



The Skills Reset: Redesigning Learning Before AI Redesigns Roles

Journal:	<i>Strategic HR Review</i>
Manuscript ID	SHR-06-2026-0069
Manuscript Type:	Practitioner Paper
Keywords:	reskilling, organisational learning, human resource development, strategic HRM, HR, Organisational Learning



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The Skills Reset: Redesigning Learning Before AI Redesigns Roles

Practitioner Paper

Abstract

Artificial intelligence is changing tasks, role boundaries and decision-making faster than many organisations are changing learning. While organisations invest in AI tools, pilots and productivity programmes, learning often remains a downstream response: a course after implementation, a reskilling initiative after role expectations have shifted, or an AI literacy module detached from work redesign. This practitioner paper introduces the Skills Reset as a strategic process through which organisations continuously reassess, renew and reconfigure the capabilities required for meaningful work in response to AI-mediated changes in tasks, roles and value creation. It presents the Skills-Reset Flywheel as a practical conceptual model with six dimensions: role foresight, capability diagnosis, learning architecture redesign, human judgement development, transition support, and feedback and renewal. The paper translates research on task-based technological change, organisational learning and dynamic capabilities into a usable framework for HR, learning and leadership practice. Its central argument is simple: in the age of AI, reskilling is necessary, but too narrow. Organisations need learning systems that anticipate role change, protect employability and strengthen human judgement before AI redesigns work.

Keywords: artificial intelligence; skills reset; reskilling; organisational learning; human judgement; HRD; workforce transformation; future of work

1. The practice problem: learning is too late in the AI transformation sequence

Most organisations will not fail at AI transformation because they lack technology. They will fail because they redesign work faster than they redesign learning. The dominant workplace conversation about AI still tends to begin with tools: which systems to buy, which processes to automate, which productivity gains to capture and which risks to govern. These questions matter. Yet they miss a deeper management challenge: whether organisations can learn quickly enough before AI changes the tasks, roles and professional identities through which people create value.

The current skills debate is often framed as a supply problem: organisations need more AI skills, data skills or prompt skills. This is partly true, but incomplete. Skills only become valuable in relation to tasks, decision rights, work design, leadership practices and organisational strategy. AI does not simply add a new digital layer to stable jobs. It can change the task bundles that constitute roles, redistribute judgement between humans and machines, and transform what counts as expertise.

Research on technological change shows that automation usually affects tasks rather than whole occupations. Routine tasks are more exposed, while complex communication, problem-solving and judgement-intensive work often become more important (Autor, Levy and Murnane, 2003; Autor, 2015). Generative AI extends this logic into knowledge work by drafting, summarising, classifying, analysing and recommending. The practical implication is clear: job titles may remain stable while the work underneath them changes substantially.

This creates a timing problem. In many organisations, AI is implemented first, work processes are adjusted second, and learning follows third. By then, employees may already experience uncertainty, loss of confidence or fear of declining relevance. A more robust approach is needed: learning must become an anticipatory capability, not a remedial service.

2. From reskilling to the Skills Reset

Reskilling remains important. Employees will need new technical skills, new AI literacy and new confidence in working with intelligent systems. However, reskilling becomes too narrow when it is treated as a bounded intervention after disruption has already occurred.

First, reskilling is often reactive. Training starts once tools have been procured or roles have already shifted. Second, it often privileges tool use over judgement. Employees may learn how to use AI, but not when to question it, how to verify outputs, or how to remain accountable for decisions. Third, it can ignore the identity dimension of work. Skill obsolescence touches status, self-efficacy, employability and trust. Employees do not experience AI-driven change only as a learning opportunity; they may also experience it as a threat.

The Skills Reset addresses these limitations. It is defined here as a strategic process through which organisations continuously reassess, renew and reconfigure the capabilities required for meaningful work in response to AI-mediated changes in tasks, roles and organisational value creation. The concept shifts the guiding question from "What training do employees need after AI implementation?" to "How must the organisation learn before, during and after AI changes work?"

This reframing connects to organisational learning and absorptive capacity. Organisations need to recognise new knowledge, assimilate it and apply it in practice (Cohen and Levinthal, 1990). It also relates to dynamic capabilities: the capacity to reconfigure competences in changing environments (Teece, 2007). In practitioner terms, the Skills Reset is the people-development side of AI strategy.

3. The Skills-Reset Flywheel

The Skills-Reset Flywheel is a practical conceptual model for AI-era capability renewal. It is designed as a flywheel rather than a linear roadmap because AI-mediated work develops recursively. As tools evolve, roles change; as roles change, capability needs shift; as capabilities develop, organisations discover new ways to use AI. The model contains six dimensions.

Role foresight means anticipating how AI may reshape tasks, responsibilities, decision rights and role boundaries before formal job descriptions change. The goal is not to produce speculative lists of "jobs at risk". The goal is to map which parts of work are likely to be automated, augmented or redesigned. This requires input from HR, leaders, technology teams, employee representatives where relevant, and employees who know how work is actually performed.

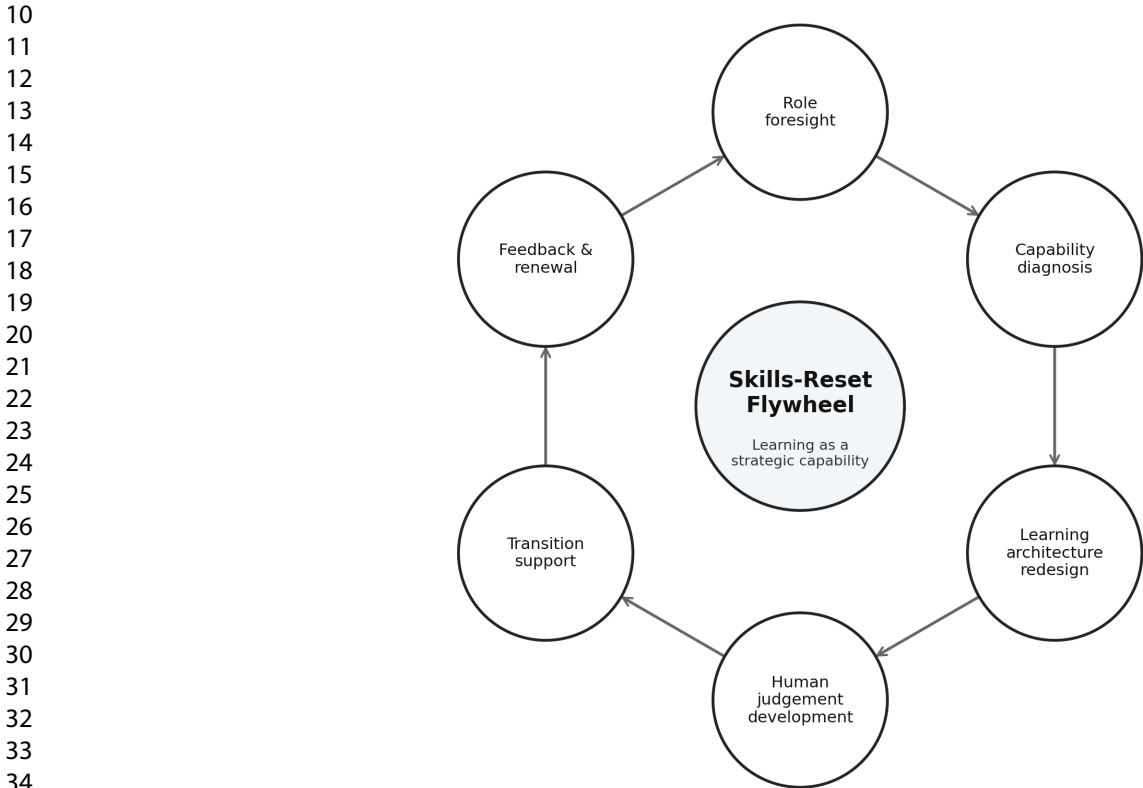
Capability diagnosis identifies which skills, behaviours and judgement capabilities are becoming more important, less relevant or fundamentally different. It should distinguish between technical skills, role competencies and broader organisational capabilities. For example, prompt writing may be a technical skill, advising stakeholders on AI-generated insights may be a role competency, and building a culture of continuous learning may be an organisational capability.

Learning architecture redesign moves organisations beyond isolated courses and static catalogues. AI-era learning requires role-based pathways, peer learning, coaching, communities of practice, learning in the flow of work, experimentation routines and leadership support. The aim is not only knowledge transfer, but transfer into work.

Human judgement development is central. AI can generate outputs quickly, but speed does not equal responsibility. Employees need critical thinking, ethical reasoning, contextual interpretation, epistemic humility and the ability to explain decisions. Tool competence is not the same as judgement competence. The more work becomes AI-mediated, the more organisations need people who know when to rely on AI, when to challenge it and how to take responsibility for consequences.

Transition support addresses the psychological and social side of capability renewal. Employees need time, trust and safety to ask basic questions, disclose uncertainty and experiment. Psychological safety

1 and employee voice are not soft add-ons; they are conditions for learning (Edmondson, 1999; Morrison,
2 2011). Without them, organisations may get compliance without genuine adaptation.
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4 Feedback and renewal ensures that the model remains dynamic. AI adoption should generate employee
5 feedback, performance insights, leadership observations, ethical concerns and learning data that feed back
6 into role foresight and capability diagnosis. Renewal is not an annual HR cycle. It is a continuous
7 organisational discipline.
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36 *Figure 1. The Skills-Reset Flywheel*

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Dimension	Practice question	Primary output
Role foresight	How will AI reshape tasks, boundaries and decision rights?	Task-level role scenarios
Capability diagnosis	Which capabilities are emerging, declining or changing?	Dynamic capability map
Learning architecture redesign	How must learning become continuous and work-embedded?	Adaptive learning ecosystem
Human judgement development	Which forms of judgement become more important?	Judgement-centred learning pathways
Transition support	How will employees be supported through role and identity change?	Trust, voice and career support
Feedback and renewal	How will learning from AI adoption update strategy?	Continuous renewal loop

53 *Table 1. Dimensions of the Skills-Reset Flywheel*

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4. The RESET model for implementation

56 For practice, the flywheel can be translated into the RESET model. It helps HR, learning teams and leaders
57 structure workshops, workforce planning conversations and AI implementation reviews. The model is
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intentionally simple. Its purpose is not to reduce complexity, but to create a shared language between technology, HR, leadership and employees.

RESET element	Core question	Practical use
R - Role foresight	How will AI reshape tasks, boundaries and decision rights?	Task mapping and role scenarios
E - Emerging capability mapping	Which capabilities are emerging, declining or changing?	Capability interviews, skills data and employee voice
S - Skill renewal architecture	How must learning be redesigned for continuous renewal?	Peer learning, role-based pathways and communities of practice
E - Employee transition support	How will employees be supported through role change?	Psychological safety, coaching and career pathways
T - Transformation feedback loop	How will AI adoption update the skills strategy?	Impact reviews, governance signals and learning metrics

Table 2. The RESET model for HR and leadership practice

5. Using the AI Role-Change Matrix

A second practical tool is the AI Role-Change Matrix. It distinguishes between AI task impact and the level of human judgement required. Where AI task impact is high and human judgement requirement is low, tasks may be candidates for automation, provided legal, ethical and quality risks are low. Where AI task impact and human judgement requirements are both high, roles should be redesigned around human-AI collaboration, accountability and new decision rights. Where AI task impact is low and judgement requirement is low, streamlining may be sufficient. Where AI task impact is low but human judgement is high, organisations should protect and develop expertise through mentoring, reflective practice and professional development.

The matrix prevents two common mistakes: treating all AI-exposed work as automatable, and treating all human work as equally protected. It supports more precise conversations about work redesign and learning priorities.

	Low human judgement requirement	High human judgement requirement
High AI task impact	Automate: suitable where rules are clear, consequences are low and judgement adds limited value.	Redesign: build human-AI collaboration, accountability and new decision rights.
Low AI task impact	Streamline: seek proportionate efficiency gains without overbuilding the learning response.	Protect and develop: invest in expertise, mentoring, ethical reasoning and professional development.

Table 3. The AI Role-Change Matrix

6. Implications for workplace management

For HR leaders, the Skills Reset means moving from programme ownership to capability system design. HR should connect AI adoption, workforce planning, employee voice and leadership development.

For learning and development teams, the focus shifts from completion rates to capability transfer. The relevant question is not how many employees completed an AI module, but whether they can apply, question and contextualise AI-supported work in practice.

For senior executives, the model makes clear that AI strategy and learning strategy are inseparable. Investment in tools without investment in organisational learning may produce adoption without transformation.

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For line managers, the Skills Reset creates a daily leadership responsibility. Managers translate role change into practice. They must create time for learning, support experimentation and avoid framing skill renewal as individual failure.

For employees, the model recognises agency. Employees are not passive recipients of reskilling. Their questions, experiments and concerns are essential sources of organisational learning.

7. Limitations and boundary conditions

The Skills Reset is a conceptual practitioner model, not an empirically validated framework. Its value lies in offering a structured vocabulary for practice, but future research should examine how the model works across sectors, occupations and organisational sizes.

The model may be more applicable to knowledge-intensive organisations with established HR and learning functions than to small organisations or frontline settings with limited resources. It should therefore be adapted rather than applied mechanically.

There is also a risk of managerial bias. If the Skills Reset is designed only by executives, HR or technology teams, it may become a top-down adaptation agenda. Decisions about future-relevant skills influence employability, status and career opportunities. Employee voice, co-design and transparent governance are essential.

Measurement is another limitation. Training hours and course completion rates cannot capture whether judgement has improved, whether employees feel safe to experiment or whether access to learning is fair. Organisations need richer indicators, including behavioural change, confidence, application, employee experience and equity of access.

Finally, the flywheel metaphor can hide friction. Real learning systems stall. Budget constraints, weak leadership, change fatigue, fragmented platforms, insufficient time and distrust can interrupt renewal. The Skills Reset must therefore be accompanied by honest attention to the conditions that allow learning to happen.

8. Conclusion

Before AI rewrites roles, organisations must rewrite how they learn. The future of work will not be determined by technology alone, nor by the number of AI tools organisations adopt. It will be shaped by the capacity of organisations to anticipate task change, renew capability, support employees and preserve human judgement in AI-mediated work.

Reskilling is necessary, but it is not enough. Organisations need learning systems that are anticipatory, inclusive, judgement-centred and connected to work redesign. The decisive question is not whether organisations will use AI. Most will. The decisive question is whether they will learn before roles are disrupted or only after disruption has become visible.

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