The Generative Capacity Erosion Hypothesis: Does Generative AI Assistance Degrade Human Ideation Capacity?

Ravi Gupta, Shabista Shabista

Independent Researcher, Independent Researcher
ravigupta1989@gmail.com, shabista0690@gmail.com

Abstract

The rapid integration of generative artificial intelligence into creative workflows raises a critical but underexplored question: does habitual AI assistance in creative tasks lead to measurable atrophy in human generative capacities? Drawing from established research on cognitive offloading—including the "Google effect" on memory and GPS-induced degradation of spatial cognition—this paper introduces the **Generative Capacity Erosion Hypothesis (GCEH)**: sustained reliance on AI co-creation tools may systematically weaken human ideation, divergent thinking, and creative self-efficacy. The hypothesis is situated within five decades of research on technology-mediated cognitive change, tracing parallels from calculators to search engines to satellite navigation. A theoretical framework distinguishes between *augmentation effects* (additive benefits) and *atrophy effects* (subtractive costs), arguing that current discourse overemphasizes the former while neglecting the latter. The paper develops operationalizable constructs for creative atrophy, outlines methodological approaches for empirical investigation, and discusses implications for the design of "creativity-preserving" AI systems. The Well-Being AI paradigm must account not only for what AI enables humans to produce, but for what sustained AI assistance may prevent humans from becoming.

Introduction

The integration of generative artificial intelligence into creative practice represents one of the most significant transformations in the history of human cultural production. Large language models can now generate poetry, compose music, draft narratives, and produce visual art at scales and speeds previously unimaginable (Ramesh et al. 2022). This capability has sparked considerable enthusiasm about AI as a tool for "creativity augmentation"—the idea that AI assistance can expand human creative potential by lowering barriers to production, providing novel stimuli, and enabling rapid iteration (Boden 2004).

Yet this optimistic framing may obscure a more troubling possibility. Just as the widespread adoption of GPS navigation has been associated with degraded spatial cognition (Dahmani and Bohbot 2020), and search engine availability with reduced memory encoding (Sparrow, Liu, and Wegner 2011), sustained reliance on AI creative assistance may systematically weaken the very cognitive capacities it ostensibly augments. This paper introduces the **Generative Capacity Erosion Hypothesis (GCEH)**: the proposal that habitual use of generative AI for creative tasks leads to measurable declines in human ideation capacity, divergent thinking ability, and creative self-efficacy.

This hypothesis challenges the dominant "AI as tool" metaphor, which implicitly assumes additive effects—that AI capabilities simply add to human capabilities without substitution costs. Drawing from cognitive psychology, neuroscience, and the history of technology-mediated cognitive change, we argue that the relationship between AI assistance and human creative capacity may be fundamentally *non-additive*, involving trade-offs that current research paradigms fail to capture.

The paper proceeds as follows. Section 2 reviews five decades of research on how digital technologies have shaped cognitive capacities, establishing precedents for technology-induced atrophy effects. Section 3 develops the theoretical framework for the Generative Capacity Erosion Hypothesis, distinguishing mechanisms and operationalizable constructs. Section 4 presents proposed methodology for empirical investigation. Section 5 discusses implications for AI design and the Well-Being AI paradigm. Section 6 concludes with limitations and future directions.

Historical Precedents: Digital Technology and Cognitive Change

The relationship between technology and cognitive capacity has been a subject of inquiry since at least the 1970s, when educational researchers first examined whether calculator use affected mathematical reasoning (Reys 1984). This section traces five decades of research across multiple technological domains, identifying patterns relevant to the Generative Capacity Erosion Hypothesis.

Phase I: Calculators and Computational Cognition (1970s–1990s)

The introduction of electronic calculators into educational settings sparked the first systematic investigation of technology-mediated cognitive trade-offs. Early concerns focused on whether calculator availability would undermine students' development of mental arithmetic skills and number sense (Hembree and Dessart 1986).

Meta-analytic reviews from this period produced mixed findings. Hembree and Dessart's influential 1986 meta-analysis found no significant negative effects of calculator use on computational skills when calculators were integrated thoughtfully into instruction (Hembree and Dessart 1986). However, subsequent research identified concerning patterns: students who relied heavily on calculators showed diminished mental computation fluency and weaker number sense compared to peers who practiced mental arithmetic regularly (McIntosh 2002).

The critical lesson from this era was methodological: short-term studies often failed to detect effects that became apparent only with sustained use over years. The distinction between *immediate performance* (which often improved with calculator access) and *underlying competency development* (which could be impaired) foreshadowed similar distinctions in later technology domains.

Phase II: The Internet and Memory Architecture (1990s–2010s)

The most influential research on technology-induced cognitive change emerged from studies of internet and search engine use. Sparrow, Liu, and Wegner's seminal 2011 study introduced the concept of "Google effects on memory," demonstrating that when individuals expect information to be digitally accessible, they encode it less effectively into long-term memory while showing enhanced recall for *where* information can be found rather than the information itself (Sparrow, Liu, and Wegner 2011).

This research established the concept of **cognitive offloading**—the strategic redistribution of cognitive tasks to external tools (Risko and Gilbert 2016). Critically, Sparrow et al. framed this not merely as a behavioral adaptation but as a fundamental reorganization of memory architecture, with the internet functioning as a form of "transactive memory" previously reserved for close social relationships.

Subsequent research extended these findings. Studies demonstrated that:

- Photo-taking impaired memory for visual experiences (Henkel 2014)
- Smartphone availability affected attentional capacity even when not in use (Ward et al. 2017)
- Habitual search engine use was associated with overconfidence in one's own knowledge (Fisher, Goddu, and Keil 2015)

These findings established a crucial precedent: technologies that enhance immediate performance can simultaneously undermine the development or maintenance of underlying cognitive capacities.

Phase III: GPS Navigation and Spatial Cognition (2000s–Present)

The most neurologically grounded evidence for technology-induced cognitive atrophy comes from research on GPS navigation and spatial cognition. This domain provides the closest analogue to the creativity case because it involves: (1) a complex cognitive capacity (spatial reasoning), (2) identifiable neural substrates (hippocampus), (3) both cross-sectional and longitudinal data, and (4) demonstrated structural brain changes.

The London taxi driver studies. Maguire and colleagues' research on London taxi drivers demonstrated that intensive spatial learning produces measurable structural changes in the hippocampus (Maguire et al. 2000). Taxi drivers who completed "The Knowledge"—a rigorous multi-year training requiring memorization of 25,000 streets—showed significantly larger posterior hippocampal gray matter volume compared to controls, with volume correlating positively with years of experience (Maguire, Woollett, and Spiers 2006).

GPS and hippocampal decline. Critically, research has now documented the inverse pattern: habitual GPS use is associated with reduced hippocampal gray matter volume and impaired spatial memory (Dahmani and Bohbot 2020). Dahmani and Bohbot's 2020 longitudinal study found that greater GPS use over a three-year period predicted steeper declines in hippocampus-dependent spatial memory, even after controlling for baseline differences. Participants who relied heavily on GPS showed lower cognitive mapping abilities, reduced use of hippocampus-dependent spatial strategies, and decreased landmark encoding during navigation.

This research establishes that technology-mediated cognitive offloading can produce not merely behavioral changes but *structural brain changes* consistent with neural atrophy in task-relevant regions.

Phase IV: Spell-Checkers and Linguistic Cognition (1990s–2010s)

Research on automated spelling and grammar correction provides additional evidence for offloading-induced skill degradation. Studies have documented that reliance on spell-checking software is associated with reduced orthographic knowledge and proofreading accuracy (Figueredo and Varnhagen 2006). College students who habitually used spell-checkers showed weaker spelling performance when required to write without technological assistance.

These effects appear to operate through reduced encoding effort: when errors are automatically corrected, the effortful processing that would normally strengthen orthographic representations is bypassed, leaving weaker memory traces.

Synthesis: The Offloading-Atrophy Pattern

Across these technological domains, a consistent pattern emerges that we term the **Offloading-Atrophy Cycle**: (1) **Initial augmentation**: Technology enables task performance that exceeds unaided human capacity; (2) **Behavioral adaptation**: Users increasingly rely on technology, reducing engagement in underlying cognitive processes; (3) **Reduced practice effects**: Diminished practice of underlying skills leads to weakened competencies; (4) **Dependency reinforcement**: Weakened competencies increase relative advantage of technological assistance; (5) **Capacity atrophy**: Sustained reduced engagement produces measurable declines in underlying cognitive capacity.

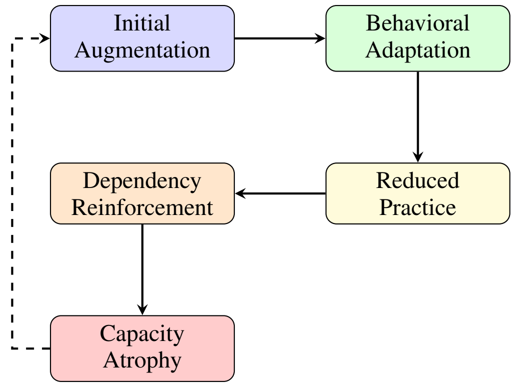

Figure 1: The Offloading-Atrophy Cycle: A recursive pattern observed across multiple technology domains.

Figure 1 illustrates this cycle.

The Generative Capacity Erosion Hypothesis: Theoretical Framework

Building on the precedents established in Section 2, we now develop the theoretical framework for understanding how AI assistance may affect human creative capacities.

Defining Creative Capacity

For the purposes of this hypothesis, we define **human creative capacity** as comprising three distinct but interrelated constructs:

Ideation fluency: The ability to generate multiple potential ideas, solutions, or possibilities in response to a creative challenge. Operationally, this corresponds to fluency scores on divergent thinking tasks (Guilford 1967).

Divergent thinking flexibility: The ability to shift between conceptual categories and approaches, producing ideas that span diverse domains. This corresponds to flexibility and originality scores on standard creativity assessments (Torrance 1966).

Creative self-efficacy: The subjective confidence in one's ability to produce creative work, which influences both engagement in creative tasks and persistence through challenges (Tierney and Farmer 2002).

Kim's (2011) analysis of Torrance Test data documented significant declines in all three constructs among American students since 1990—a period coinciding with the proliferation of digital technologies (Kim 2011). While this correlation does not establish causation, it provides ecological validity for investigating technology-creativity relationships.

Mechanisms of Creative Atrophy

We propose four mechanisms through which AI creative assistance may induce atrophy effects:

Mechanism 1: Ideation effort reduction. Creative ideation is cognitively effortful, requiring sustained working memory engagement, inhibition of obvious responses, and exploration of associative networks (Beaty et al. 2016). When AI systems provide ready-made ideas, options, or starting points, this effortful processing is bypassed. Just as calculator availability reduces mental arithmetic practice, AI availability may reduce ideation practice, weakening the cognitive "muscles" involved in independent idea generation.

Mechanism 2: Tolerance for ambiguity erosion. Creative processes require sustained engagement with uncertainty, ambiguity, and the discomfort of not-yet-knowing (Zenasni, Besançon, and Lubart 2008). AI systems that rapidly resolve ambiguity by generating concrete outputs may reduce users' tolerance for—and hence practice with—the uncomfortable early stages of creative work. Over time, this may impair the capacity to remain productively engaged with ill-defined problems.

Mechanism 3: Self-efficacy displacement. When creative outputs are co-produced with AI, attributions of creative agency become ambiguous. Users may increasingly attribute successful outcomes to the AI rather than to their own abilities, producing what Bandura termed "outcome expectations" divorced from "efficacy expectations" (Bandura 1977). This displacement may undermine the development of robust creative self-efficacy.

Mechanism 4: Evaluative capacity atrophy. The ability to evaluate creative quality—distinguishing promising ideas from unpromising ones—develops through repeated cycles of generation and feedback. When AI systems handle generation, users may lose opportunities to develop and refine their evaluative judgment. Paradoxically, this could leave users less able to effectively guide or evaluate AI-generated content.

Dimension	Augmentation	Atrophy
Timing	Immediate, concurrent	Delayed, cumulative
Measurement	Performance with AI	Performance without AI
Valence	Positive (enhanced output)	Negative (reduced capacity)
Visibility	Highly visible	Often invisible
Research focus	Dominant	Neglected

Table 1. Distinguishing Augmentation and Atrophy Effects

The Augmentation-Atrophy Distinction

A critical contribution of this framework is the distinction between **augmentation effects** and **atrophy effects**, summarized in Table 1.

Current research paradigms overwhelmingly focus on augmentation effects: does AI assistance improve the quality, quantity, or efficiency of creative outputs? This focus is methodologically convenient—augmentation effects are immediate and measurable during assisted performance—but systematically blind to atrophy effects, which manifest only during *unassisted* performance after sustained assisted practice.

Generative Capacity Erosion Mechanisms and Effects

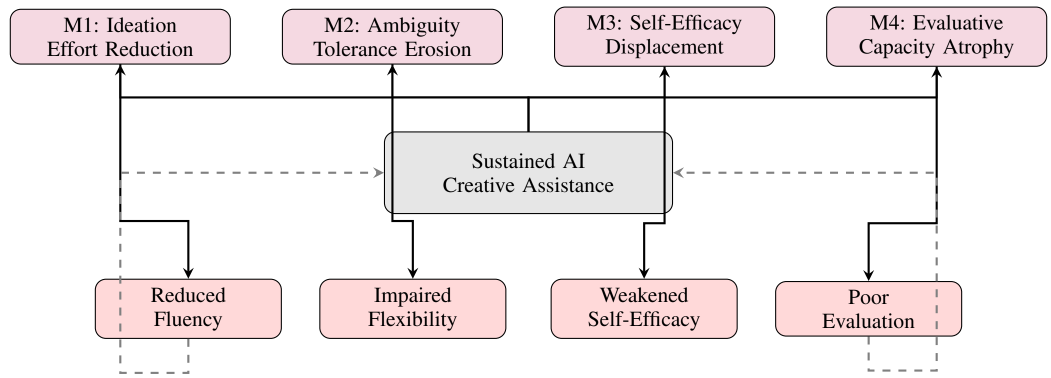

Figure 2: Theoretical framework: Four proposed mechanisms linking AI creative assistance to atrophy effects, with feedback loops reinforcing dependency.

Moderating Factors

We hypothesize that the strength of atrophy effects will be moderated by several factors:

Duration and intensity of AI use: Following the GPS research, we expect dose-dependent relationships—more sustained and intensive AI use associated with stronger atrophy effects.

Type of creative task: Atrophy effects may be stronger for tasks where AI provides complete solutions (e.g., image generation from prompts) than for tasks where AI provides scaffolding for human-driven processes.

User expertise: Novices may be more vulnerable to atrophy effects, as they have not yet developed robust underlying competencies. However, experts may also be vulnerable if AI assistance reduces their engagement in practice.

Metacognitive awareness: Users who consciously monitor their own creative development and strategically limit AI reliance may mitigate atrophy effects.

Proposed Methodology for Empirical Investigation

Testing the Generative Capacity Erosion Hypothesis requires methodological innovations that address the limitations of prior research on human-AI collaboration.

Longitudinal Design Requirements

Cross-sectional studies comparing heavy versus light AI users cannot distinguish atrophy effects from self-selection effects (individuals with lower creative capacity may be more likely to adopt AI assistance). Following the GPS research methodology (Dahmani and Bohbot 2020), we propose:

Cohort tracking: Recruit participants before significant AI creative tool adoption and track creative capacity over 2–4 years as AI use varies naturally.

Within-subject design: Measure both AI-assisted and unassisted creative performance at multiple time points, enabling detection of diverging trajectories.

Ecological validity: Rather than laboratory-only assessments, incorporate real-world creative outputs and validated self-reports of creative engagement.

Measurement Instruments

Divergent thinking assessment: Administer Torrance Tests of Creative Thinking (TTCT) or Alternative Uses Tasks at baseline and follow-up, under strictly unassisted conditions. These provide fluency, flexibility, and originality scores with established psychometric properties (Kim 2006).

Creative self-efficacy: Use validated instruments such as the Creative Self-Efficacy Scale (Tierney and Farmer 2002) to track changes in confidence independent of AI availability.

AI use quantification: Develop and validate self-report measures of AI creative tool use intensity, modeled on the GPS dependency scales used in navigation research (Dahmani and Bohbot 2020).

Creative practice logs: Have participants maintain logs of creative activities, noting AI assistance levels, to capture behavioral changes over time.

Neuroimaging Extension

Following the London taxi driver paradigm, neuroimaging could provide convergent evidence:

Regions of interest: Prefrontal cortex regions associated with divergent thinking and creative cognition (Beaty et al. 2016) could be assessed for volume or activation changes associated with AI use patterns.

Functional connectivity: Changes in default mode network connectivity—implicated in creative ideation—could provide neural signatures of atrophy effects.

Proposed Hypotheses

Based on the theoretical framework, we propose the following testable hypotheses:

H1: Individuals with higher AI creative tool usage will show greater declines in unassisted divergent thinking scores over a two-year period, controlling for baseline scores.

H2: The relationship between AI use and creative capacity decline will be mediated by reduced engagement in unassisted creative practice.

H3: Creative self-efficacy will decline more steeply among heavy AI users than light users.

H4: Neuroimaging will reveal reduced gray matter volume or functional connectivity in creativity-associated regions among heavy AI users.

Implications for AI Design and the Well-Being AI Paradigm

If the Generative Capacity Erosion Hypothesis is supported, it has significant implications for the design of AI creative tools and for the broader Well-Being AI paradigm emphasized by this symposium.

Beyond Output Optimization

Current AI design prioritizes output quality and user satisfaction. The GCEH suggests these metrics may be misleading: systems optimizing for satisfaction by minimizing creative friction may simultaneously maximize atrophy effects. We propose that Well-Being AI incorporate **creativity preservation** as a design objective through: scaffolding rather than substitution, productive friction introduction, practice encouragement via "training modes," and metacognitive support helping users monitor their creative development.

Implications for the Well-Being AI Paradigm

The GCEH suggests that Well-Being AI must attend not only to what AI enables humans to *produce* but to what sustained AI assistance may prevent humans from *becoming*. A framework that measures only outputs—even meaningful, valuable outputs—systematically ignores developmental effects on human capacities.

This reframes the symposium's central question. "Will AI light up human creativity or replace it?" may be a false dichotomy. The more troubling possibility is that AI could appear to light up creativity in the short term—producing more creative outputs, enabling more people to engage in creative activities—while simultaneously dimming it in the long term by eroding the cognitive foundations on which human creativity depends.

Historical Timeline: Technology and Cognitive Trade-offs

Figure 3 presents a timeline situating the Generative Capacity Erosion Hypothesis within five decades of research on technology-mediated cognitive change. Each technological wave has produced initial enthusiasm followed by growing recognition of trade-offs.

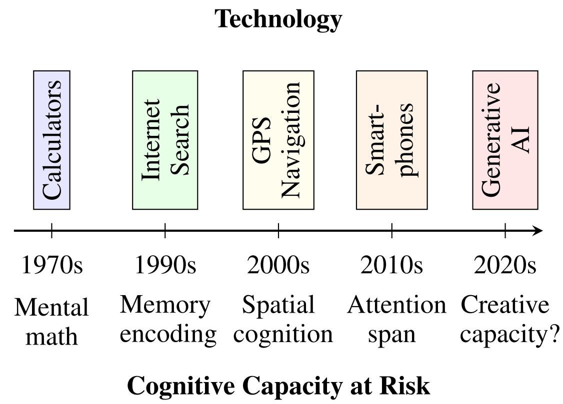

Figure 3: Timeline of technology adoption and associated cognitive trade-offs identified in research literature.

The Dual-Edge Nature and Generational Concerns

The pattern across technological eras suggests a general principle: cognitive tools that enhance performance by reducing effort simultaneously reduce practice effects that maintain underlying capacities. What distinguishes generative AI is its *scope*—while calculators offloaded arithmetic and GPS offloaded navigation, generative AI can assist with virtually any cognitive task, including the full spectrum of creative cognition. If creativity represents a "meta-capacity" integrating other cognitive processes (Sternberg and Lubart 1999), AI spanning multiple domains may produce more pervasive atrophy effects.

A particularly urgent concern involves generational effects. Individuals developing during formative periods with constant AI availability may never develop certain cognitive capacities at all. Csikszentmihalyi's research emphasizes that robust creativity emerges through sustained, challenging engagement during critical developmental periods (Csikszentmihalyi 1996). If AI reduces challenge during these periods, developmental trajectories may be fundamentally altered, making children and young adults a population of particular concern.

Theoretical Solutions: Lessons from Past Technologies

The historical precedents reviewed in Section 2 provide not only evidence for atrophy effects but also—crucially—evidence for *successful interventions* that mitigated these effects while preserving technological benefits. This section synthesizes lessons from calculator policy, spatial navigation research, and memory training to propose a multi-level framework for preserving human creative capacity in the age of generative AI.

Lessons from Calculator Integration

The calculator debates of the 1970s–1990s resolved not through prohibition but through **strategic integration** (Hembree and Dessart 1986). Key principles: (1) **"Estimate First" Protocol**—requiring mental estimates before

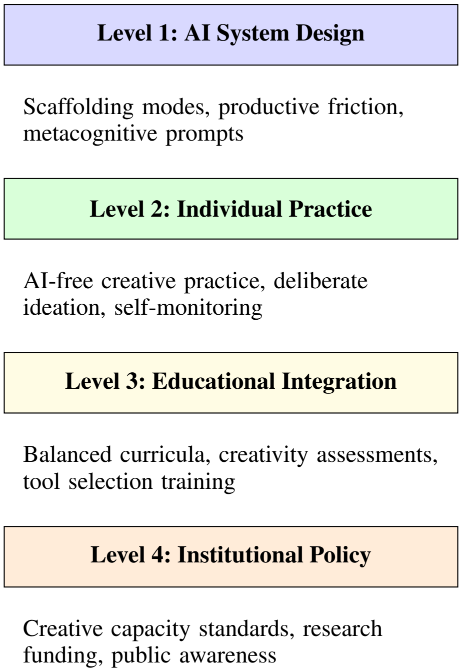

Figure 4: Multi-level framework for creativity preservation across AI design, individual practice, education, and policy.

calculator use maintained number sense engagement (McIntosh 2002); (2) **Calculator-Free Zones**—designating specific activities as calculator-free while permitting use for complex computations; (3) **Self-Regulation Training**—teaching conscious decisions about appropriate tool use; and (4) **Parallel Practice**—maintaining mental arithmetic alongside calculator availability prevented atrophy.

Lessons from Spatial Navigation Research

Recent GPS research has moved toward developing interventions that preserve spatial capacity: (1) **Active Navigation Design**—Clemenson et al.'s "auditory compass" GPS provides directional guidance without turn-by-turn instructions, maintaining decision-making engagement (Clemenson et al. 2021); (2) **Spatial Training Interventions**—Lövdén et al. showed that four months of navigation training protected hippocampal volume against age-related decline, with effects persisting four months post-training (Lövdén et al. 2012); and (3) **"Exploration Prescription"**—periodic deliberate exploration without GPS maintains spatial faculties through regular challenging engagement.

A Multi-Level Framework for Creativity Preservation

Synthesizing these lessons, we propose a multi-level framework (Figure 4) for preserving human creative capacity while retaining AI benefits.

Level 1: AI System Design Principles Drawing from the "active navigation" paradigm, we propose that AI creative tools incorporate: (1) **Scaffolding Modes** that provide structure and prompts while requiring human ideation to fill content; (2) **Productive Friction** through brief delays before generation or requirements for human input at key stages; (3) **"Ideate First" Protocols** requiring users to generate initial ideas before accessing AI assistance; (4) **Training Modes** that provide feedback on user-generated ideas without generating alternatives; and (5) **Metacognitive Prompts** that periodically encourage users to reflect on their creative process and practice independently.

Level 2: Individual Practice Recommendations For individuals, we recommend: **AI-Free Creative Practice** through regular unassisted ideation sessions; **Deliberate Ideation** by generating multiple ideas independently before consulting AI; **Creative Self-Monitoring** by tracking unassisted output for signs of declining fluency; and **Varied Assistance Levels** across projects to ensure some involve substantial unassisted work.

Level 3: Educational Integration The calculator integration literature suggests: **AI-Free Curricular Zones** designating assignments focused on developing human ideation capacity; **Unassisted Assessment** components to ensure students develop independent creative capacity; **Tool Selection Training** to develop metacognitive awareness about when AI assistance is appropriate; and **Parallel Practice Requirements** maintaining regular unassisted creative practice alongside AI-assisted work.

Level 4: Institutional and Policy Approaches At the institutional level: **Creative Capacity Standards** that explicitly include human creative capacity alongside AI-assisted production quality; **Research Investment** to empirically test atrophy hypotheses and intervention effectiveness; and **Public Awareness** campaigns to inform individual choices about AI use.

The "Creative Fitness" Paradigm

We propose reframing the human-AI relationship through a **"creative fitness"** paradigm: just as physical fitness requires regular exercise despite motorized transportation, creative fitness requires regular unassisted creative exercise despite AI availability. AI tools become analogous to vehicles—valuable for efficiency but not substitutes for exercise. This paradigm emphasizes that creative capacity requires regular challenging engagement to maintain, the goal is strategic AI use while preserving underlying capacity, and institutions bear responsibility for providing "creative exercise" opportunities. Table 2 summarizes proposed interventions.

Limitations and Future Directions

Limitations. The Generative Capacity Erosion Hypothesis remains theoretical, awaiting direct empirical validation. Our operationalization through divergent thinking metrics captures some but not all aspects of creative capacity. Different AI tools may have different atrophy profiles requiring domain-specific investigation. We have not fully theorized how individual differences moderate atrophy effects, nor how social and cultural contexts interact with individual-level processes.

Level	Key Interventions
AI Design	Scaffolding modes, productive friction, ideate-first protocols, training modes, metacognitive prompts
Individual	AI-free practice, deliberate ideation, self-monitoring, varied assistance levels
Education	AI-free zones, unassisted assessment, tool selection training, parallel practice
Policy	Capacity standards, research funding, public awareness campaigns

Table 2. Summary of Proposed Creativity-Preserving Interventions

Counter-arguments. Some argue that humans have always used cognitive tools without harm. However, historical tools typically augmented output while requiring substantial human engagement; generative AI differs by potentially substituting for core creative processes. The "adaptive reallocation" hypothesis—that freed cognitive resources are redirected to higher-level tasks—requires empirical validation; GPS research suggests such reallocation does not occur automatically.

Future directions. Priority areas include: (1) longitudinal empirical testing of atrophy hypotheses; (2) developmental studies examining AI effects during formative periods; (3) domain-specific investigation across writing, visual art, music, and scientific creativity; (4) intervention research testing the effectiveness of proposed solutions; and (5) neuroimaging studies examining structural and functional brain changes associated with AI creative tool use patterns.

Conclusion

This paper has introduced the Generative Capacity Erosion Hypothesis: the proposal that sustained reliance on AI creative assistance may systematically weaken human ideation capacity, divergent thinking, and creative self-efficacy. Drawing from five decades of research on technology-mediated cognitive change—from calculators to GPS navigation—we have identified consistent patterns of offloading-induced atrophy that may extend to the creative domain.

The implications are significant. If generative capacity erosion is real, then current approaches to human-AI creative collaboration may be optimizing for short-term gains while incurring hidden long-term costs. The Well-Being AI paradigm must therefore expand its evaluative horizon: beyond what AI-assisted humans can produce *now*, to what unassisted humans will be capable of producing *tomorrow*.

We do not argue that AI creative tools should be abandoned. The precedent of calculator research suggests that thoughtful integration, which preserves opportunities for human practice and development, can mitigate atrophy effects while retaining technological benefits. But achieving this balance requires first acknowledging that atrophy effects exist and deserve systematic investigation.

The question is not merely whether AI will augment human creativity or replace human creatives. It is whether AI will augment creativity while simultaneously eroding the human capacity to be creative at all. This possibility demands urgent empirical attention and should shape the design of AI systems intended to serve human flourishing.

References

Bandura, A. 1977. Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, 84(2): 191.

Beaty, R. E.; Benedek, M.; Wilkins, R. W.; Jauk, E.; Fink, A.; Silvia, P. J.; Hodges, D. A.; Koschutnig, K.; and Neubauer, A. C. 2016. Creative cognition and brain network dynamics. *Trends in Cognitive Sciences*, 20(2): 87–95.

Boden, M. A. 2004. *The creative mind: Myths and mechanisms*. Routledge.

Clemenson, G. D.; Maselli, A.; Fiannaca, A. J.; Miller, A.; and Gonzalez-Castillo, M. 2021. Rethinking GPS navigation: creating cognitive maps through auditory clues. *Scientific Reports*, 11(1): 7764.

Csikszentmihalyi, M. 1996. The creative personality. *Psychology Today*, 29(4): 36–40.

Dahmani, L.; and Bohbot, V. D. 2020. Habitual use of GPS negatively impacts spatial memory during self-guided navigation. *Scientific Reports*, 10(1): 6310.

Figueredo, L.; and Varnhagen, C. K. 2006. The impact of computer-assisted instruction on the development of spelling skills. *Canadian Journal of School Psychology*, 21(1-2): 102–119.

Fisher, M.; Goddu, M. K.; and Keil, F. C. 2015. Searching for explanations: How the Internet inflates estimates of internal knowledge. *Journal of Experimental Psychology: General*, 144(3): 674.

Guilford, J. P. 1967. *The nature of human intelligence*. McGraw-Hill.

Hembree, R.; and Dessart, D. J. 1986. Effects of hand-held calculators in precollege mathematics education: A meta-analysis. *Journal for Research in Mathematics Education*, 17(2): 83–99.

Henkel, L. A. 2014. Point-and-shoot memories: The influence of taking photos on memory for a museum tour. *Psychological Science*, 25(2): 396–402.

Kim, K. H. 2006. Can we trust creativity tests? A review of the Torrance Tests of Creative Thinking (TTCT). *Creativity Research Journal*, 18(1): 3–14.

Kim, K. H. 2011. The creativity crisis: The decrease in creative thinking scores on the Torrance Tests of Creative Thinking. *Creativity Research Journal*, 23(4): 285–295.

Lövdén, M.; Schaefer, S.; Noack, H.; Bodammer, N. C.; Kühn, S.; Heinze, H.-J.; Düzel, E.; Bäckman, L.; and Lindenberger, U. 2012. Spatial navigation training protects the hippocampus against age-related changes during early and late adulthood. *Neurobiology of Aging*, 33(3): 620–e9.

Maguire, E. A.; Gadian, D. G.; Johnsrude, I. S.; Good, C. D.; Ashburner, J.; Frackowiak, R. S.; and Frith, C. D. 2000. Navigation-related structural change in the hippocampi of taxi drivers. *Proceedings of the National Academy of Sciences*, 97(8): 4398–4403.

Maguire, E. A.; Woollett, K.; and Spiers, H. J. 2006. London taxi drivers and bus drivers: A structural MRI and neuropsychological analysis. *Hippocampus*, 16(12): 1091–1101.

McIntosh, A. 2002. Mental computation: A strategies approach. *Department of Education, Tasmania*.

Ramesh, A.; Dhariwal, P.; Nichol, A.; Chu, C.; and Chen, M. 2022. Hierarchical text-conditional image generation with CLIP latents. *arXiv preprint arXiv:2204.06125*.

Reys, R. E. 1984. Mental computation and estimation: Past, present, and future. *The Elementary School Journal*, 84(5): 547–557.

Risko, E. F.; and Gilbert, S. J. 2016. Cognitive offloading. *Trends in Cognitive Sciences*, 20(9): 676–688.

Sparrow, B.; Liu, J.; and Wegner, D. M. 2011. Google effects on memory: Cognitive consequences of having information at our fingertips. *Science*, 333(6043): 776–778.

Sternberg, R. J.; and Lubart, T. I. 1999. The concept of creativity: Prospects and paradigms. *Handbook of Creativity*, 3–15.

Tierney, P.; and Farmer, S. M. 2002. Creative self-efficacy: Its potential antecedents and relationship to creative performance. *Academy of Management Journal*, 45(6): 1137–1148.

Torrance, E. P. 1966. *Torrance Tests of Creative Thinking: Norms-technical manual*. Personnel Press.

Ward, A. F.; Duke, K.; Gneezy, A.; and Bos, M. W. 2017. Brain drain: The mere presence of one's own smartphone reduces available cognitive capacity. *Journal of the Association for Consumer Research*, 2(2): 140–154.

Zenasni, F.; Besançon, M.; and Lubart, T. 2008. Creativity and tolerance of ambiguity: An empirical study. *The Journal of Creative Behavior*, 42(1): 61–73.