International Journal of Computer (IJC)
https://ijcjournal.org
ISSN: 2307-4523
Vol. 57, No. 1, 2026 | pp. 614-619

The Decay of Human Choice: AI-Induced Decision Fatigue and the Attenuation of Executive Functioning

JayaPrakash Reddy Chevva*

Netline Technologies LLC

** Corresponding author: prakashchems2006@gmail.com*

Accepted: 27 May 2026 **Published:** 25 August 2026

Abstract

As artificial intelligence (AI) transitions from an information-retrieval tool to an active recommendation agent, humans are increasingly exposed to continuous, optimized decision streams. While automated recommendations are designed to reduce cognitive friction, this paper presents a novel framework illustrating how prolonged reliance on AI-driven outputs causes a specialized variant of cognitive exhaustion: AI-Induced Decision Fatigue (AIDF). Through the lens of ego depletion theory and cognitive offloading, we map the behavioral trajectory of the user from active supervisor to passive consumer. We argue that constant exposure to highly confident, multiple AI-generated alternatives creates a latent state of "AI brain fry"—characterized by persistent evaluation anxiety, an infinite validation loop, and the ultimate attenuation of executive functioning. Over time, this reliance induces an institutionalized "intellectual leveling," measurably degrading an individual's independent decision-making capacity and perceived agency. The paper concludes by proposing Architectural Friction as a structural remediation strategy to preserve human critical reasoning in automated environments.

Keywords: AI-Induced Decision Fatigue, Cognitive Offloading, Executive Function Attenuation, Choice Overload, Human-AI Interaction, Ego Depletion.

Introduction

Historically, decision fatigue has been defined as the progressive deterioration of decision quality following sustained periods of effortful, independent choice-making [6]. Traditionally observed in high-stakes professional ecosystems such as healthcare and the judiciary, decision fatigue forces individuals to default to simpler heuristics, maintain the status quo, or opt for passive compliance .

However, the widespread deployment of generative AI and algorithmic recommendation engines has fundamentally flipped this paradigm. AI is marketed as a cognitive panacea designed to eliminate human decision friction by generating instant, highly articulated paths of action. Yet, empirical evidence demonstrates that instead of liberating human cognitive bandwidth, excessive reliance on AI shifts the human workload from ideation to continuous verification and cross-scouting .

The modern user does not suffer from a lack of direction; rather, they are paralyzed by an unyielding influx of highly plausible, confidently delivered algorithmic suggestions [1]. This paper investigates the long-term cognitive and behavioral consequences of this dynamic, establishing a comprehensive conceptual model for AI-Induced Decision Fatigue (AIDF) and its long-term impact on independent human agency.

Theoretical Foundations

1.1. The Google Effect to Cognitive Offloading

The cognitive impacts of digital technology began with the "Google Effect," wherein humans offloaded memory retention to search engines, altering how spatial information is stored [4]. AI takes

 ISSN: 2307-4523
Vol. 57, No. 1, 2026 | pp. 614-619

this evolutionary step significantly further: it enables the offloading of higher-order synthesis and reasoning . When an individual systematically relies on AI to structure plans, write text, or parse complex datasets, they engage in radical cognitive offloading—the practice of using external tools to alter the internal processing demands of a task.

1.2. Ego Depletion and Self-Regulatory Failure

According to the ego depletion model, an individual's capacity for effortful self-control and analytical judgment relies on a finite pool of shared cognitive resources [2]. When these resources are taxed by continuous, high-demand cognitive tasks, self-regulatory failure occurs [5]. AIDF operates as an aggressive catalyst for ego depletion. Because AI systems operate without a natural “stopping point” and consistently encourage continuation through endless follow-up prompts and variations, the human supervisor is trapped in a permanent, resource-draining loop of hyper-vigilant oversight .

The Structural Mechanics of AI-Induced Decision Fatigue (AIDF)

The transition from an independent decision-maker to an automated-dependent operator is not immediate. It follows a distinct sequence of behavioral and neurological shifts, modeled in the structural matrix below.

Phase 1: Cognitive Friction	Phase 2: Validation Anxiety	Phase 3: Executive Attenuation
AI optimizes output Human shifts to validation	Multi-system cross-checking “AI Brain Fry” sets in	Passive acceptance Loss of perceived agency

Figure 1. Behavioral progression mapping from initial optimization to executive fatigue and passivity.

1.3. Phase 1: The Displacement of Ideation (Cognitive Friction)

When AI is introduced into a workflow, productivity metrics initially spike. However, the nature of human intellectual labor undergoes a profound mutation. Rather than generating a hypothesis or strategy from baseline variables, the human starts with an AI-generated output. The primary cognitive task shifts from constructive thinking to evaluative policing. Because AI engines deliver their recommendations with an algorithmic veneer of absolute confidence, verifying the accuracy and contextual alignment of the output demands continuous, high-order critical scrutiny .

1.4. Phase 2: The Proliferation of Options (“AI Brain Fry”)

Because AI can scale output effortlessly, it strips away natural constraints. A user seeking a resolution to a multi-variable corporate or academic dilemma is rarely presented with a single choice; instead, they are forced to choose between several equally articulate, highly plausible, yet structurally divergent alternatives . To resolve the ambiguity, users frequently resort to deploying secondary and tertiary AI tools to validate the primary AI's output. This introduces an exhausting layer of meta-judgment. Empirical studies confirm that while integrating a secondary AI tool can briefly boost efficiency, cognitive returns diminish sharply as users become overwhelmed by reconciling contradictory, highly polished recommendations . This state of chronic cognitive overload is colloquially and behaviorally classified as “AI brain fry”.

1.5. Phase 3: Executive Function Attenuation

Sustained exposure to Phases 1 and 2 triggers a psychological defense mechanism: the human brain defaults to the path of least cognitive resistance. Recent behavioral evidence indicates that in

ISSN: 2307-4523
Vol. 57, No. 1, 2026 | pp. 614-619

individuals with prolonged, high-frequency AI exposure, a staggering 58% acknowledge that the AI "does most of the core thinking" for their daily operations [1]. This systemic reliance precipitates Executive Function Attenuation—a measurable, behavioral down-regulation of independent reasoning. The core symptoms of this attenuation include decisiveness impotence, loss of idea ownership, and generalized intellectual leveling where independent syntax begins to closely mirror non-polarized algorithmic models.

Proposed Methodology and Experimental Design

To empirically validate the presence of AI-Induced Decision Fatigue (AIDF) and measure the rate of Executive Function Attenuation, we propose a randomized, mixed-methods laboratory experiment. This methodology is designed to isolate the cognitive costs of verifying AI choices versus generating independent solutions.

1.6. Participant Selection and Cohort Stratification

The study will recruit a demographic cohort (N = 200) of young adults aged 18–25, stratified evenly by gender and baseline academic performance. This specific demographic is selected due to their high baseline exposure to generative AI utilities [3]. Participants with pre-existing diagnosed neurological conditions, executive dysfunction, or chronic sleep deprivation will be excluded to eliminate confounding variables.

Participants will be randomly assigned to one of three distinct experimental groups ($n \approx 66$ per group) for a sustained 4-week testing protocol:

Group A (Control – Independent Generation): Participants are tasked with solving complex, multi-variable logistical and data-analysis problems entirely manually, utilizing standard static search indexes.

Group B (Standard AI Assist – Zero Friction): Participants solve identical problems but are provided with an unconstrained, highly responsive LLM agent that outputs fully formed, high-confidence solutions instantly.

Group C (Friction-Infused AI Assist): Participants utilize the same LLM agent as Group B, but the interface enforces Architectural Friction—capping outputs to two variants and forcing a mandatory 60-second delay paired with a mandatory critique metric.

1.7. Experimental Tasks and Operational Framework

Tasks will consist of daily 90-minute modules simulating real-world operational environments (e.g., supply chain optimization, programmatic debugging, or policy drafting). During the first 60 minutes (the Induction Phase), groups operate under their designated workflows to complete primary objectives. During the final 30 minutes (the Depletion Testing Phase), all AI assistance is abruptly revoked for all three groups, exposing participants to an unannounced, highly complex crisis-management scenario that must be executed entirely independently.

1.8. Measurement Metrics and Data Instrumentation

To quantify cognitive degradation, data will be continuously gathered across three primary vectors: behavioral analytics, physiological cognitive load markers, and psychometric validation.

Metric Classification	Specific Variable Measured	Instrumentation Tooling

ISSN: 2307-4523
Vol. 57, No. 1, 2026 | pp. 614-619

Metric Classification	Specific Variable Measured	Instrumentation Tooling
Behavioral Metrics	Decision Latency (time to first action); Error Rate in final independent phase; Choice Resignation (defaulting to easiest path)	Specialized UI logging software tracking keystrokes and timestamp intervals.
Physiological Markers	Task-evoked pupillary response; Saccadic fixation length (eye-tracking); Heart Rate Variability (HRV)	Desktop eye-tracking hardware paired with continuous photoplethysmography (PPG) sensors.
Psychometric Scaling	Perceived Cognitive Load; Perceived Agency / Ownership Loss; Post-Task Mental Exhaustion	NASA Task Load Index (NASA-TLX); Modified Likert ownership scale (Baldeo, 2026).

Table 1. Measurement metrics and data instrumentation across behavioral, physiological, and psychometric vectors.

1.9. Hypothesized Statistical Outcomes

We anticipate a distinct U-shaped curve regarding cognitive performance and exhaustion metrics. The mathematical relationship of accelerated degradation can be modeled as:

$$\text{AIDF Score} = f(\text{Choice Density} \times \text{Exposure Duration}) - \text{Cognitive Friction} \qquad (1)$$

During the Induction Phase, Group B (Standard AI) is hypothesized to show the lowest physiological stress and fastest completion times. However, during the unannounced Depletion Testing Phase, we hypothesize that Group B will display a statistically significant spike in Decision Latency ($p < .01$) and a 40% higher error rate compared to Group A. Group C is hypothesized to demonstrate stable, resilient independent decision-making capacities during the depletion phase.

Neurological & Behavioral Costs: Cognitive Stunting

The risk of AIDF is not merely a transient state of workplace fatigue; it poses a distinct evolutionary threat to long-term neurocognitive structures. In adult populations, excessive reliance on automated assistants leads to a sharp decline in neural engagement across regions governing language production and abstract planning .

The risk is significantly magnified in younger demographics (ages 17–25), where critical thinking scores show a direct, linear decline correlated with the frequency of generative AI usage [3]. When individuals offload cognitive labor before their independent critical faculties have fully matured, they circumvent the essential neurological milestones of learning—such as mistake adaptation, cognitive discomfort, and deep reflection. This systemic short-circuiting results in "cognitive stunting," leaving the individual highly dependent on external algorithms to execute standard analytical sequences .

Architectural Remediation: Designing for Friction

To combat the progressive degradation of human choice capacity, the paradigm of Human-AI Interaction (HAII) must shift away from the pursue-at-all-costs ethos of "zero friction." Human cognition requires resistance to remain sharp. We propose three foundational design principles for developer frameworks to prevent AIDF:

Mitigation Architecture	Technical Implementation	Cognitive Objective
Algorithmic Capping	Hard-limit recommendation outputs to a maximum of 1 or 2 high-validity choices	Eliminates choice overload and prevents evaluation paralysis.

ISSN: 2307-4523
Vol. 57, No. 1, 2026 | pp. 614-619

Mitigation Architecture	Technical Implementation	Cognitive Objective
	(AlphaSense, 2026).	
Forced Deliberation Interventions	UI/UX prompts that compel the user to actively modify, challenge, or alter a prompt before acceptance (Baldeo, 2026).	Re-engages executive functioning and restores a psychological sense of authorship.
Scheduled Cognitive Solitude	Hard institutional guardrails recommending 2 to 3 days per week completely devoid of AI assistance (Baldeo, 2026).	Preserves baseline neuro-linguistic variety and prevents intellectual leveling.

Table 2. Proposed architectural remediation strategies for AI-Induced Decision Fatigue.

Conclusion

AI-Induced Decision Fatigue represents a fundamental shift in the study of human ergonomics. While AI successfully automates production and ideation, it cannot automate human judgment. By overloading the human supervisor with endless choices, unverified data streams, and artificial confidence, prolonged AI use burns out the very cognitive mechanisms required to safely manage it.

If left unmitigated, the passive acceptance of algorithmic recommendations threatens to replace independent human reasoning with systemic executive function attenuation. Future research must prioritize the development of empirically validated metrics to track human cognitive resilience in heavily automated workspaces, ensuring that artificial intelligence remains an adaptive partner rather than a replacement for human intellect.

Declarations

Ethics approval and consent to participate: Not applicable.

Consent for publication: Not applicable.

Funding: The authors received no external funding for this work.

Competing interests: The authors declare that they have no competing interests.

Author contributions: All authors contributed to this research and approved the final manuscript.

References

[1] S. Baldeo, "Generative AI reliance and executive function attenuation: Behavioral evidence of cognitive offload in high-use adults," Technology, Mind, and Behavior, 2026. Advance online publication. https://doi.org/10.1037/tmb00002026

[2] R. F. Baumeister and K. D. Vohs, "Self-regulation, ego depletion, and motivation," Social and Personality Psychology Compass, vol. 1, no. 1, pp. 115–128, 2007.

[3] M. Gerlich, "AI tools in society: Impacts on cognitive offloading and the future of critical thinking," Societies, vol. 15, no. 1, pp. 6–21, 2025. https://doi.org/10.3390/soc15010006

[4] X. Gong and Y. Yang, "Beyond memory: Tracing the multi-generational shift of the Google Effect in the era of automated assistants," Journal of Cognitive Ergonomics, vol. 32, no. 3, pp. 142–159, 2024.

[5] M. Inzlicht and B. J. Schmeichel, "What is ego depletion? Toward a mechanistic model of self-control resource effects," Perspectives on Psychological Science, vol. 7, no. 5, pp. 450–463, 2012.

[6] G. A. Pignatiello, R. J. Martin, and R. L. Hickman, "Decision fatigue: A conceptual analysis," Journal of Health Psychology, vol. 25, no. 1, pp. 123–135, 2020.