When Skills Are Not Enough: Human Capability in an AI Economy

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Synopsis

Artificial intelligence is transforming how work is performed, yet most workforce systems still measure human contribution using frameworks designed for industrial economies, where value was tied to the execution of tasks and the accumulation of skills to match those required for job roles. As AI increasingly automates task-based work, this assumption becomes unreliable. This paper argues that the emerging AI economy requires a clearer distinction between skills and human capability. Skills describe what people can do in stable conditions; capabilities describe the durable human abilities through which people exercise judgement, build relationships, interpret context, and act responsibly under uncertainty. The paper concludes that the scarcest asset in an AI-enabled economy is not skill, but intelligence expressed in context.

Audience

This paper is intended for thought leaders in business, public sector, and academia seeking to understand how we measure and value skills and human capabilities.

AI Disclosure Statement

In preparing this paper, AI tools were used to support original research, synthesise data, and refine language during the final editing process. AI-assisted image generation was also employed to create illustrative graphics for the cover image.

All content was reviewed, validated, and finalised by the authors to ensure it reflected the paper's original intent, upheld scholarly integrity, and was grounded in the cited evidence base. No generative AI tools were used to produce core research findings, original data, or final authorial judgements

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AI and the limits of skills-first workforce systems

Why We Still Confuse Skills with Capabilities

The rapid diffusion of artificial intelligence (AI) has reignited an old debate about what actually creates value in human systems. Governments, employers, and global institutions continue to frame workforce readiness in terms of skills: explicit, discrete, teachable, and supposedly measurable units of competence. Yet this framing is increasingly misaligned with how human contribution is developed, expressed, and recognised within AI-enabled economies.

AI systems currently excel at automating repeatable, bounded tasks, reducing the marginal cost of execution and accelerating pattern recognition at scale. As a result, many activities historically labelled as skilled work are now either automated outright or cognitively offloaded to machines. This pattern reflects not the limits of AI capability but the deployment choices of human systems, which tend to prioritise optimisation of the least cognitively complex work.

Writing, coding, scheduling, diagnosis, and elements of creative synthesis can now be partially or fully delegated to AI systems trained on vast prior datasets. These systems are already reshaping how skills are applied across talent systems, influencing hiring, learning, development, assessment, and recognition.

This creates a paradox. As workforce systems continue to rely on historical data to benchmark jobs and task-bounded skill acquisition, AI systematically crowds out precisely the less well-defined, innately human abilities that matter most. As AI capability increases, the economic value of codified skills declines, not because skills are unimportant, but because they are the domain AI is best able to absorb. What rises in value instead are human abilities that remain irreducible to task execution: judgement under uncertainty, ethical reasoning under consequence, sensemaking through relationships, adaptation to situated challenges, and the capacity to forge shared purpose over the long term.

Yet Skills-First policies persist. They continue to treat human development as an accumulation problem rather than a capability expression problem. This mismatch helps explain why many AI-enabled organisations report productivity gains alongside declining engagement, fragile decision-making, and rising ethical risk (O'Hanlon & Bowles, 2025).

Recent Skills-First reforms, including the Singapore Skills-First policy agenda, move in the right direction by explicitly acknowledging that skills alone are insufficient in conditions of rapid technological and economic change, and that adaptability, learning capacity, and system responsiveness matter (Ho et al., 2026). However, these reforms stop short of resolving the core issue. Human capability is typically treated as a collective or system-level extension of skills, rather than as a distinct unit of value with different properties, evidence requirements, and economic implications.

The issue is not that skills are unimportant. It is that skills are inputs, not outcomes.

The issue is not that skills are unimportant. It is that skills are inputs, not outcomes. On their own, they do not explain adaptability, resilience, or the generation of long-term human, social, and ecological value.

When workforce systems classify capability as skill, investment follows the wrong signal. Capital flows toward task optimisation, credential accumulation, and skills matching platforms, even as the marginal returns on those investments decline.

The Key Argument

Skills describe what people can do in stable conditions.

Capabilities describe the durable abilities expressed through how people think, behave, build relationships, adapt, and act under uncertainty.

As AI automates task-based work, the economic value of skills declines while the value of human capability rises.

Workforce systems and national taxonomies that continue to measure skills rather than capabilities risk misallocating investment and undervaluing human contribution.

The Structural Distinction

Skills versus capabilities

This is the critical divergence.

At the heart of current workforce, education, and AI policy lies a persistent conceptual error: the failure to distinguish skills from capabilities as fundamentally different forms of human value. This fault line explains why Skills-First reforms repeatedly underperform in conditions of rapid technological change, and why AI intensifies rather than resolves the problem.

Recent critiques of national skills frameworks have highlighted not only conceptual limitations, but governance risks. A few national Future Skills Frameworks have used the Human Capability Standards as a basis but ignored behavioural indicators to focus on the demonstrated skills (Working Futures™, Jan. 2025). Bevan (2026), for example, argues that centralised skills taxonomies often create false coherence, standardising weak signals and slowing system adaptation. This critique aligns with capability-based approaches that treat skills as contextual inputs rather than stable units of value.

Recent empirical research on the dynamics of AI capability reinforces this distinction by showing that intelligence does not arise from task performance alone, but emerges through non-linear, path-dependent interactions between humans, AI architecture, data, and the deployment context (van Noordt & Tangi, 2023). Capability, whether human or organisational, cannot be reliably inferred from discrete tasks or static job classifications. This mirrors a parallel failure in workforce systems, where skills are routinely treated as proxies for human capital despite being poor predictors of judgement, engagement, adaptability, and generalised intelligence. In both domains, an overreliance on task-based metrics creates a false sense of progress, suppresses higher-order capability, and channels investment toward short-term optimisation rather than long-term intelligence and value creation (Mikalef & Gupta, 2021).

Skills and capabilities define fundamentally different forms of human value.

A capability-based definition of the distinction

Skills are best understood as instrumental inputs. They describe what a person can do in relatively stable, known conditions. Skills are:

- Acquired through instruction, repetition, and practice
- Task-specific performed under defined conditions (Autor, et al., 2003)
- Largely agnostic of the person or situation
- Explicit and underpinned by codified knowledge
- Transferable where conditions and activities are similar
- Observable through execution (McClelland, 1973)

Skills retain economic value only while the tasks they support remain scarce or difficult to automate. As AI systems increasingly perform or accelerate cognitive tasks across occupations, the value attached to many skills becomes conditional and subject to rapid depreciation (Massenkoff & McCrory, 2026).

For over two decades, the Working Futures™ Human Capability Standards Reference Framework (HCS) has treated the distinction between skills and capabilities as structural rather than semantic (Bowles, 1999; Bowles, 2022; Working Futures, May 2025). It reflects a different theory of value, agency, and responsibility in complex human systems, particularly under conditions of uncertainty and interdependence (O'Hanlon & Bowles, 2025).

While AI-enabled collation and translation shift attention away from the pursuit of a single skills taxonomy, translation alone cannot resolve the deeper problem of value recognition beyond national education and work systems (Bevan, 2026; Ho et al., 2026). Translating skills across frameworks continues to treat skills as the primary unit of human contribution. The HCS ontology was designed explicitly as a Rosetta Stone across skills systems, not by harmonising skills or competency labels, but by interpreting skill based on their relationship and capacity to support evidence of a demonstrated performance and enabling behaviours.

Capability-based approaches reframe workforce development by shifting attention from the accumulation of inputs to the validation of outcomes, evidenced in real-world contexts against standards expressed across seven levels of proficiency. These standards do not standardise skill or behavioural descriptors or prescribe how skills must be performed. Instead, they define the level of capability that must be demonstrated.

In this framework, capabilities describe how people think, engage, lead, and adapt across contexts, particularly where conditions are uncertain, ambiguous, complex, or consequential. Human capabilities are:

- Context-transcending rather than task-bound

- Oriented to whole-of-workforce and system performance, not job execution
- Mobile across boundaries of discipline, role, culture, or location
- Expressed through choice, judgement, and consequence, not competence alone
- Relational and value-laden
- Entwined and often embedded in the culture, relationships, or challenges faced

Capabilities are not possessed in the abstract, nor can they be inferred reliably from training records, credentials, or role performance. They are demonstrated over time through patterns of decision-making and impact, particularly where no predefined rule or existing occupation exists.

This framing aligns with Sen's capability approach, which shifts attention from resources and outputs to what people are actually able to do and become within real social conditions (Sen, 1985). Capability becomes inseparable from collective responsibility, institutional purpose, or the conditions that enable or constrain human agency.

It also aligns with Teece's dynamic capabilities theory, which locates capability not in individual skill accumulation but in the shared capacity of systems to sense, adapt, and reconfigure in response to change (Teece et al., 1997). Such capabilities emerge through coordinated action, governance, and culture, rather than through task proficiency alone.

Otto Scharmer's work on leading from the emerging future sharpens why skills-based and task-centric approaches break down in the presence of AI. Scharmer argues that the most consequential human work does not involve executing predefined tasks, but sensing, interpreting, and acting in situations where the future cannot yet be fully specified (Scharmer, 2009). From this perspective, skills and AI systems remain inherently backward-looking. They operate on codified representations of past experience and optimise within existing frames.

What AI and skills frameworks cannot do is engage in *presencing*, the human capacity to attend deeply, suspend habitual judgement, and allow new possibilities to emerge through collective sensemaking and responsibility (Scharmer & Kaufer, 2013). This capacity is neither an explicit skill nor a cognitive technique. It is a capability of attention, intention, and moral agency, exercised under uncertainty and with accountability for consequences.

The implication is clear. Many of the most valuable expressions of human capability, including judgement, ethical reasoning, systems thinking, stewardship, and trust-building, are co-produced. They arise between people, across teams, organisations, and communities, and are borne out in shared outcomes over time. Skills are tangible and observable, making them easier to codify and substitute with machines. Capabilities are not. They are embedded in relationships, shaped by context and consequence, and inseparable from responsibility for outcomes beyond the immediate task. When systems optimise primarily for skills, they risk eroding the very capabilities required to enhance individual and collective capacity to adapt, be resilient, and act with long-term shared purpose.

AI can absorb tasks but humans are accountable for the consequences.

Alignment with intelligence research

AI researcher François Chollet corroborates this distinction. In his work on measuring machine intelligence, Chollet shows that performance on tasks—even many tasks—does not constitute intelligence. Intelligence, in his formulation, is the efficiency with which new skills are acquired and applied under novelty and constraint (Chollet, 2019).

In Chollet's framework:

Skills

- Are task-bound
- Are acquired through exposure and repetition
- Can be scaled with data and computational effort
- Are not evidence of intelligence

Abilities

- Enable transfer across unknown tasks
- Are revealed under novelty and constraint
- Reflect efficiency of generalisation, not performance
- Cannot be reduced to benchmarks

Chollet is explicit: performance on known tasks says little about intelligence. Systems that excel through memorisation, pattern matching, or prior exposure may appear competent while lacking any genuine capacity to generalise (Chollet, 2019). As he argues, "measuring skill alone does not move us forward" (Chollet, 2019). Intelligence only becomes visible when systems are required to learn and adapt under novelty, constraint, and limited prior exposure.

This distinction is not philosophical but methodological. It underpins Chollet's critique of benchmark-driven AI research and his call for evaluation approaches that test generalisation rather than task mastery. It also explains why many high-performing AI systems plateau outside narrow domains, and why claims of achieving artificial general intelligence (AGI) based on accumulated task performance remain premature.

Limits of Skills-Centric Workforce Frameworks

WEF's category error (systemic)

The World Economic Forum (WEF) has responded to AI disruption by expanding its skills taxonomy to include so-called "human skills", commonly listing judgement, empathy, ethical reasoning, systems thinking, and collaboration (WEF, 2025). The intention is sound. The classification is not.

"At least *human skills*" is closer to the truth than alternatives such as *soft skills* or *general skills*. In the Working Futures™ approach, however, these attributes have never been treated the same as other skills. They are understood as higher-order human abilities (Bowles, 2023). This distinction predates the current AI debate and reflects a deeper theory of human value grounded in learning, organisational development, and innovation research, where capability is situated, relational, and consequential, rather than reducible to skill accumulation or task performance (Sen, 1985; Brown, Collins, & Duguid, 1989; Teece et al., 1997).

Chollet's work provides technical corroboration of this position. In his terms, these attributes cannot be classified as skills because they are not task-bound, cannot be reliably trained through exposure alone, and cannot be evaluated through performance on predefined problems (Chollet, 2019). They are revealed only when individuals must generalise within situated conditions.

Accordingly, abilities such as critical and systems thinking, empathy, ethical reasoning, and collaboration are:

- contextual rather than task-specific
- tacit and relational rather than individualistic
- value-laden rather than instrumentally neutral
- expressed differently depending on the people, power, culture, and consequences

By labelling these qualities as skills, WEF commits a category error. It collapses capability into trainable units, obscuring the very properties that make these abilities valuable.

This misclassification has structural consequences.

First, it reframes capability as something that can be delivered through short courses or micro-interventions, rather than cultivated through experience, reflection, and collaborative interactions over time. Attention shifts from demonstrated contribution (outcomes) to learning activity and skill acquisition (inputs), reinforcing the same task-centric logic that AI systems now optimise.

Second, it encourages measurement by proxy. Abilities such as complex human judgement is inferred from completing existing courses or achieving learning outcomes or micro-credentials that record participation rather than capability in action.

Third, it implies substitutability. Once framed as skills, these abilities appear decomposable, codifiable, and therefore automatable or replaceable with similar titled skills, despite being precisely the human capacities that resist automation.

None of these assumptions hold.

Measurement: where the divergence becomes structural

Chollet insists that valid measurement must respect reality. Any meaningful assessment of intelligence must:

- Control for prior exposure
- Use novel tasks
- Test generalisation efficiency
- Avoid optimisation against the metric

This is why he rejects:

- Game benchmarks
- Multi-task leaderboards
- Skill accumulation metrics

WEF measurement practices, by contrast, remain task-proxy based. Despite rhetorical shifts toward "human skills", assessment still relies on:

- Self-report instruments
- Course completion
- Role-based taxonomies
- Behavioural indicators abstracted from context

These measures lack authenticity and reward familiarity, not judgement (Bowles, Sept. 2025). They capture performance in known frames, not action under uncertainty.

What they systematically miss are:

- Judgement that considers system consequences
- Moral reasoning under pressure
- Relational trust built over time
- Stewardship across social and ecological systems

Table 1 Comparative Analysis: Chollet vs WEF/ Davos on Intelligence, Skills, and Human Value

Dimension	François Chollet – On the Measure of Intelligence (2019)	World Economic Forum/ Davos Human Skills Narrative	Critical Implication for Workforce, ESG, and Policy
Core problem being addressed	AI research is mismeasuring intelligence by benchmarking task performance instead of general learning capacity.	AI is automating routine work, creating demand for "human skills" that machines cannot replicate.	Both identify a problem with task automation, but approach it from different analytical depths.
Definition of intelligence	Intelligence is skill-acquisition efficiency under novelty, constraint, and uncertainty.	Human advantage lies in creativity, judgement, empathy, collaboration, and adaptability.	Chollet defines a *capacity*; WEF describes a *list*. The distinction is foundational.
Skills vs capabilities	Skills are task-specific outputs; abilities (capabilities) enable transfer across unknown tasks. Skills are not intelligence.	"Human skills" are treated as discrete, trainable competencies.	WEF collapses capabilities into skills, creating a category error that weakens policy and credential design.
Role of repetition and scale	High performance achieved through repetition, data scale, and priors does not indicate intelligence.	Continuous reskilling and upskilling are promoted as the solution.	Reskilling without addressing capability development risks accelerating commoditisation of humans.
Generalisation	True intelligence appears only when systems face novel tasks not seen in training.	Transferable skills are encouraged, but usually assessed in familiar or simulated contexts.	Apparent transfer may reflect familiarity, not real adaptive capacity.
Measurement approach	Strong critique of benchmarks that reward developer-aware optimisation or known task distributions.	Heavy reliance on surveys, skill taxonomies, credentials, and self-report indicators.	WEF measurement methods mirror the very flaws Chollet warns against.
Validity of evaluation	Valid measures must control for priors, experience, and scope, and reveal learning efficiency.	Indicators focus on participation, proficiency claims, or behavioural proxies.	Current indicators reward exposure, not demonstrated judgement or adaptation.
Anthropocentric assumptions	Intelligence measures are inherently value-bound and human-referenced.	Human skills are framed as economically valuable, but values remain implicit.	Values are assumed, not operationalised, leaving social and ecological claims weak.
Role of context	Context matters; abilities only reveal themselves under real constraints and uncertainty.	Skills are often abstracted from context to enable portability and scaling.	Decontextualisation strips away meaning, consequence, and trust.
Treatment of judgement	Judgement is implicit in generalisation and abstraction, not reducible to rules.	Judgement is listed as a "skill" to be developed.	Judgement is a capability exercised in consequence, not a skill acquired in isolation.
Emotional and relational dimensions	Largely outside scope; acknowledged as difficult to formalise or benchmark.	Empathy, collaboration, and leadership are highlighted as key human skills.	WEF elevates these rhetorically but lacks mechanisms to evidence or sustain them.
Ethics and values	Ethics are not directly measured; intelligence benchmarks avoid moral domains.	Ethical reasoning and responsible leadership are promoted as future skills.	Ethics cannot be credentialled without grounding in real decisions and outcomes.
Temporal dimension	Intelligence is revealed over time through learning efficiency and adaptation.	Skills frameworks are largely static or periodically updated.	Static frameworks fail to capture longitudinal contribution or stewardship.
Ecological relevance	Ecological systems fall outside AI benchmarkable task domains.	Sustainability and climate transition are cited as drivers for human skills.	There is a mismatch between long-horizon ecological value and short-cycle skill metrics.
Social value creation	Social outcomes are not captured by task performance metrics.	Human skills are linked to trust, inclusion, and cohesion.	Claims of social value lack evidentiary infrastructure.
Economic framing	Warns against mistaking benchmark success for real progress.	Frames human skills as future employability currency.	Without better measures, "human skills" risk becoming the next depreciating asset.
Risk identified	AI progress may be illusory, optimising the wrong objective functions.	Workforce systems may lag technological change without reskilling.	The deeper risk is misallocating investment toward skills that remain invisible or undervalued.
What is missing	A way to connect intelligence measures to lived human and societal value.	A way to evidence and reward human contribution beyond employability.	This gap undermines ESG, workforce mobility, and long-term public value.
System-level implication	Intelligence research needs new benchmarks focused on abstraction and generalisation.	Workforce systems need new models for recognising human contribution.	A capability-based, outcome-anchored infrastructure is required.
Overall limitation	Stops at cognition and learning efficiency by design.	Stops at rhetoric without resolving measurement and value translation.	Neither alone solves the problem of recognising human, social, and ecological capital.

The Missing Dimension: Value and Consequence

Chollet deliberately stops at cognition (Chollet, 2019). Intelligence, in his formulation, is defined relative to tasks, and tasks are defined relative to human values. The values themselves are not measured. This is both intentional and defensible within AI research.

However, once intelligence is situated in human systems, this omission becomes decisive.

Capabilities matter beyond the outcomes they produce. They are more than human capital expressed through productivity and economic outputs. They include social and ecological effects that unfold over time. Judgement matters because poor judgement destroys trust. Systems thinking matters because local optimisation can generate risk or consequences that reduce systems viability. Ethical reasoning matters because legitimacy, not efficiency, sustains institutions, and reinforces brand trust. Empathy and genuine human connection matter because this stimulates not only collaboration and a shared responsibility for customer service but also stimulates creativity and innovation.

Skills-based systems struggle here because they lack a way to link capability expression to consequences.

What we need to realise

Three realisations follow.

1. AI accelerates the commodification of skills

As AI takes on an increasing number of skilled tasks, the scarcity of such skills diminishes, resulting in a reduction in their marginal value. In the short term, training individuals or systems in additional skills without consideration of outcomes may appear economically efficient, however, this approach becomes progressively less rational over the long-term.

2. Capabilities are only visible through outcomes

Capabilities cannot be inferred from inputs. They are revealed through:

- Decisions made under uncertainty
- Trade-offs accepted under constraint
- Relationships sustained under pressure
- Impacts generated beyond immediate performance

This is why capability cannot be credentialled in the classroom alone. It must be evidenced through authentic action.

3. Value now sits outside the firm and beyond the job

The most consequential outcomes of human capability increasingly occur:

- Across careers, not a job role
- Across industries, not an occupation
- Across future challenges, not current performance
- Across society, not an organisation

Skills-First frameworks are unable to recognise this value, regardless of how many job- or task-based skills lists are created. This limitation is inherent in most first-generation AI-based platforms that haven't built generalised intelligence or context-based solutions into their design.

Capability is revealed through consequences

Skills describe the inputs people bring to work: the tasks they perform and the knowledge they apply.

Capabilities emerge when people combine intelligence, relationships, and judgement to pursue a shared purpose. They become visible through the outcomes created together: decisions made, trust sustained, problems resolved, and value realised beyond the immediate task.

As AI automates bounded work, the greatest economic value increasingly lies in using AI to amplify human capability and strengthen our collective capacity to adapt.

The Economic Cost of Mistaking Skills for Capability

Modern skills, employment, and education systems systematically undervalue human contribution, not because value is absent, but because it is misclassified. By treating skills as a proxy for capability, these systems misidentify where economic value is created and, as a result, underprice human, social, and ecological returns.

Skills-based frameworks are optimised to recognise inputs: what individuals have learned, which tasks they can perform, and how efficiently those tasks are executed within defined roles. This logic holds in stable, low-uncertainty environments. It fails in conditions characterised by ambiguity, interdependence, and long-horizon consequences, which now define much of contemporary work.

The scarcest asset in an AI economy is intelligence expressed in context.

The consequence is not merely conceptual error, but material under-recognition of value that has already been created. When capability is collapsed into skills architecture, investment solely flows toward task optimisation and process efficiency rather than building capability and adaptive capacity. The result is systemic economic misallocation.

Judgement exercised under uncertainty is routinely missed because it cannot be attributed to discrete tasks or benchmarked against predefined standards. Relational and collective contributions such as trust-building, ethical leadership, safety, non-financial risk management, project coordination across boundaries, and shared sensemaking are discounted because they are co-produced and unfold across systems rather than roles. Temporal value, including stewardship, governance, sustainability, and institutional adaptive capacity, is similarly obscured because it accumulates over time rather than within performance cycles.

AI intensifies this loss. As AI absorbs an increasing share of task-based work, job boundaries collapse and the remaining human contribution shifts toward forms of value that are less observable, less codifiable, and harder to attribute. Systems that continue to optimise around what can be measured increasingly marginalise what sustains long-term performance, legitimacy, and social trust. Short-term efficiency gains are achieved at the expense of the cultural and relational conditions that underpin durable value creation.

This creates a structural distortion in how value is recognised and financed. As human systems become increasingly dependent on judgement, ethical reasoning, and collective adaptation, the infrastructures used to measure and reward contribution remain anchored to task performance. Capital therefore continues to flow toward AI-enhanced talent marketplaces built on skill matching and learning systems focused on task competence, even as the long-term economic returns of those investments are traded for short-term gains.

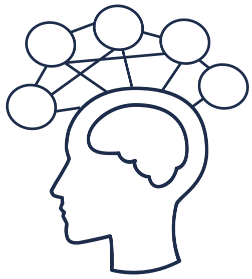
Recent Skills-First reforms, including the Singapore Skills-First working paper, acknowledge that skills alone are insufficient under conditions of rapid technological and economic change (Ho et al., 2026). However, these reforms stop short of resolving the underlying problem. Human capability is still treated as an aggregate extension of skills, rather than as a distinct unit of value with different properties, evidence requirements, and economic implications.

This distinction matters. Capabilities are not simply higher-order skills. They are expressed through judgement, responsibility, and consequence across contexts, and generate value that cannot be inferred from task performance or skill possession alone. When capability is collapsed back into skills architecture, value blindness is preserved rather than resolved.

The issue, therefore, is not a lack of intent or frameworks. It is economic blindness. By mistaking skills for capability, contemporary systems leave substantial human, social, and ecological value unrecognised and unsupported. This is not a future risk. It is a present and compounding loss.

Until systems of recognition and financial reporting shift from inputs and tasks to capability expressed through human abilities revealed under uncertainty and consequence, the full economic potential of human contribution in an AI-enabled world will remain unrealised.

Conclusion



The debate about AI and work is not fundamentally about technology. It is about what is measured, what is valued, and what is allowed to count as evidence.

Chollet shows why skills cannot represent intelligence. WEF demonstrates the political difficulty of abandoning skills-based language. Standards that set scientific anchors for human capability resolve the impasse by shifting attention from inputs to outcomes, from tasks to consequences, and from performance to value creation beyond the organisation to incorporate social and ecological benefit.

In an AI-enabled economy, the scarcest asset is not skill. It is intelligence expressed in context.

Until systems of recognition and reward reflect that reality, productivity gains will remain shallow, and the deepest sources of value will continue to sit just outside the frame where the most important capital gains have and will be made.

Implications for workforce systems

Skills remain essential but are declining in marginal value as AI absorbs task-based work.

Capability must be evidenced through demonstrated outcomes, not training or credentials alone.

Workforce metrics must shift from measuring inputs and task performance to recognising consequences and value created.

AI should amplify human capability and intelligence rather than merely replace human activity.

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