may perform rapidly with AI; however, if they use outputs without learning the reasoning underlying the solution, pathways to expertise may weaken. Training should therefore encompass not only producing more output with AI, but also sustaining fundamental judgment without AI and critically evaluating AI outputs. Job rotation, case review, peer review, and periods of "AI-free practice" in particular tasks may preserve skill resilience.

5.4. Job Security, Inequality, and Employee Voice

The integration of AI into organizational processes does not mean merely the adoption of a new technology for employees; it can also create uncertainty regarding the continuity of their jobs, the future content of their tasks, and the value of the professional resources they possess. In particular, the capacity of AI systems to perform cognitive tasks previously carried out by humans can increase employees' concerns that their jobs, or important components of their jobs, may be substituted by technology.

Recent research indicates that AI-related job insecurity is not limited to fear of complete job loss, but may also include a qualitative form of insecurity concerning the deterioration of valued features of work because of AI. Job-security concerns in AI transformation should therefore be treated not as temporary resistance that can simply be resolved through communication, but as genuine job and career uncertainty created for employees by technological transformation (Fu & Zhang, 2026).

Inequality in the organizational outcomes of AI need not be distributed evenly among employees. How the technology is developed, implemented, and used can affect which employees benefit from AI, who is subjected to more intensive evaluation and control, and under what conditions existing inequalities are reinforced. Recent literature examining the relationship between AI and workplace inequality shows that inequality does not arise only from biases encoded in algorithms; evaluative, compensation-related, and relational forms of inequality may emerge throughout the development, implementation, and use of AI systems within organizations. The organizational effects of AI should therefore be assessed not as outcomes predetermined by technology, but as processes shaped by the decisions and practices of organizational actors (Karunakaran et al., 2025).

Employee voice in AI transformation should not be conceived as a participation mechanism limited to soliciting employee opinions before implementation. Because AI and algorithmic management systems can change employees' tasks, the way their performance is evaluated, skill requirements, and working conditions, it is important that employees and their representatives be able to participate in decisions concerning the adoption and use of these systems. International examples concerning the use of AI in the workplace indicate that social dialogue can enable employee representatives to influence AI-related decisions in areas such as employment and skill effects, algorithmic management practices, and working conditions. Institutionalizing employee voice through ongoing social dialogue and representation mechanisms throughout the implementation and development of AI, rather than through one-off

consultation processes, can therefore be regarded as an important element of a more inclusive AI transformation (Doellgast et al., 2026).

6. A New Paradigm?

Whether AI requires a new paradigm in change management can be discussed, on the basis of the literature, through three possibilities: paradigm continuity, paradigm transformation, and paradigm extension.

According to the paradigm continuity view, AI is not wholly disconnected from technological changes that organizations have encountered before. Issues such as the joint adaptation of technology and employees, work redesign, preparing employees for change, and achieving alignment between social and technical systems were already central to change management. Makarius et al. (2020), for example, explain the integration of AI into organizations through established theoretical approaches such as socio-technical systems and organizational socialization. Their perspective demonstrates that successful AI integration requires technology and employees to be considered together. From this viewpoint, AI does not constitute a rupture that entirely invalidates established change management knowledge; rather, it introduces new conditions under which existing change mechanisms must operate.

The paradigm transformation view, by contrast, emphasizes that the learnability, generativity, and increasing autonomy of contemporary AI systems alter traditional assumptions concerning agency, expertise, authority, and decision-making in organizations. AI is no longer merely a passive tool used by employees; it can participate in knowledge production, judgment, coordination, and decision processes. Chalmers et al. (2026) show that different forms of AI reshape the location of expertise, judgment, coordination, and authority in organizations, generating new theoretical questions concerning the locus of agency and decision architectures. These characteristics challenge the assumption that change is a linear process designed solely by humans and directed toward a predetermined end state.

Nevertheless, the literature examined in this chapter supports an interpretation of paradigm extension rather than complete paradigm transformation. AI does not eliminate established change mechanisms such as leadership, trust, participation, sensemaking, and organizational learning; instead, it changes the socio-technical context in which these mechanisms operate. As Makarius et al. (2020) also demonstrate, the organizational value of AI depends on the successful integration of technology and employees.

To clarify the distinction between established change management assumptions and the proposed paradigm extension, Table 1 compares the two perspectives across five dimensions: temporality, agency, end state, success criteria, and governance. This comparison illustrates that the implications of AI are not limited to the introduction of a new technology. They also concern how change unfolds over time, which actors participate in shaping it, how organizational stability is understood, how success is evaluated, and how responsibility for technological and organizational outcomes is governed.

Table 1. Comparison of established change management assumptions and paradigm extension in the age of AI

Comparison Dimension	Established Understanding of Change	Paradigm Extension in the Age of AI
Temporality	Change is generally treated as an episodic process or project with defined beginning and end points.	Episodic change and continuous adaptation processes must be managed together.
Agency	Managers, leaders, and human change agents are positioned as the principal actors of change.	Agency extends to a broader socio-technical ecosystem including managers and employees as well as AI systems, technology providers, and regulatory actors.
End state	Change aims to reach a relatively stable state in which new practices have been institutionalized.	Rather than a definitive and permanent end state, temporary stability, continuous learning, and regular reassessment come to the fore.

Success criteria	Adoption, use, institutionalization of change, and organizational performance are the principal indicators of success.	In addition to performance, trust, fairness, organizational learning, accountability, and the reversibility of interventions when necessary are evaluated.
Governance	Emphasis is placed on planning and implementing change and on post-implementation control.	Monitoring, evaluation, risk management, and continuous assurance mechanisms are required throughout the AI system life cycle.

As shown in Table 1, the proposed paradigm extension involves changes in the assumptions underlying established change management approaches rather than the wholesale replacement of those approaches. First, the temporal dimension shifts from a predominantly episodic understanding of change toward the combined management of implementation and continuous adaptation. Second, agency is distributed across a wider socio-technical ecosystem in which human actors and AI systems jointly influence organizational processes, although their responsibilities and decision rights are not necessarily equivalent. Third, the notion of a stable end state is qualified by the need for ongoing learning and reassessment as AI systems, data, and work practices evolve.

The comparison also highlights a broader understanding of organizational success and governance. Adoption and performance remain relevant, but they are insufficient when considered independently of trust, fairness, accountability, employee effects, and the capacity to revise or reverse interventions when necessary. Similarly, governance cannot be confined to planning, implementation, and post-implementation control; it must also include the monitoring of system performance and organizational consequences throughout the AI life cycle.

These dimensions are interrelated. Continuous adaptation requires broader participation and feedback; distributed agency requires explicit decision rights and accountability; and the reassessment of outcomes requires governance arrangements capable of responding to new evidence. Table 1 therefore supports the argument that AI extends established

change management thinking by integrating continuous learning, socio-technical redesign, and life-cycle governance into the management of organizational change.

This extension does not require abandoning established theories, but rather explicitly recognizing their boundary conditions. When Lewin's action research, Weick and Quinn's continuous change, socio-technical joint optimization, and double-loop learning are considered together, a substantial portion of AI transformation can be explained. What is distinctive is the integration of these approaches with AI life-cycle governance and distributed decision architecture. Accordingly, the central contribution is not the claim that AI has rendered established change management theories obsolete, but that their application must be extended to account for the continuous, distributed, and socio-technical nature of AI-mediated organizational change.

7. Organizational Change Management in the Age of Artificial Intelligence: An Integrated Model

This chapter proposes the "double-loop AI change governance" model to explain AI-mediated change. The model consists of four layers: AI characteristics, organizational change mechanisms, mediating processes, and outcomes. Two simultaneous governance loops operate across these layers.

Figure 1 presents the Double-Loop AI Change Governance Model, which conceptualizes AI-enabled organizational change through four interdependent layers: AI characteristics, organizational change mechanisms, mediating processes, and outcomes**.** These layers are connected through two concurrent governance loops that guide organizational design, monitor the effects of AI implementation, and support continuous adjustment. The first layer, AI Characteristics**,** captures the capabilities, limitations, outputs, and potential risks of AI systems. The second layer, Organizational Change Mechanisms**,** concerns

how organizations define the problem to be addressed, classify tasks as automation, augmentation, or joint human–AI execution, establish decision rights and human-oversight thresholds, and redesign roles, competencies, and incentives. Together, these first two layers establish the technological and organizational conditions under which AI is introduced into work. The third layer, Mediating Processes**,** explains how AI-related characteristics and organizational change mechanisms are translated into organizational and employee outcomes. It comprises trust, perceived justice, organizational learning, and the quality of human–AI collaboration. These mechanisms are positioned between organizational change mechanisms and outcomes because they help explain how employees and organizations interpret, experience, and respond to AI-enabled change. The fourth layer, Outcomes**,** encompasses organizational and employee consequences, including change effectiveness and unintended effects. Feedback from these outcomes informs the reassessment of organizational objectives and change arrangements.

Two concurrent governance loops operate across all four layers. Governance Loop 1-Work and Organizational Design begins with defining the organizational problem and determining the appropriate role of AI. It proceeds through task classification, the allocation of decision rights, the establishment of human-oversight thresholds, and the redesign of roles, competencies, and incentives. Its central question is: *For what organizational purpose, in which tasks, and under whose responsibility should AI be used?*

Governance Loop 2-Lifecycle Assurance monitors the AI system and its organizational effects throughout the implementation lifecycle. Its scope includes model performance, errors, data drift, discriminatory outcomes, security, employee autonomy, and skill effects. Evidence generated through monitoring can trigger technical corrections and, where necessary, a reconsideration of the objectives, task allocation, or work-design choices established through Governance Loop 1. The two loops therefore operate concurrently: one guides organizational design and the allocation of responsibility, while the other evaluates system performance

and its broader consequences and feeds the resulting evidence back into design and governance decisions.

The relationships among the four layers and the operation of the two governance loops are shaped by contextual conditions, including organizational culture, leadership, AI maturity, employees' AI literacy, task uncertainty, and ethical governance. These conditions may influence the strength and direction of the relationships represented in the model.

Taken together, the model frames AI-enabled organizational change as an iterative socio-technical governance process rather than a one-time technology implementation. Figure 1 makes the relationship between the four layers, the mediating processes, the two governance loops, and contextual conditions explicit. In the figure, the four layers are arranged from left to right, with mediating processes positioned as the third layer between organizational change mechanisms and outcomes; Governance Loop 1 is shown above the layers, Governance Loop 2 below them, and the return arrow linking the two loops indicates that monitoring evidence and observed outcomes feed back into design decisions. The contextual conditions frame the entire model.

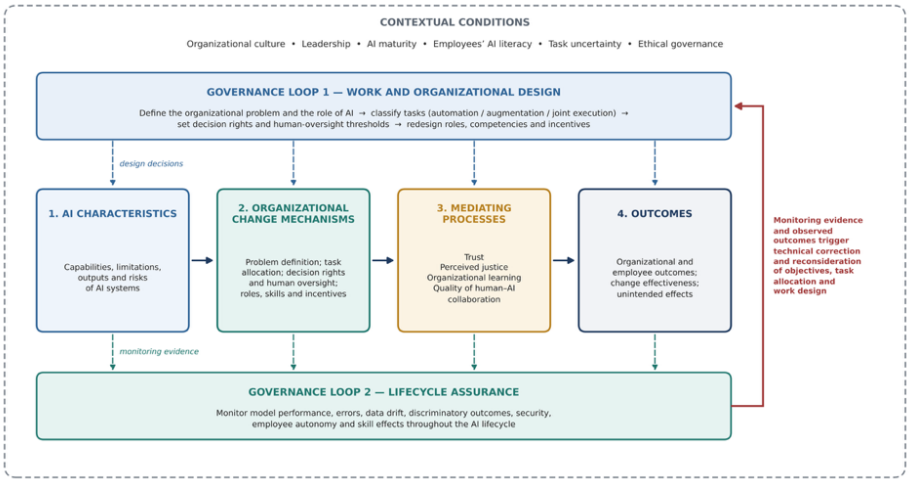


Figure 1. Double-Loop AI Change Governance Model

The model integrates four interdependent layers—AI characteristics, organizational change mechanisms, mediating processes, and outcomes—with two concurrent governance loops: work and

organizational design (Loop 1, shown above the layers) and lifecycle assurance (Loop 2, shown below the layers). Mediating processes comprise trust, perceived justice, organizational learning, and the quality of human–AI collaboration. Contextual conditions frame the model, while monitoring evidence and observed outcomes inform ongoing technical correction and organizational redesign.

Eight theoretical propositions can be derived from the model:

1. As the frequency with which the AI system is updated increases, the effectiveness of episodic change programs will become more dependent on continuous feedback and adaptive capacity.
2. Clearly defining decision rights between humans and AI will strengthen the positive effect of AI use on performance.
3. Meaningful employee participation in design and evaluation processes will increase appropriate trust through perceived procedural justice.
4. When algorithmic opacity is high, the absence of explanation and contestation mechanisms will increase resistance to change and informal avoidance behaviors.
5. The short-term productivity gains from AI-enabled standardization will be accompanied by long-term learning loss when critical judgment and practices of expertise development are not preserved.
6. Psychological safety will strengthen the relationship between employees' reporting of AI errors and risks and the organization's corrective capacity.
7. Double-loop governance that jointly monitors technical performance and employee impacts will produce more sustainable outcomes than single-loop governance that monitors model accuracy alone.
8. In organizations with high AI maturity, change management success will be explained more by the capacity for redesign and reversibility than by the adoption of individual projects.

These propositions make the model empirically testable. Longitudinal case studies, multilevel surveys, digital trace data, and field experiments can be used to examine the relationships between governance loops and employee and performance outcomes. The purpose of the model, however, is not to offer a single universal implementation prescription. Because the costs of error, professional autonomy, and regulatory conditions differ across healthcare, finance, manufacturing, and creative industries, the design principles should be adapted to context.

8. Discussion

The central contribution of this chapter is to explain AI-mediated organizational change as a socio-technical process in which technology shapes the course of change while remaining embedded in human decisions, institutional arrangements, and workplace practices. AI can influence which problems become visible, which options are considered, and how work is evaluated. Its organizational influence therefore extends beyond implementation, but this influence should not be confused with independent agency or moral responsibility: accountability remains with the people and institutions that design, procure, govern, and use these systems.

The Double-Loop AI Change Governance Model brings this argument together by connecting organizational and work design with life-cycle assurance. Its value lies in treating these activities as mutually corrective rather than as separate stages. Decisions about the purpose of AI, task allocation, and human authority shape the effects that must be monitored; evidence about performance, fairness, employee experience, and unintended consequences can, in turn, require the organization to revisit those original design choices. Trust, perceived justice, organizational learning, and the quality of human–AI collaboration help explain how this governance process translates into outcomes. The model thus integrates established change-management insights with an explicit mechanism for reassessing both the technology and the organizational arrangements around it.

This synthesis also changes how employee participation and resistance should be interpreted. Employee feedback is not only a means of securing acceptance: it can reveal mismatches between system outputs, professional knowledge, organizational values, and the realities of work. For this information to improve decisions, organizations need credible channels for questioning and correcting AI-supported decisions, clearly assigned decision rights, and sufficient authority to modify or suspend systems when warranted. These arrangements connect learning and participation to accountability rather than treating them as separate implementation activities.

The chapter's principal limitation is its conceptual character. The proposed relationships and eight propositions have not been empirically tested, and their relevance may vary across sectors, tasks, regulatory settings, and levels of AI maturity. Future research could examine the model longitudinally, comparing how the two governance loops affect decision quality, employee outcomes, organizational learning, and the ability to correct or reverse harmful interventions. Such research would help establish the conditions under which the proposed framework offers explanatory and practical value.

9. Conclusion

This chapter concludes that AI calls for an extension of change-management thinking, not the wholesale replacement of established theories. The distinctive challenge is to govern change when the technology being introduced can also shape decisions, work practices, and the information used to guide subsequent interventions. The contribution of the Double-Loop AI Change Governance Model is to make this recursive relationship explicit by linking organizational design choices to ongoing life-cycle assurance.

The broader implication is that responsible AI-enabled change depends on an organization's ability to learn from the consequences of its own design decisions. A change initiative should therefore be judged not only by whether a system is adopted or produces immediate efficiency

gains, but also by whether the organization can recognize adverse effects, preserve meaningful human judgment, assign accountability, and revise its approach in light of new evidence. This capacity for informed reassessment is the defining governance capability advanced in this chapter.

Declarations

Ethics Committee Approval: This chapter does not fall within the scope of research requiring ethics committee approval, such as studies involving the collection of data from participants through surveys, interviews, focus groups, observations, experiments, or other qualitative and quantitative approaches; the experimental or scientific use of humans or animals (including materials/data); clinical studies conducted on humans; studies conducted on animals; or retrospective studies subject to personal data protection legislation. Therefore, ethics committee approval was not deemed necessary.

Use of Artificial Intelligence: In this chapter, generative artificial intelligence tools, specifically ChatGPT (OpenAI), Gemini, Consensus, and Manus, were used to assist with dataset analysis, language editing, the summarization of papers and references, and the development and refinement of a conceptual figure. The author reviewed all outputs and retains full responsibility for the content, interpretation, and final version of the chapter.

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