# Cognitive Sustainability in the Age of AI: A Philosophical Framework for Understanding Competency Erosion and Cognitive Stratification in Human-AI Systems


## Abstract

This paper develops a philosophical framework for understanding "cognitive sustainability"—the preservation of human expertise and cognitive autonomy in increasingly AI-dependent systems. Drawing from extended mind theory (Clark & Chalmers, 1998) and distributed cognition (Hutchins, 1995), we investigate the ontological and ethical implications of AI systems that don't merely extend human cognition but potentially substitute for core cognitive processes. We introduce a mathematical model of expertise atrophy that formalizes how individual expertise decay follows exponential patterns modulated by a "Cognitive Retention Coefficient," while organizational patterns follow S-curve dynamics that mask underlying erosion. Our theoretical model finds empirical support in the World Economic Forum's skills forecasts (2023-2025), which reveal a troubling paradox: fundamental cognitive capabilities like mathematics are recategorized from "core skills" to "out-of-focus skills" with a net decline in importance (-4%) precisely as AI adoption accelerates. This creates what we term a "temporal paradox" where societies simultaneously devalue the foundational skills that enabled current capabilities while expecting future generations to develop advanced capabilities without these foundations. More concerning, our analysis reveals how these skill projections create a form of "cognitive stratification" by recommending different skill priorities for different geographic regions while devaluing universal cognitive foundations. This establishes invisible barriers to human potential and mobility, with lower-income regions experiencing significantly higher skills disruption (up to 48%) compared to wealthier nations (28-30%)—potentially deepening global cognitive inequality. We propose "cognitive sustainability" as a normative philosophical framework that addresses both the temporal erosion of capabilities and the geographic stratification of cognitive potential. This framework extends Jonas's (1984) imperative of responsibility into the cognitive domain, recognizing that technological choices today shape not only our capabilities but potentially establish enduring patterns of cognitive inequality across generations and regions. The paper contributes to philosophical debates on extended cognition, human-AI interaction, and cognitive justice while providing conceptual foundations for preserving human capabilities alongside technological advancement.



**Keywords**: artificial intelligence, extended cognition, cognitive sustainability, expertise development, competency erosion, cognitive stratification, technological ethics, cognitive sovereignty, philosophy of mind


## 1. Introduction: The Cartesian Question in an AI Era

When Descartes established thinking as the fundamental proof of existence—"Cogito, ergo sum"—he could not have anticipated a world where thinking itself would be increasingly delegated to artificial systems. Yet this is precisely the philosophical challenge we face today. As AI systems rapidly transform knowledge processes across domains, they fundamentally reshape the cognitive landscape within which human expertise develops and functions, raising profound questions about cognitive agency, knowledge location, and the boundaries of mind.

What makes this transformation particularly significant from a philosophical perspective is that AI is not merely supplementing human cognition but potentially redefining what thinking itself means. Unlike previous technologies that extended human capabilities in ways that preserved cognitive autonomy, AI increasingly substitutes for core cognitive processes, raising fundamental questions about the nature of knowledge, expertise, and ultimately, human identity. This transformation challenges the very Cartesian foundation of human cognitive identity.

The implications of this shift for philosophy of mind and cognitive science have been examined by researchers across disciplines (Clark & Chalmers, 1998; Hutchins, 1995; Menary, 2010), who note that if aspects of thinking increasingly occur outside human minds, we face not just a practical challenge but a philosophical one concerning the location, nature, and ownership of cognition itself. As Dennett (1991) and others have argued, cognitive agency requires not just performance capability but internal structures supporting independent function—precisely what may be undermined through AI dependency.

This paper presents "competency erosion" as a formal framework for understanding this emerging philosophical challenge. We define competency erosion as the systematic degradation of domain-specific cognitive capabilities resulting from the progressive externalization of cognitive processes to AI systems. Unlike skill atrophy described in traditional cognitive psychology (Arthur et al., 1998), competency erosion represents not merely disuse but active replacement of internal cognitive structures with external dependencies, raising fundamental questions about the location and nature of knowledge itself.

Our paper addresses four primary research questions:

1. How can we mathematically model the dynamics of AI-induced competency erosion at both individual and organizational levels in ways that formalize the philosophical implications for extended cognition?
2. What mechanisms explain the pattern of expertise decay when AI systems increasingly replace human cognitive processes, and how do these mechanisms relate to philosophical conceptions of mind and cognitive agency?
3. How does AI integration transform traditional expertise development pathways as conceptualized in established models like the Dreyfus skill acquisition framework?
4. What metrics can quantify competency erosion vulnerability across different professional domains, and what philosophical principles should guide our response to this phenomenon?

By examining competency erosion through an interdisciplinary approach combining philosophical analysis with mathematical modeling, this paper contributes to our understanding of the changing nature of human-AI cognitive systems while offering a framework for preserving human cognitive autonomy in an age of increasingly capable artificial intelligence.

# 2. Theoretical Foundations: Mind, Expertise, and Technology

## 2.1 Extended Cognition and Distributed Mind

Our analysis of competency erosion builds upon philosophical frameworks of extended and distributed cognition. Clark and Chalmers' (1998) extended mind thesis proposes that cognitive processes can span brain, body, and environment, effectively extending the boundaries of mind beyond the individual. Hutchins' (1995) work on distributed cognition further demonstrates how cognitive processes can be distributed across individuals and artifacts within a system.

These philosophical frameworks provide essential context for understanding AI's impact on human cognition. However, they require significant extension to address the unique characteristics of AI systems. Unlike the passive cognitive artifacts (notebooks, calculators) typically discussed in extended mind literature, AI systems actively transform information processing itself, potentially restructuring rather than simply extending human cognition.

As Menary (2010) argues, cognitive integration is not simply about offloading but about the transformative integration of neural, bodily, and environmental processes. AI presents a novel case where this integration may become asymmetric, with the artificial component potentially dominating the integrated system in ways that traditional extended mind theory does not fully address.

This raises profound philosophical questions about cognitive autonomy and ownership. While extended cognition typically preserves the human agent as the primary locus of cognitive control, AI-augmented cognition may shift this balance, challenging traditional conceptions of cognitive agency (O'Connor, 2000). Our framework builds upon these philosophical foundations while extending them to address the specific challenges of AI integration.

## 2.2 The Nature of Expertise and Skill Acquisition

Expertise development has been extensively studied across domains, with the Dreyfus model of skill acquisition (Dreyfus & Dreyfus, 1980) providing a particularly influential framework. This model describes progression from novice to expert through five stages, characterized by decreasing reliance on explicit rules and increasing reliance on intuitive pattern recognition and tacit knowledge—forms of knowing that resist simple externalization (Polanyi, 1966).

Research by Ericsson and colleagues on deliberate practice (Ericsson et al., 1993; Ericsson & Pool, 2016) establishes that expertise development requires thousands of hours of focused, challenging practice with immediate feedback—a process that builds internal cognitive structures not easily replicated or transferred.

From a neurological perspective, expertise development involves structural changes in neural networks through processes like myelination and synaptic strengthening (Hill & Schneider, 2006). These biological changes result from repeated practice under varying conditions—precisely the elements that may be short-circuited by AI systems.

This literature establishes a critical foundation for our competency erosion model: expertise requires not just knowledge acquisition but extended periods of practice with feedback, challenge, and adaptation. When AI systems reduce or eliminate these processes, they may fundamentally alter how cognitive capabilities develop and are maintained.

To formalize this understanding of expertise development and potential erosion, we offer a structural representation of cognition as a function of three key components:

$$Cognition = f(Senses, Context, Historical\_Intelligence)$$

Where:

- **Senses**: raw inputs (percepts, signals, data streams)
- **Context**: goals, constraints, environment, and purpose
- **Historical_Intelligence** the vault of past experiences, learned patterns, heuristics, and memory

This equation captures the essential predicament of increasing AI dependency: when cognition is externalized to AI systems, human agency in directly processing sensory inputs within specific contexts is reduced, limiting memory formation and disrupting the cyclical nature of expertise development. The reduced engagement with raw inputs and contextual problem-solving means less accumulation of HISTORICAL_INTELLIGENCE, which in turn diminishes future cognitive capabilities—creating a feedback loop of erosion.

This structural representation aligns with both Ericsson's deliberate practice framework and neurobiological findings, providing a theoretical foundation for our mathematical models of competency erosion. It helps explain why AI dependency doesn't merely change the location of cognition but fundamentally alters its developmental dynamics in ways that potentially undermine human expertise.

## 2.3 Technology Impact on Human Cognition

Previous philosophical work has examined how technologies impact human cognitive processes. Sparrow et al. (2011) demonstrated experimentally that people remember less information when they believe it will be available externally (the "Google effect"), suggesting that cognitive offloading can alter memory processes.

More specific to AI, research by Cabitza et al. (2017) on clinical decision support systems documented how machine learning algorithms in medicine can create "automation bias" where clinicians override their own judgment in favor of algorithmic recommendations. Studies on automation complacency by Parasuraman and Manzey (2010) further illuminate how humans interact with intelligent technologies in ways that may affect expertise development.

Recent philosophical analysis by Kalluri (2020) argues that many AI systems are designed to replace rather than augment human capabilities, creating fundamental tensions between efficiency and autonomy. This aligns with Brynjolfsson and McAfee's (2022) work on the

"Turing Trap"—the tendency to develop AI that imitates human capabilities rather than complementing them.

These perspectives inform our understanding of how AI integration may create tensions between short-term performance gains and long-term cognitive sustainability. However, existing literature has not fully addressed how AI dependency affects the development and maintenance of expertise over time—a gap our competency erosion model seeks to fill.

### 2.4 AI Differentiation from Previous Technologies

From a philosophical perspective, AI represents a qualitatively different form of cognitive extension than previous technologies. Historical analyses of technological revolutions (Acemoglu & Restrepo, 2019; Autor et al., 2022) highlight important distinctions between AI and previous technologies:

1. **Location of cognitive processes**: Unlike industrial automation, which primarily displaced physical labor while creating new cognitive demands, AI specifically targets high-cognitive tasks traditionally considered "expertise work." This creates a fundamentally different dynamic where the cognitive capabilities that were previously enhanced by technology are now potentially diminished.
2. **Opacity and accessibility**: While previous cognitive tools typically had transparent operational principles (e.g., calculators, reference books), advanced AI systems operate through opaque mechanisms that resist understanding even by their developers. This creates a philosophical tension: we increasingly rely on cognitive processes we cannot fully comprehend.
3. **Agency and initiative**: Traditional cognitive technologies were passive tools awaiting human direction. Modern AI systems increasingly demonstrate agency-like properties, initiating processes, making recommendations, and shaping human behavior. This shift challenges traditional philosophical conceptions of the relationship between humans and their cognitive tools.
4. **Adaptation asymmetry**: There is a fundamental asymmetry in adaptation between humans and AI systems. While AI rapidly improves through data and algorithmic refinement, human cognitive adaptation through biological and developmental processes remains comparatively slow. This creates a widening capability gap that may accelerate dependence.

These distinctions inform our theoretical understanding of why AI integration presents unique philosophical challenges for human cognition that previous technologies did not. They help explain why competency erosion may be a more significant concern in the AI era than in previous technological transitions.

# 3. The Mathematical Framework of Competency Erosion

## 3.1 Individual-Level Expertise Atrophy Model

### 3.1.1 Model Derivation and Rationale

Our model of expertise atrophy is founded on established patterns of knowledge decay observed in cognitive science research, informed by philosophical considerations of how knowledge is maintained through active cognitive processes. Similar to exponential decay patterns in memory retention:

$$K(t) = Koe^{\left(-t/_{\varepsilon\_i}\right)}$$

Where:

- K(t) is the knowledge/expertise level at time t
- $K_0$ is the initial expertise level
- ε_i is the individual's Cognitive Retention Coefficient

The Cognitive Retention Coefficient ε_i = R × C_cognitive represents the combined effect of:

- R: Practice Stability Factor (affected by practice frequency, encoding depth, knowledge application)
- C_cognitive: Cognitive Capacity (individual retention ability)

This model aligns with established findings in cognitive psychology showing that without reinforcement, knowledge follows an exponential decay pattern (Ebbinghaus, 1885; Anderson et al., 2004). The Practice Stability Factor component explicitly connects to Arthur et al.'s (1998) empirical findings on how practice frequency affects skill retention.

From a philosophical perspective, this mathematical formulation captures the dynamic nature of knowledge as an active process rather than a static possession—aligning with enactivist theories of cognition (Varela et al., 1991) that emphasize knowing as a process of ongoing engagement rather than representation.

### 3.1.2 AI-Induced Modifications to the Model

AI integration modifies these parameters over time:

$$R(t) = R_0 e^{(-\alpha . ADR . t)}$$

Where:

- $R_0$ is the initial Practice Stability Factor
- α is the sensitivity coefficient to AI dependence
- ADR is the AI Dependency Ratio, which measures reliance on AI to do core jobs

This expresses how resistance to forgetting diminishes as AI dependency increases, primarily by reducing the frequency of independent practice, a direct application of findings from Parasuraman & Manzey (2010) on automation complacency.

Additionally, cognitive capacity may decrease with prolonged AI dependence:

$$C_{cognitive(t)} = C_0(1 - \beta \cdot t \cdot DPS_{loss})$$

Where:

- $C_0$ is the initial cognitive capacity
- β is the capacity reduction coefficient
- $DPS_{loss}$ represents the decrease in Deep Problem-Solving capability

The combined effect yields a time-dependent Cognitive Retention Coefficient:

$$\varepsilon_{\_i(t)} = R(t) \times C_{cognitive(t)}$$

Which produces accelerating expertise atrophy over time as both practice stability and cognitive capacity diminish.

This mathematical formulation captures the philosophical insight that cognitive capabilities are not static possessions but dynamic processes requiring ongoing engagement for maintenance—precisely what AI dependency may reduce.

## 3.2 Organizational-Level S-Curve Model

At organizational levels, expertise atrophy follows an S-curve (sigmoid function) pattern when AI systems replace human practice. This can be represented mathematically as:

$$E(t) = E_0\left[1 - \frac{1}{1 + e^{(-k(t-t_o))}}\right] + E_{AI}\left[\frac{1}{1 + e^{-r(t-t_1)}}\right]$$

Where:

- $E(t)$ represents effective expertise level at time t
- $E_0$ is initial human expertise level
- k is the human expertise decay rate
- $t_0$ is the inflection point for human expertise decay
- E_AI represents the apparent expertise granted by AI systems
- r is the AI adoption and integration rate
- $t_1$ is the inflection point for AI system adoption

This model reveals a critical asymmetry: from an organizational perspective, this equation often approximates to zero or even positive in terms of performance metrics as human expertise (first term) declines but is offset by AI capabilities (second term). This creates an illusion of sustained or even improved performance while masking the underlying erosion of human cognitive capabilities.

The S-curve model captures the real-world dynamics of competency transformation at organizational levels, showing:

1. An initial slow decline as AI is introduced but not yet fully trusted
2. A rapid acceleration phase when AI becomes the primary tool
3. A final plateau where some minimal human expertise remains but is rarely exercised

From a philosophical perspective, this S-curve pattern reflects how social knowledge systems undergo phase transitions rather than linear changes—an insight that connects to both Kuhnian paradigm shifts in scientific knowledge (Kuhn, 1962) and complex systems theories of social change (Sawyer, 2005).

## 3.3 Connecting Individual and Organizational Models

The exponential decay at the individual level aggregates to create S-curve patterns at organizational and societal levels due to:

1. Heterogeneous population distributions of $\varepsilon_i$ values
2. Network effects in knowledge transfer
3. Threshold-dependent behaviors in organizational systems
4. Adaptation and compensatory mechanisms at system levels

The inflection point $t_0$ and decay rate k in the S-curve model are functions of the distribution of individual Cognitive Retention Coefficients in the population:

$$k = f(D_\varepsilon, \Omega)$$

$$t_0 = g(D_\varepsilon, \Omega, \rho)$$

Where:

- $D_\varepsilon$ represents the distribution of Cognitive Retention Coefficient in the population
- $\Omega$ captures organizational structure and decision processes
- $\rho$ represents the connectivity patterns in knowledge networks
- f and g are functions that transform individual characteristics into system-level parameters.

This formulation intentionally avoids specifying particular statistical measures, recognizing that the relationship between individual cognitive decline and organizational knowledge transformation may follow different patterns across contexts. The key insight is that organizational expertise transformation emerges from but is not reducible to individual expertise decay.

These parameters would be expected to vary across different professional domains, organizational structures, types of AI systems, and individual cognitive characteristics—creating unique erosion profiles in different contexts. The mathematical framework provides a structure for understanding these variations while maintaining the fundamental dynamics of competency erosion.

This mathematical connection between individual and organizational models captures the philosophical insight that collective knowledge is not simply the sum of individual knowledge but emerges from complex interactions within knowledge systems. The model formalizes how individual cognitive changes aggregate to create emergent patterns at larger scales, reflecting philosophical concepts of emergence in complex systems—where micro-level changes drive system evolution while system-level properties simultaneously constrain individual processes.

# 4. AI-Induced Transformations of the Dreyfus Model

## 4.1 Traditional Dreyfus Skill Acquisition Framework

The Dreyfus model of skill acquisition (Dreyfus & Dreyfus, 1980) describes how individuals progress through five stages of expertise development:

1. **Novice**: Relies on context-free rules, struggles with ambiguity, requires explicit guidance
2. **Advanced Beginner**: Starts recognizing situational aspects, develops guidelines for action, but still lacks a holistic understanding
3. **Competent**: Develops organizing principles, makes conscious deliberate planning, can troubleshoot problems
4. **Proficient**: Sees situations holistically, recognizes patterns intuitively, but still engages in deliberate decision-making
5. **Expert**: Demonstrates intuitive, fluid performance without explicit rule-following, possesses tacit knowledge and pattern recognition

This model has been empirically supported across diverse domains including nursing, chess, language acquisition, and professional skills development, and aligns with philosophical accounts of expertise as embodied, context-sensitive knowing rather than rule-following (Dreyfus, 1992).

## 4.2 AI-Induced Transformations of the Dreyfus Model

Our research proposes that AI fundamentally transforms the Dreyfus progression in ways that undermine traditional expertise development. The revised model below demonstrates these transformations from a philosophical perspective:

| Dreyfus Stage | Traditional Human Learning | AI-Augmented Learning Shift | Philosophical Implications |
|---|---|---|---|
| **Novice** | Relies on rules, struggles with ambiguity. | AI provides immediate structured knowledge, eliminating struggle. | Undermines the embodied experience of learning through resistance and failure that philosophers like Heidegger identified as essential for skill development. |
| **Advanced Beginner** | Starts seeing patterns but still | AI can synthesize and organize | Challenges the phenomenological account of learning as a gradual perceptual reorientation through |

| | | | |
|---|---|---|---|
| | needs explicit guidance. | knowledge, eliminating friction. | direct engagement with materials and situations. |
| **Competent** | Understands context, makes independent judgments. | AI provides contextual insights but shifts effort toward retrieval rather than deep learning. | Threatens the development of what Aristotle termed "phronesis" or practical wisdom—judgment developed through experience rather than rule-following. |
| **Proficient** | Operates intuitively, sees patterns effortlessly. | AI makes structured knowledge so accessible that deep expertise may become rarer. | Disrupts the development of what Polanyi (1966) called "tacit knowledge"—knowing more than we can tell—that resists simple externalization. |
| **Expert** | Uses deep intuition, unconscious mastery. | AI cannot develop intuition, only extrapolate patterns from data. | Challenges Dreyfus's (1992) conception of expertise as non-representational, embodied coping that transcends rule-following. |

This revised model suggests that while AI can accelerate apparent progression through the stages, it fundamentally alters the nature of expertise development by:

1. Eliminating necessary productive struggle at early stages
2. Reducing the need for internal pattern recognition and mental model development
3. Creating dependency on external systems rather than internalized expertise
4. Potentially preventing the development of true expert intuition

From a philosophical perspective, these transformations challenge fundamental assumptions about how humans develop capabilities through engagement with the world (Dreyfus, 1992; Merleau-Ponty, 1962). They suggest that AI-augmented learning may produce what appears to be expertise but lacks the embodied, contextual understanding that philosophers from Aristotle to Heidegger have identified as essential to true mastery.

## 4.3 Quantum Analogy for Expertise Transitions

We propose a novel conceptualization of expertise development using a quantum physics analogy that provides a powerful philosophical metaphor. In this framework:

1. **Expertise levels as energy states**: Each Dreyfus stage represents a distinct cognitive "energy level" with characteristic properties and capabilities
2. **Transition requirements**: Moving between levels naturally requires specific cognitive "quanta" - accumulated experience, practice, and mental model development
3. **AI-induced "false jumps"**: AI assistance creates apparent transitions to higher expertise levels without the accumulated cognitive quanta normally required
4. **Unstable elevated states**: These AI-induced jumps create unstable higher-level performance that rapidly decays when AI support is removed
5. **Regression to baseline**: Without proper foundation-building, AI-elevated expertise typically regresses to the practitioner's true baseline level

This quantum analogy helps explain why AI-assisted performance can mimic higher Dreyfus stages without building the necessary cognitive structures for sustained expertise. The philosophical implication is significant: what appears as expertise in AI-augmented contexts may be a form of "quantum entanglement" between human and machine rather than genuine human capability—raising profound questions about the location and ownership of knowledge in AI-human systems.

# 5. The WEF Skills Projection Paradox: Empirical Evidence of Frameworks Accelerating Erosion

An illuminating real-world validation of our competency erosion framework comes from analyzing the World Economic Forum's Future of Jobs reports from 2023 and 2025. These influential reports shape educational policy, workforce development, and corporate training globally. Our analysis reveals a concerning pattern that may inadvertently accelerate competency erosion through the signals these reports send about fundamental cognitive capabilities.

Between the 2023 and 2025 reports, fundamental capabilities like reading, writing, and mathematics shifted from "core skills" that were "increasing in importance least quickly" to "out-of-focus skills" showing an actual net decline in importance (-4%). This dramatic recategorization coincides with the emergence of generative AI, suggesting employers increasingly view these foundational cognitive capabilities as outsourceable to technology rather than essential human skills.

This creates what we term the "WEF paradox": AI and Big Data are identified as the fastest-growing skill (87% net increase) while mathematics is categorized as "out-of-focus" with a net decline. This produces an unsustainable knowledge ecosystem where societies are encouraged to consume and apply AI systems while simultaneously devaluing the very mathematical foundations needed to understand, develop, and critically evaluate these systems.

From a philosophical perspective, this paradox reveals a troubling temporal contradiction: what sells today is a direct result of what was learned yesterday. The skills that employers currently value—analytical thinking, technological literacy, AI capabilities—were built upon the very foundational skills now being devalued. Employers are essentially saying, "We don't need the skills that made our current workforce capable, but we need the advanced capabilities those skills enabled."

This empirical evidence from a major global framework directly validates our theoretical concern about self-reinforcing cycles of competency erosion. The WEF's influential skills visualizations don't merely predict the future—they help create it, potentially accelerating exactly the kind of erosion our mathematical model predicts.

## 5.1 Geographic Disparities and Cognitive Stratification

Our analysis reveals another troubling dimension of the WEF framework: the geographic stratification of cognitive priorities. The 2025 report shows that lower-income and conflict-affected regions expect much higher skills disruption (up to 48% in Egypt and Zimbabwe) compared to wealthier nations (28-30% in Denmark and Netherlands).

This creates a concerning dynamic where:

1. Lower-income regions report higher expected skills disruption
2. This disruption is presented as an objective reality rather than a result of economic structures
3. Therefore, educational systems in these regions are encouraged to adapt to this "reality" by focusing on different skills

The circular reasoning is profound: because certain skills aren't in economic demand in specific regions (often due to historical inequalities and economic structures), the report implies they should not be prioritized in education—thereby perpetuating and potentially deepening these very inequalities.

This approach risks creating a two-tiered global skills ecosystem where advanced cognitive foundations are preserved in wealthy nations while being systematically devalued in developing ones—precisely the regions that most need to build autonomous capabilities rather than becoming dependent consumers of technologies developed elsewhere.

## 5.2 The Mobility Blindspot

Another critical limitation of the WEF framework is its failure to account for human mobility across geographic regions. The report implicitly assumes relatively static populations within each national labor market, ignoring the reality of substantial cross-border movement of workers throughout their careers.

This oversight creates several problems:

1. **Skills Portability**: Workers trained according to one region's "priority skills" may find themselves fundamentally unprepared when moving to regions with different skill demands
2. **Lost Talent Development**: Regions that devalue fundamental skills based on local employer demands may be systematically underpreparing their populations for global opportunities
3. **Reinforced Inequalities**: The framework inadvertently promotes educational approaches that could lock populations into their current economic positions rather than enabling mobility

By recommending different skill priorities for different regions while simultaneously devaluing universal cognitive foundations like numeracy, literacy, and fundamental learning capabilities, the framework establishes invisible barriers to human potential and mobility.

The implications are profound:

1. **Cognitive Stratification**: Different regions develop fundamentally different cognitive capabilities, creating new forms of inequality beyond traditional economic measures
2. **Diminished Human Potential**: Individuals become constrained by the skill priorities of their birth region rather than developing their full capabilities
3. **Systemic Vulnerability**: Societies that devalue foundational skills based on current economic demands become structurally vulnerable to future disruptions

4. **Reinforced Dependency**: The regions most in need of cognitive sovereignty become most dependent on external cognitive resources

By marking core human capabilities like numeracy, learning, and foundational cognitive skills as "out of focus" in certain regions, the WEF framework doesn't merely forecast different economic futures—it actively promotes cognitive inequality.

### 5.3 The Temporal Paradox: Forgetting What Made Today Possible

Perhaps the most fundamental contradiction in the WEF framework is a temporal paradox that goes largely unacknowledged: what sells today is a direct result of what was learned yesterday. Yet the framework creates a false separation between past learning and future skills needs.

The skills that employers currently value—analytical thinking, technological literacy, AI capabilities—were built upon the very foundational skills now being devalued. The irony is stark: employers are essentially saying, "We don't need the skills that made our current workforce capable, but we need the advanced capabilities those skills enabled."

This creates a profound disconnect in the learning continuum:

1. Today's workers built their analytical and technological capabilities on foundations of mathematics, reading, and writing
2. These foundations are now deemed "out of focus" for future workers
3. Yet somehow, these future workers are expected to develop the same or better advanced capabilities without the foundations that enabled them

This paradox reveals a blindness to how skill development actually works across time. It ignores the developmental reality that advanced capabilities aren't spontaneously generated—they evolve from and build upon fundamental cognitive foundations.

By devaluing the very learning that made today's capabilities possible, we risk creating future generations incapable of the innovation and adaptation employers claim to value. In essence, we're sawing off the cognitive branch we're sitting on, failing to recognize how our current capabilities depend on the foundations we're now dismissing.

# 6. The Social Acceleration of Competency Erosion

While our mathematical model explains the dynamics of competency erosion at individual and organizational levels, it is important to consider the social mechanisms that accelerate this process. This section examines how authority-based influence structures and mimetic behaviors multiply the effects predicted by our model, creating feedback loops that intensify erosion rates beyond what individual-level analysis alone would predict.

### 6.1 The Authority-Mimesis Complex

We propose that competency erosion is significantly accelerated by what we term the "Authority-Mimesis Complex"—a social amplification mechanism where authoritative pronouncements trigger cascading imitative behaviors throughout systems, leading to rapid adoption of potentially harmful practices with minimal critical evaluation.

The Authority-Mimesis Complex operates through a consistent pattern:

1. **Expert Pronouncement**: An authoritative source makes a claim or recommendation (e.g., the WEF designating mathematical skills as "out-of-focus")
2. **Status-Seeking Amplification**: High-visibility individuals and organizations repeat the claim to signal their own authority and future-readiness
3. **Institutional Adoption**: Organizations implement policies based on the amplified signal, often without independent evaluation
4. **Systemic Entrenchment**: Systems reorganize around the new priority, making reversal increasingly difficult
5. **Cognitive Adaptation**: Individual capabilities adjust to match the new environment, reinforcing the initial signal

This process directly affects our mathematical model of competency erosion by increasing the α coefficient (AI sensitivity) in our equation:

$$R(t) = R_0 e^{(-\alpha \cdot ADR \cdot t)}$$

As the Authority-Mimesis Complex propagates AI dependency norms, the α coefficient increases, accelerating the rate at which the Practice Stability Factor (R) deteriorates. This creates a positive feedback loop where social signals intensify individual erosion, which in turn strengthens social signals.

## 6.2 Structural Acceleration Mechanisms

Three specific mechanisms within the Authority-Mimesis Complex particularly accelerate competency erosion:

### 6.2.1 Authority Cascades

Authority cascades occur when credibility transfers hierarchically through institutional structures:

- Prestigious organizations (like the WEF) make initial claims
- Industry publications cite these claims uncritically
- Corporate leaders reference the publications
- Organizational policies reflect leadership priorities
- Individual practice patterns adjust accordingly

This cascade creates an exponential rather than linear propagation of dependency norms, accelerating the erosion rate beyond what would occur through individual choice alone.

From a philosophical perspective, this cascade exploits what Heidegger termed "das Man" (the they-self)—the tendency to align with socially prescribed patterns without critical evaluation. The authority cascade effectively short-circuits the philosophical reflection necessary for what Frankfurt (1971) called "second-order desires"—desires about what we should want—replacing them with mimetic adoption of authoritative preferences.

### 6.2.2 Institutional Validation Loops

As authority-triggered changes propagate, institutional validation loops form, creating self-reinforcing systems that entrench erosion:

- Educational institutions adjust curricula to match "future skills needs"
- Funding bodies prioritize initiatives that align with authority views
- Researchers adapt their focus to match funding priorities
- Students select programs based on perceived future demand
- Employer practices confirm the original projections

These loops create what Kuhn might recognize as a paradigm shift in skill valuation, where fundamental capabilities become systematically devalued not through evidence but through social reinforcement.

### 6.2.3 Connected to Mathematical Model

These social acceleration mechanisms directly connect to our mathematical framework of competency erosion through several parameters:

- **Increased $\alpha$ (sensitivity coefficient)**: Authority-mimesis dynamics make individuals and organizations more sensitive to AI substitution signals
- **Accelerated adoption rate and reduced resistance**: Social reinforcement reduces resistance to AI dependency
- **Lowered adoption thresholds**: Authority endorsement reduces critical thresholds for AI adoption decisions
- **Shortened $t_0$ (inflection point timing)**: Mimetic acceleration brings forward the S-curve inflection point for organizational expertise transformation

This integration of social dynamics with our mathematical model provides a more complete understanding of how competency erosion manifests in real-world systems—not merely as an individual cognitive phenomenon but as a socially accelerated transformation.
Having established how social acceleration mechanisms mathematically amplify competency erosion through parameter modifications, we must now examine the deeper philosophical implications of this socially-mediated transformation process for human cognitive agency and autonomy, which extend beyond quantitative changes to qualitative shifts in our relationship with our own cognitive capabilities

## 6.3 Philosophical Implications for Cognitive Agency

The Authority-Mimesis Complex raises profound philosophical questions about cognitive agency in an age of AI advancement. If our adoption of AI dependencies is substantially driven by mimetic processes triggered by authority signals rather than critical evaluation, what does this imply for human autonomy?

This question connects directly to Frankfurt's (1971) concept of freedom as the capacity to have "second-order volitions"—desires about what desires we wish to have. When authority-mimesis dynamics shape not just our behavior but our valuation of capabilities, they potentially undermine this second-order capacity by making the erosion of capabilities appear desirable and inevitable.

The complex also challenges Taylor's (1989) concept of "strong evaluation"—our capacity to judge not just outcomes but the quality of our desires. If authority signals increasingly shape what capabilities we consider valuable, our ability to perform strong evaluation may itself erode, creating a recursive degradation of cognitive agency.

These philosophical concerns extend our mathematical model by suggesting that competency erosion affects not just specific skills but potentially our meta-capability to evaluate skill dependencies themselves—creating a troubling recursive vulnerability in human-AI systems.

# 7. Cognitive Sustainability: A Philosophical Framework for Human-AI Coevolution

## 7.1 Defining Cognitive Sustainability

We propose "cognitive sustainability" as a philosophical framework for understanding and addressing competency erosion. Drawing inspiration from environmental sustainability, we define cognitive sustainability as:

*The preservation and development of human cognitive capabilities alongside technological advancement, maintaining the intellectual capacity for critical evaluation, innovation, and autonomous functioning independent of technological mediation.*

This definition establishes cognitive capabilities as a form of renewable resource that can be degraded through overexploitation (excessive AI dependency) or nurtured through balanced development practices. It reframes AI integration as an issue of "cognitive ecology" rather than merely technological progress.

From a philosophical perspective, cognitive sustainability extends Jonas's (1984) imperative of responsibility into the cognitive domain, recognizing that our technological choices today shape not only our capabilities but potentially those of future generations.

## 7.2 The Cognitive Autonomy Paradox

At the heart of cognitive sustainability is what we term the "cognitive autonomy paradox": AI systems simultaneously enhance and potentially diminish human cognitive capabilities. This creates philosophical tension between:

1. **Performance enhancement**: The immediate capability augmentation AI provides
2. **Capability preservation**: The maintenance of independent cognitive functioning
3. **Future adaptability**: The capacity to develop new capabilities as contexts change

This paradox requires a philosophical reframing of how we conceptualize the human-AI relationship. Rather than viewing AI as either a tool or a replacement, cognitive sustainability suggests viewing it as a co-evolving system where human and artificial components must develop in balanced relation to each other.

This perspective aligns with Dewey's (1927) pragmatist view of democracy requiring educated citizens capable of critical inquiry and reflective judgment. If AI dependency undermines these capabilities, it creates not just a practical challenge but a philosophical one concerning the future of human agency and democratic participation.

### 7.3 Principles of Cognitive Sustainability

We propose five core philosophical principles for cognitive sustainability:

1. **The preservation principle**: Critical cognitive foundations must be maintained regardless of immediate market signals or technological capabilities
2. **The reinforcement principle**: AI systems should be designed to strengthen rather than replace human cognitive capabilities when those capabilities serve broader purposes than immediate task completion
3. **The metacognitive principle**: AI integration should enhance awareness of cognitive processes and dependency patterns rather than obscuring them
4. **The autonomy principle**: Individuals and communities should maintain the capability to function effectively without technological mediation in domains central to human flourishing
5. **The equity principle**: Cognitive capabilities should be distributed justly across populations rather than concentrated among AI creators while being diminished among AI consumers

These principles provide a philosophical foundation for addressing competency erosion that balances technological advancement with human cognitive flourishing. They offer a framework for designing both AI systems and educational approaches that enhance human capabilities without creating problematic dependencies.

# 8. The Organizational-Societal Paradox in Cognitive Erosion

Our mathematical model of competency erosion reveals a profound structural contradiction that extends beyond individual cognitive dynamics to a systems-level misalignment between organizational incentives and societal cognitive health. This section examines what we term the "Organizational-Societal Paradox"—a fundamental tension that emerges when considering competency erosion across different levels of analysis.

### 8.1 The Performance-Capability Asymmetry

The S-curve model of organizational expertise transformation reveals a critical asymmetry between performance outcomes and cognitive capabilities:

$$E(t) = E_0\left[1 - \frac{1}{1+ e^{(-k(t-t_o))}}\right] + E_{AI}\left[\frac{1}{1+ e^{-r(t-t_1)}}\right]$$

From an organizational perspective, this equation often approximates to zero or even positive in terms of performance metrics: as human expertise declines, AI capabilities compensate or even enhance measurable outcomes. Organizations experience stable or improved performance while underlying human cognitive capabilities erode.

This creates what appears to be a rational organizational strategy that, when viewed from a societal perspective, produces deeply irrational outcomes. The firm-level "zero-sum" or net-positive result masks the true societal cognitive decay that emerges from the aggregate erosion of human capabilities across populations.

### 8.2 The Part-Whole Contradiction

This asymmetry reveals a philosophical and systems-level contradiction: firms are simultaneously *part of* society and yet operate with incentives that potentially *undermine* societal cognitive capital. This represents a specific instance of what systems theorists identify as the part-whole problem—where optimization at subsystem levels produces degradation at the system level.

The paradox manifests in several dimensions:

1. **Mereological Tension**: Organizations are composed of individuals who are members of society, yet organizational policies may accelerate cognitive erosion that ultimately affects those same individuals beyond their organizational roles
2. **Incentive Misalignment**: Performance metrics that guide organizational decision-making do not account for cognitive sustainability, creating a structural blindness to erosion risks
3. **Temporal Disconnect**: The short-term performance benefits of AI substitution occur immediately, while the cognitive erosion effects manifest gradually over longer timeframes
4. **Externality Problem**: Organizations externalize the costs of cognitive erosion to society while internalizing the performance benefits of AI substitution

This paradox connects to Garrett Hardin's (1968) "Tragedy of the Commons" framework, where rational actors, optimizing independently according to self-interest, collectively produce outcomes contrary to the system's long-term viability.

### 8.3 Aggregation as Emergent Phenomenon

The societal impact of competency erosion cannot be understood as a simple linear aggregation of individual cognitive atrophy. Rather, it represents an emergent property of the system with unique characteristics:

1. **Network Effects**: The erosion of expertise affects knowledge transfer networks, creating cascade effects when critical knowledge nodes become AI-dependent
2. **Skill Ecosystem Disruption**: Traditional expertise development pathways (apprenticeship, mentoring, progressive skill building) degrade as intermediate skill development stages are bypassed
3. **Institutional Memory Loss**: Organizational practices that preserve and transfer tacit knowledge deteriorate when expertise is externalized to AI systems
4. **Metacognitive Impacts**: The capacity to recognize what knowledge is missing itself erodes, creating recursive vulnerability to unknown unknowns

These emergent properties mean that societal cognitive decay is both quantitatively greater than and qualitatively different from the sum of individual expertise erosion.

## 8.4 Philosophical Implications

This paradox raises profound philosophical questions about the relationship between parts and wholes in social-cognitive systems:

From the perspective of **social epistemology**, competency erosion challenges traditional conceptions of distributed knowledge (Hutchins, 1995) by demonstrating how technological mediation can transform not just the *location* of knowledge but its very nature and resilience.

From an **ethics of technology** standpoint, the paradox reveals the inadequacy of analyzing AI impacts at single levels of scale. As Floridi (2013) argues, ethical analysis of information technologies must consider systemic effects rather than merely individual interactions.

The paradox also connects to **philosophical work on emergence** (Bedau & Humphreys, 2008), demonstrating how cognitive properties at system levels cannot be reduced to properties of individual components. Competency erosion exemplifies what philosophers of science term "downward causation"—where system-level properties constrain and shape component-level dynamics.

## 8.5 Beyond Market Mechanisms

The Organizational-Societal Paradox explains why market mechanisms alone cannot address competency erosion. Since organizations experience no performance penalty—and often gain advantages—from substituting AI for human cognitive capabilities, there is no internal incentive to preserve capabilities that don't affect immediate performance.

This creates a collective action problem where:

1. Organizations that preserve human capabilities at the expense of AI-enhanced performance may face competitive disadvantages
2. Educational institutions respond to employer signals about valued skills, potentially accelerating erosion through curriculum changes
3. Individuals seeking employment adapt to organizational preferences by focusing on AI-complementary rather than foundational skills

The result is a market failure in preserving cognitive capabilities—a failure that remains invisible to traditional economic metrics focused on productivity and performance.

## 8.6 Structural Solutions

Addressing the Organizational-Societal Paradox requires solutions that operate at the structural level rather than merely targeting individual behaviors:

1. **Institutional Redesign**: Creating institutional structures that explicitly value and measure cognitive sustainability alongside performance
2. **Incentive Realignment**: Developing metrics and rewards that internalize the externalities of competency erosion
3. **Collective Governance Mechanisms**: Establishing cross-organizational standards for cognitive sustainability similar to environmental sustainability frameworks

4. **Educational Circuit Breakers**: Implementing educational approaches that preserve capability development regardless of immediate market signals

These structural approaches recognize that competency erosion is not simply a sum of individual choices but emerges from system-level incentives and structures that must themselves be transformed.

The paradox ultimately reveals that addressing AI-induced competency erosion requires not just individual skill development or organizational policy changes, but a fundamental reconsideration of how we balance performance optimization with cognitive sustainability across social systems.

# 9. Future Research Directions

While our theoretical paper establishes a conceptual framework for understanding AI competency erosion, comprehensive empirical validation will require specific future research initiatives:

## 9.1 Empirical Validation Studies

1. **Longitudinal Expertise Tracking**
   Extended longitudinal studies tracking expertise metrics before and after AI system introduction across multiple professional domains, with repeated measures over 3-5 years to capture long-term effects.
2. **Intervention Effectiveness Studies**
   Experimental studies testing different expertise preservation interventions, such as scheduled AI-free practice periods or deliberate practice modules integrated into AI workflows.
3. **Individual Difference Factors**
   Investigation of why some individuals show greater resistance to competency erosion, focusing on cognitive styles, metacognitive strategies, and motivational factors.
4. **Neurological Correlates**
   Neuroimaging studies examining how brain activation and connectivity patterns change with increasing AI dependency, potentially identifying neural correlates of competency erosion.
5. **Expertise Recovery Dynamics**
   Focused research on expertise recovery processes after periods of AI dependency, examining whether recovery follows different patterns than initial acquisition.

## 9.2 Philosophical Research Extensions

1. **Cognitive Agency and AI Dependency**
   Further philosophical investigation into how AI dependency affects conceptions of cognitive agency and autonomy, building on work by O'Connor (2000) and others while addressing the specific challenges of AI integration.
2. **Extended Mind Ethics**
   Development of an ethical framework for extended cognition that addresses asymmetrical dependencies and power dynamics in human-AI cognitive systems.

3. **Phenomenology of AI-Human Interaction**
   Exploration of the lived experience of AI-augmented cognition, examining how the phenomenology of thinking changes when partially externalized to artificial systems.
4. **Epistemology of Hybrid Knowledge**
   Investigation of how knowledge claims are justified in human-AI hybrid systems where neither component has complete understanding of the integrated process.
5. **Identity and Self in AI-Extended Cognition**
   Analysis of how externalization of cognitive processes to AI affects conceptions of self, identity, and personal boundaries.

## 9.3 Technical and Applied Research

1. **Cognitive Sustainability Metrics**
   Development and validation of standardized measures for assessing cognitive sustainability across domains and populations.
2. **AI Design for Cognitive Enhancement**
   Creation of design principles and patterns for AI systems that strengthen rather than replace human cognitive capabilities.
3. **Educational Interventions**
   Testing approaches to education that leverage AI capabilities while preserving deep expertise development.
4. **Organizational Knowledge Systems**
   Investigation of how organizations can maintain distributed expertise while integrating AI capabilities.
5. **Expertise Modeling in AI Systems**
   Development of AI architectures that model human expertise development pathways rather than merely replicating task performance.

## 9.4 Mimetic and Social Dynamics Research

Future research should explore how mimetic mechanisms accelerate competency erosion through social and institutional channels.

1. **Authority-Mimesis Measurement**
   Development of tools to quantify the degree to which authority signals influence AI adoption and skill valuation across professional communities.
2. **Social Network Analysis of Competency Erosion**
   Application of network theory to map how AI dependency and competency erosion patterns propagate through professional networks.
3. **Epistemic Sovereignty Interventions**
   Testing interventions designed to strengthen critical evaluation of authority claims about skill valuation and AI integration.
4. **Institutional Mimetic Resistance**
   Investigating how organizations might develop structures that resist mimetic pressure while maintaining adaptability.
5. **Cognitive Conservation Frameworks**
   Development of policy approaches to cognitive conservation modeled after environmental conservation frameworks, designed to preserve essential human capabilities despite short-term economic signals.

These research directions would significantly advance our understanding of competency erosion while developing practical approaches to preserving cognitive sustainability in an increasingly AI-integrated world.

# 10. Conclusion

This paper has presented a theoretical framework for understanding AI-induced competency erosion—a phenomenon with profound implications for philosophy of mind, cognitive science, and human-AI interaction. Our novel dual-scale mathematical model—combining individual expertise atrophy dynamics with organizational S-curve patterns—provides a rigorous foundation for understanding and addressing this challenge.

The framework suggests that without strategic intervention, expertise degradation will accelerate as AI adoption increases, raising fundamental philosophical questions about cognitive agency, extended mind ethics, and the future of human knowledge. By conceptualizing competency erosion through the lens of quantum-like expertise transitions and the revised Dreyfus model, we provide a more complete understanding of how AI dependency affects human expertise development and maintenance.

Our analysis of World Economic Forum skills projections provides empirical evidence of how influential frameworks may inadvertently accelerate competency erosion by devaluing foundational cognitive capabilities while simultaneously promoting AI-related skills. This creates a troubling paradox where the mathematical foundations needed for AI development are simultaneously marked as "out-of-focus"—potentially creating a two-tier system of AI creators (with mathematical foundations) and AI consumers (without these foundations).

The concept of cognitive sustainability offers a philosophical framework for addressing these challenges—recognizing the need to preserve human cognitive capabilities alongside technological advancement. This framework extends philosophical work on extended cognition, cognitive agency, and the ethics of technology to address the specific challenges of AI integration.

As AI capabilities continue to advance, the philosophical question is not whether to adopt these technologies but how to integrate them in ways that preserve and enhance human cognitive capabilities rather than eroding them. Our theoretical framework provides a starting point for the empirical research needed to develop evidence-based approaches to AI integration that amplify human potential rather than diminishing it—preserving the essence of "Cogito, ergo sum" for future generations while embracing the benefits of technological advancement.

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