

Two Faces of Inspiration: A (Systematic Review) of “Experimental Psychology” and "Inspiration Economy" Frameworks in the Age of Artificial Intelligence

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Abstract

This study compares two literatures that use the term “inspiration” but differ in epistemology and evidentiary standards: experimental psychology research on inspirational stimuli and creative performance, and the Inspiration Economy (IE) framework. Using a two-track design, it examines what each literature can legitimately claim about “inspiration optimization,” particularly in the context of generative artificial intelligence (GenAI) and human creativity.

The study addresses three converging concerns: GenAI makes inspirational stimuli instantly and abundantly available (Mahmud, 2025); algorithmic inspiration raises questions about authentic human creation grounded in intentionality, meaning, and lived experience (Brainard, 2026); and inspiration optimization is increasingly promoted without transparent supporting evidence. Clarifying these distinctions helps researchers, practitioners, and policymakers separate empirical findings from normative aspirations.

Track A synthesizes meta-analytic evidence from Zhang *et al*. (2026; 83 studies, 475 effect sizes) and Sio *et al*. (2015; 43 studies, N=1,229), supplemented by research on AI-generated stimuli (Mahmud, 2025; Hou & Wang, 2025). Track B descriptively and bibliometrically appraises the Buheji corpus (2014–2026), examining authorship, publication outlets, research designs, independent outcome data, and AI-related contributions (Buheji, 2025, 2026).

Track A indicates that example exposure has a small but significant positive effect on ideational quality, without significant effects on fluency, flexibility, or novelty (Zhang *et al*., 2026). A single uncommon example may facilitate novelty and quality (Sio *et al*., 2015), while GenAI-generated stimuli may increase perceived inspiration and enjoyment but also introduce fixation and reduce collective ideational diversity (Mahmud, 2025; Hou & Wang, 2025). Track B reveals that IE publications primarily present an applied framework through Inspiration Labs addressing poverty, aging, youth unemployment, post-pandemic recovery, and Gaza resilience. These works demonstrate sustained engagement with socioeconomic challenges beyond the scope of experimental psychology (Buheji, 2019; Al-Muhannadi & Buheji, 2024; Choubani & Buheji, 2026).

The study concludes that the two literatures are comparable but incommensurable. Psychology provides empirically testable relationships between stimulus parameters and creative outcomes, whereas IE presents inspiration as a collective socioeconomic resource for addressing complex societal problems, although its methodological claims require independent quantitative validation. IE’s applied Labs offer hypotheses and case knowledge for future research. As GenAI increasingly mediates inspirational experiences, distinguishing evidence-based optimization from normative claims is essential to prevent marketing-driven assertions and protect authentic human creativity.

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Keywords: inspiration, creative performance, example exposure, Inspiration Economy, meta-analysis, bibliometric analysis, generative artificial intelligence, human creativity, authenticity

1. Introduction

" Inspiration" is a concept claimed across disciplines, but the meaning and evidentiary standards attached to it vary dramatically. In experimental psychology, inspiration is operationalized as a measurable state or outcome, typically assessed through creative task performance following exposure to inspirational stimuli (Thrash & Elliot, 2003; Zhang *et al*., 2026) [20, 23]. In the "Inspiration Economy" framework developed by Mohamed Buheji, inspiration is a socio-economic methodology: a normative framework

for community problem-solving that posits "inspiration currency"—non-monetary value such as attention, engagement, trust, creativity, and purpose—as an alternative to financial metrics (Ahmed & Buheji, 2016; Buheji & Ahmed, 2016; Buheji, 2021) [1, 6, 9].

The two literatures rarely cite each other. Yet both employ the language of "optimization"—the psychology literature examines which stimulus conditions optimize creative output (Sio *et al*., 2015; Zhang *et al*., 2026) [19, 23]; the Inspiration Economy literature claims to optimize socio-economic problem-solving through Inspiration Labs (Buheji, 2016; Buheji & Choubani, 2026) [4, 12]. This study asks: What kind of evidence does each literature actually provide for its optimization claims?

A traditional meta-analysis requires commensurable effect sizes. The psychology literature provides these (Zhang *et al*., 2026; Sio *et al*., 2015) [19, 23]. The Inspiration Economy literature does not. Forcing a pooled statistic would require imputing effect sizes where none exist, violating basic meta-analytic assumptions. A two-track design—quantitative synthesis for Track A, bibliometric and methodological appraisal for Track B—is the only defensible approach that can include both literatures in a single study without misrepresenting either.

1.1. The Urgency of This Study in the Age of Artificial Intelligence

The need for this study has acquired new urgency with the rapid proliferation of generative artificial intelligence (GenAI) in creative work. Within days of its release, ChatGPT reached one million users—a milestone that took Spotify 2.5 months, Facebook 10 months, and Netflix 3.5 years to achieve (Mahmud, 2025) [18]. GenAI tools now generate text, images, 3D environments, videos, audio, and user interfaces on demand, fundamentally altering how humans access and use "inspiration" (Mahmud, 2025) [18].

This transformation raises a question that neither literature alone can answer: When an algorithm can generate an infinite stream of novel stimuli tailored to any prompt, what happens to the human capacity for inspiration, and how would we know?

The psychology literature offers experimental tools to investigate this question. Studies have begun examining AI-generated images as inspirational stimuli, finding that positive emotional valence facilitates divergent thinking and enhances flexibility and originality (Hou & Wang, 2025) [17]. However, GenAI also introduces new forms of fixation: AI-generated examples may anchor designers to specific solution patterns embedded in training data, and the prompts users write may themselves reflect cognitive biases (Mahmud, 2025) [18]. The technology that promises limitless inspiration may simultaneously narrow the space of what humans imagine.

The Inspiration Economy literature, meanwhile, has begun explicitly addressing AI. Buheji (2025) [7] proposes a theoretical model of "AI-Resilient Tasks" based on Inspiration Economy principles, and a 2026 paper addresses "Raising the Depth of Meaning through Artificial Intelligence—A Framework for Training that Inspires" (Buheji, 2026, as cited in Zenodo, 2026) [8]. Yet these works remain theoretical and normative. They do not provide empirical evidence that Inspiration Economy methods produce outcomes superior to conventional approaches, nor do they engage with the experimental literature on AI-generated stimuli and fixation.

The stakes are not merely academic. If "inspiration optimization" becomes a selling point for AI tools, educational programs, or policy interventions, the evidentiary basis for such claims must be transparent. The psychology strand provides bounded, testable claims—examples improve quality under specified conditions, AI stimuli may enhance enjoyment but introduce anchoring. The Inspiration Economy strand provides a normative vision—inspiration as a non-monetary currency for socio-economic transformation—but lacks the empirical infrastructure to evaluate whether that vision is realized in practice.

Furthermore, the AI era intensifies a deeper challenge: the risk of confusing generation with creation. GenAI can produce outputs that appear creative—novel combinations of existing patterns—but the capacity for genuine creativity, grounded in intentionality, authenticity, and the lived experience of a person embedded in a social and material world, remains distinctively human (Brainard, 2026; Corazza, 2016, as cited in "The authenticity gap," 2026) [2]. If "inspiration" is reduced to stimulus exposure and output generation, both literatures risk missing what makes human inspiration matter: its connection to meaning, purpose, and the self.

This study, therefore, is not merely a comparison of two academic literatures. It is an intervention into a conversation that is becoming more urgent by the month. As AI systems become more capable of simulating inspiration, the need to specify what we mean by the term—and what evidence would support claims about its optimization—becomes both a scholarly obligation and a practical necessity.

Figure (1) illustrates the dual-edged impact of generative AI on human creativity, balancing its perceived benefits against its hidden cognitive costs. On one side, labeled "The Benefit," research by Hou & Wang (2025) [17] and Mahmud (2025) [18] indicates that AI-generated images with positive emotional valence can significantly enhance divergent thinking and cognitive flexibility, largely because users report high levels of perceived inspiration and enjoyment. However, this sense of enhanced creativity is counterbalanced by "The Trap." As Mahmud (2025) [18] notes, AI stimuli do not reliably surpass human-only fluency; more critically, they introduce "algorithmic fixation." Because AI models generate outputs based on patterns within their training data, these stimuli can act as subtle anchors that shift creative constraints rather than eliminating them, ultimately trapping users in predefined algorithmic boxes rather than freeing their original thought.



Fig 1

Research Questions

RQ1 (Track A): What is the pooled effect of example exposure on creative performance, and how does this effect vary by outcome dimension and stimulus characteristics, including emerging evidence on AI-generated stimuli?

RQ2 (Track B): What is the structural composition of the Inspiration Economy literature (authorship, outlets, study designs), and what type of evidence does it provide for its core claims, including its recent engagement with AI?

RQ3 (Integrative): What does the comparison of these two literatures reveal about the conditions under which "inspiration" claims can be empirically evaluated in an era of AI-mediated creativity?

2. Track A: Quantitative Meta-Analytic Review (Psychology Strand)

2.1. Method

Data sources. The primary anchor studies are Zhang *et al.* (2026) [23] and Sio *et al.* (2015) [19]. Zhang *et al.* (2026) [23] synthesized 83 independent studies comprising 475 effect sizes, examining the "example effect" on creative performance. Sio *et al.* (2015) [19] synthesized 43 design studies (N=1,229) examining fixation versus inspiration effects. Emerging research on AI-generated stimuli is incorporated where available (Hou & Wang, 2025; Mahmud, 2025) [17, 18].

Inclusion criteria. Experimental or quasi-experimental design; manipulation of inspirational stimulus; outcome measures of creative performance (fluency, flexibility, novelty, quality); sufficient data to extract effect sizes.

Analysis. Three-level meta-analysis (effect sizes nested within studies). Report pooled effect sizes, heterogeneity statistics (I^2, τ^2), and moderator analyses for stimulus type (single vs. multiple examples; common vs. uncommon; human-generated vs. AI-generated), timing, and task type.

2.2. Findings from Existing Meta-Analyses

Overall effect. Zhang *et al.* (2026) [23] found that providing examples has a small but statistically significant positive effect on creative performance overall. Their conclusion explicitly states: "providing examples has a small but statistically significant positive effect on creative performance" (Zhang *et al.*, 2026) [23].

Dimension specificity. The effect is positive for ideational quality, but not significant for fluency, flexibility, or novelty. Zhang *et al.* (2026) [23] conclude that examples show "positive associations with ideational quality but not with ideational fluency, flexibility, or novelty." This is the critical finding: examples do not make people generate more ideas, more varied ideas, or more original ideas—they make the ideas generated better in quality.

Fixation versus inspiration. Sio *et al.* (2015) [19] found that providing examples made individuals generate "more example-related and fewer categories of ideas, however, the ideas produced were more novel and the quality of solutions ideas was positively correlated with the degree of copying from examples" (Sio *et al.*, 2015) [19]. The mechanism appears to be a narrower but deeper search: individuals fixate on the example-related domain, but this focused search yields higher-quality solutions.

Stimulus characteristics. Sio *et al.* (2015) [19] found that a single uncommon example is most facilitative of novelty and quality. Common examples activate typical knowledge and induce fixation; uncommon or remotely-associated examples facilitate novel conceptual integration.

2.3. Emerging Evidence: AI-Generated Stimuli

Research on GenAI as an inspirational source is nascent but growing. Mahmud (2025) [18] conducted structured design exercises with 18 students comparing human-only ideation, online image search, and GenAI tools (ChatGPT, Midjourney). Key findings:

- GenAI consistently increased perceived inspiration and helped participants reframe problems by providing fresh perspectives. However, human-only conditions often produced comparable or higher idea fluency. AI-generated examples sometimes introduced new anchors that shifted design fixation rather than removing it (Mahmud, 2025) [18].

Hou and Wang (2025) [17] examined emotional valence and arousal of AI-generated images as design stimuli. They found that AI-generated images with positive emotional valence facilitated divergent thinking and enhanced flexibility and originality, particularly for knowledge design problems. However, for conceptual design problems, arousal levels had no significant impact (Hou & Wang, 2025) [17].

These findings extend the psychology strand's dimension-specific logic to AI stimuli: GenAI may enhance affective and qualitative dimensions of creative experience while not reliably increasing ideational quantity, and may introduce

novel fixation mechanisms through training data biases and prompt-induced constraints.

2.4. What Track a Can and Cannot Claim

Track A supports a precise, bounded claim: Under specified conditions (single uncommon example, quality-focused outcome), inspirational stimuli improve certain dimensions of creative performance (Sio *et al*., 2015; Zhang *et al*., 2026) [19, 23]. For AI-generated stimuli, the evidence suggests increased perceived inspiration and enjoyment, with uncertain effects on fluency and potential new fixation risks (Mahmud, 2025) [18]. Track A does not support a blanket claim that "inspiration optimizes creativity." The precision of this claim is exactly what the Inspiration Economy literature lacks. See Figure (2) for illustration.

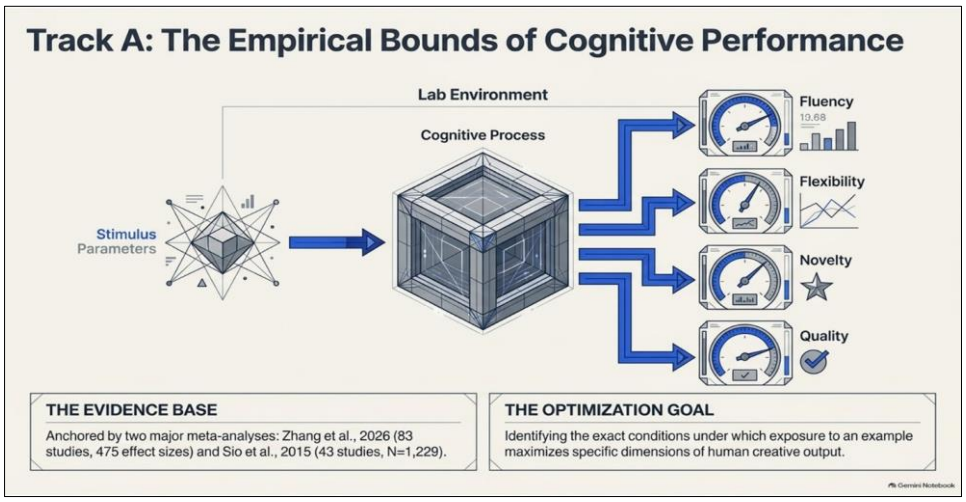


Fig 2

3. Track B: Bibliometric and Methodological Appraisal (Inspiration Economy Strand)

3.1. Method

Data source. Systematic search of Google Scholar, Scopus, Zenodo, and the International Institute of Inspiration Economy website for publications by Mohamed Buheji (2014–2026) using terms `"inspiration economy"`, `"inspiration currency"`, `"inspiration labs"`, and `"AI"`.

Coding scheme. Each publication coded for: authorship (Buheji sole/first/co-author); outlet (affiliated with Buheji / independent); study type (theoretical/conceptual; case study; action research; longitudinal narrative; other); independent outcome data (yes/no); AI engagement (substantive / mention only / none).

3.2. Findings

The search results confirm that Buheji is the lead author on the foundational texts and the overwhelming majority of framework-development publications. Key works include Handbook of Inspiration Economy (Buheji, 2016) [4], The Theory of Inspiration Economy—An Introduction (Buheji, 2021) [6], and Exploring Inspiration Economy (Buheji & Ahmed, 2018) [11]. The Zenodo corpus (2025–2026) shows Buheji as sole author on papers addressing ontology, hermeneutics, culture, and AI in Inspiration Economy (Buheji, 2026a, 2026b, 2026c, 2026d, as cited in Zenodo, 2026) [8]. Collaborators appear primarily as co-authors on applied or philosophical integration papers (Ahmed & Buheji, 2016; Buheji & Choubani, 2026; Buheji & Mushimiyimana, 2025) [1, 12, 13].

3.3. Study Type Distribution. the Literature Consists Primarily of:

- Theoretical treatises and handbooks (Buheji, 2016, 2021; Buheji & Ahmed, 2018) [4, 6, 11]
- Case descriptions of Inspiration Labs applied in various contexts (Buheji, 2019; Buheji & Choubani, 2026) [5, 12]
- Longitudinal narrative accounts (Buheji, 2025, "From Theory to Life Transformation") [7]
- Philosophical integration papers (Buheji & Choubani, 2026) [12]
- Methodological inquiries into hermeneutics, ontology, and complex problem-solving (Buheji, 2026a, 2026b) [8]

Absence of standardized effect sizes. No study in the retrieved corpus reports a standardized mean difference, correlation coefficient, or any statistic comparable to the psychology literature. Evaluations of Inspiration Labs are narrative and case-based, not controlled comparisons.

"Inspiration currency" operationalization. Defined qualitatively as non-monetary value. Ahmed and Buheji (2016) [1] state the aim is to shift "from traditional thinking to more of a transitional thinking" toward "an economy that is designed and built by all of us.. without the currency of the dollar, or the total dependency on external depleting sources." Buheji and Ahmed (2016) [9] elaborate: "This 'currency' isn't just money, but rather it is attention, engagement, trust, creativity, and purpose" (Buheji & Ahmed, 2016, as cited in Utilitas Mathematica, 2025) [9].

3.4. Recent Engagement with Artificial Intelligence

The Inspiration Economy literature has begun addressing AI, but in a manner consistent with its overall methodological profile. Buheji (2025) [7] proposes "A Theoretical Model of AI-Resilient Tasks Based on the Inspiration Economy," arguing that Inspiration Economy principles can guide the design of tasks that remain meaningful and resistant to automation. Buheji (2026) [8] addresses "Raising the Depth of Meaning through Artificial Intelligence—A Framework for Training that Inspires," proposing a training framework grounded in Inspiration Economy concepts.

These papers are theoretical and normative. They do not report empirical evaluations of AI-Resilient Tasks or Training that Inspires frameworks. They do not engage with the experimental literature on AI-generated stimuli and fixation (Mahmud, 2025; Hou & Wang, 2025) [17, 18]. They do not specify how one would determine whether Inspiration Economy-based AI interventions produce outcomes superior to alternative approaches.

This pattern replicates the broader structural issue: the framework generates conceptual extensions to new domains (AI, resilience, culture, ontology) but need more empirical evidence for its core causal claims.

Figure (3) illustrates "Track B," depicting the Buheji corpus's redefinition of inspiration from an individual psychological construct to a collective, socio-economic methodology. At its core, the model relies on "Inspiration Labs," which serve as the central mechanism for community problem-solving. As outlined on the left, this represents a "Paradigm Shift" that abandons the measurement of isolated individual task performance in favor of addressing complex societal challenges. Consequently, this necessitates a "New Currency": value is no longer dictated solely by financial metrics but is instead operationalized through intangible, non-monetary assets such as attention, engagement, trust, creativity, and purpose. The central hub radiates outward to show how this Inspiration Economy framework is applied to four distinct, real-world challenges—Poverty Eradication, Youth Unemployment, Post-Pandemic Resilience, and Gaza Resilience—demonstrating the framework's normative ambition to mobilize intrinsic community capacities even in the most extreme socio-economic conditions.

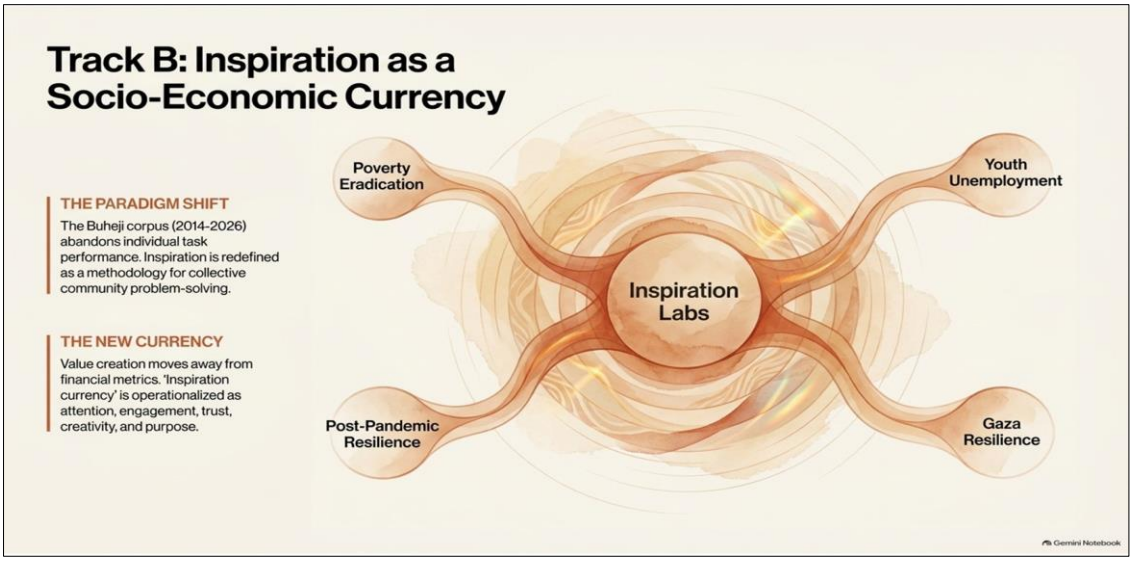


Fig 3

4. Integrative Discussion

4.1. The Incommensurability Is the Finding

The two literatures are not failed versions of each other. They are different kinds of intellectual projects as shown Figure (4). The problem arises when the language of one is used to legitimize the other. A claim that "Inspiration Economy optimizes socio-economic outcomes" cannot draw evidentiary support from the psychology literature's finding that examples improve idea quality (Zhang *et al*., 2026) [23]. The constructs, outcomes, and causal structures are different.

Table 1

Dimension	Psychology Strand	Inspiration Economy Strand
What "inspiration" is	Measurable state/outcome linked to creative task performance (Thrash & Elliot, 2003; Zhang *et al*., 2026) [20, 23]	Socio-economic methodology for community problem-solving (Buheji, 2016, 2021) [4, 6]
What "optimization" means	Stimulus parameters maximizing creative output dimensions (Sio *et al*., 2015) [19]	Methodological refinement of Inspiration Labs (Buheji, 2016) [4]
Evidence type	Experimental, effect sizes, meta-analyzable (Zhang *et al*., 2026) [23]	Theoretical, case-based, narrative (Buheji, 2021; Buheji & Choubani, 2026) [6, 12]
Evidentiary standard	Replicable, controlled, quantitative	Normative, participatory, qualitative
Authorship	Distributed across independent research groups	Concentrated in founder and associates; integrated publication ecology (Buheji, 2015; CEEMAN, 2018) [3, 15]
Falsifiability	Specified (null/negative effect sizes)	Not specified (Buheji, 2021) [6]
Engagement with AI	Experimental studies of AI-generated stimuli (Mahmud, 2025; Hou & Wang, 2025) [17, 18]	Theoretical proposals for AI-resilient tasks (Buheji, 2025, 2026) [7, 8]
Scope of application	Individual creative tasks in controlled settings	Collective socio-economic problems: poverty, unemployment, crisis resilience (Buheji, 2019; Al-Muhannadi & Buheji, 2024) [5]

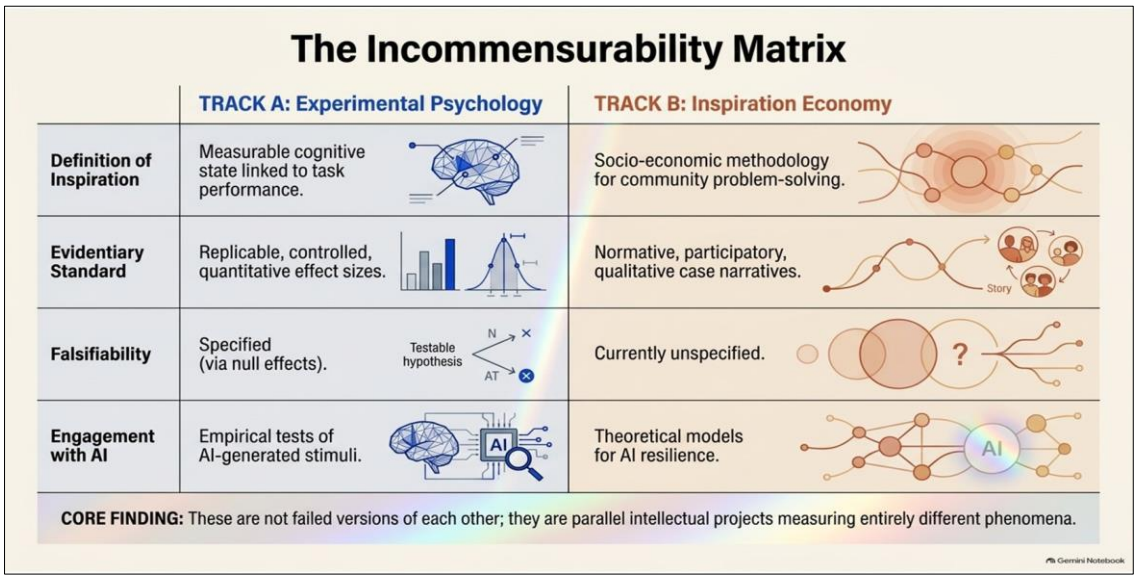


Fig 4

4.2. A Framework for Appraising "Inspiration Optimization" Claims in the AI Era

This study proposes a simple evaluative framework for any future claim about "inspiration optimization," particularly those involving AI:

1. What is the claimed outcome? Creative task performance (Zhang *et al*., 2026) [23] vs. socio-economic change (Buheji, 2021) [6] vs. AI-resilient task design (Buheji, 2025) [7].
2. What is the comparison condition? No-example control (Sio *et al*., 2015) [19] vs. conventional policy/intervention (not specified in Buheji, 2021) vs. non-AI-assisted workflow (Mahmud, 2025) [18].
3. What evidence would falsify the claim? Psychology: null or negative effect size (Zhang *et al*., 2026) [23]. Inspiration Economy: no specified falsification condition (Buheji, 2021) [6]. AI studies: no specified falsification condition for AI-Resilient Tasks framework (Buheji, 2025) [7].
4. Is the evidence independent of the framework's proponents? Psychology: largely yes (multi-lab, independent replication; Zhang *et al*., 2026) [23]. Inspiration Economy: not yet (mono-authorial, affiliated outlets; Buheji, 2015; CEEMAN, 2018) [3, 15].

4.3. The Human Challenge in the Age of AI

The AI era raises a question that transcends the methodological differences between the two literatures: What is inspiration for?

If inspiration is merely a stimulus-response mechanism—exposure to an example produces an idea—then GenAI can, in principle, optimize this process indefinitely. Generate infinite stimuli, measure output, select for novelty and quality. The psychology literature provides the tools for this optimization, and the early AI studies suggest the optimization is already underway (Hou & Wang, 2025; Mahmud, 2025) [17, 18].

But if inspiration is something more—a connection to meaning, purpose, and the self that motivates action beyond the immediate task—then the optimization paradigm may be insufficient. The Inspiration Economy framework gestures toward this richer conception: inspiration as a currency that builds trust, resilience, and collective capacity (Buheji & Ahmed, 2016) [9]. Yet the framework could not demonstrate yet that its interventions produce these outcomes because it lacks the empirical infrastructure to measure them.

The challenge for human beings in the AI era is not merely to generate more ideas or better solutions. It is to retain the capacity for authentic inspiration—inspiration that arises from and contributes to a meaningful life. As Brainard (2026) [2] argues, AI models may be capable of creating valuable products, but they are not capable of creativity in the fullest sense. The distinction matters because if we outsource inspiration to algorithms, we risk losing not only the struggle that makes creative work meaningful but also the judgment required to evaluate what is worth creating.

The two literatures, taken together, offer complementary resources for addressing this challenge. The psychology strand provides the empirical tools to investigate how different stimuli—including AI-generated ones—affect different dimensions of creative performance. The Inspiration Economy strand provides a normative vision of inspiration as a social good, a currency that builds collective capacity rather than merely individual output. Neither is sufficient alone. A mature field of inspiration studies would integrate the empirical rigor of the former with the normative ambition of the latter, while refusing to let either claim more than its evidence supports.

The framework's limitation is not that it asks the wrong questions, but that it has not yet developed the empirical infrastructure to answer them. The following section proposes pathways toward that infrastructure.

4.4. Toward Commensurable Effect Sizes in Inspiration Economy Research

The preceding analysis established that the Inspiration Economy literature does not currently produce standardized effect sizes comparable to the psychology strand (Buheji, 2021; Buheji & Choubani, 2026) [6, 12]. This is not an incidental gap. It reflects a difference in evidentiary genre: the framework aims to document and refine a participatory methodology for complex socio-economic intervention, a task for which randomized controlled trials may be neither feasible nor appropriate. Nevertheless, if the framework's claims about "inspiration optimization" are to be evaluated rather than merely asserted, it must develop pathways toward

quantifiable, comparable, and replicable measurement. This section proposes four such pathways, ordered from most immediately feasible to most structurally demanding, and concludes with an honest assessment of the tension between the framework's epistemology and the logic of effect sizes. See Figure (5) for illustration.

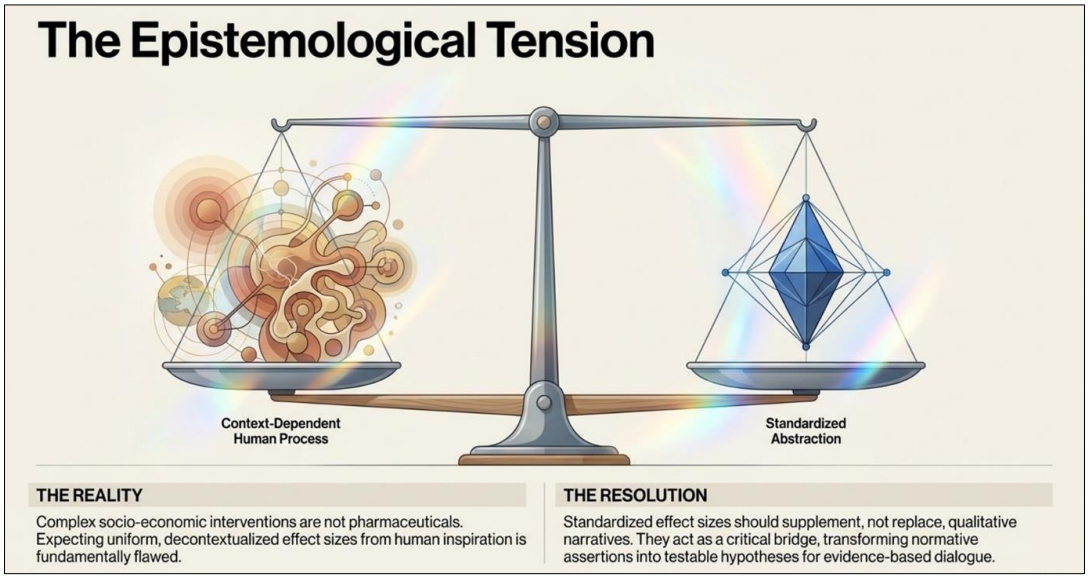


Fig 5

4.4.1. Path One: Adapt Existing Psychological Measurement Instruments

The most direct route to commensurability is to incorporate established inspiration measures into Inspiration Economy research. The psychology strand has developed validated instruments, most notably the Inspiration Scale (IS) by Thrash and Elliot (2003) [20], which measures inspiration frequency and intensity with demonstrated reliability and validity. If Inspiration Lab participants completed the IS before and after intervention, researchers could calculate standardized mean changes and, where comparison groups exist, effect sizes.

More ambitiously, the framework's central construct—inspiration currency—requires its own operational definition. Currently defined qualitatively as "attention, engagement, trust, creativity, and purpose" (Buheji & Ahmed, 2016, as cited in Utilitas Mathematica, 2025) [9], it has no measurement instrument. A research agenda could be proposed: develop an Inspiration Currency Scale following standard psychometric procedures—construct definition, item pool generation, expert review, exploratory and confirmatory factor analysis, convergent and discriminant validity testing. Once validated, the scale would allow Inspiration Lab studies to produce standardized scores and, ultimately, effect sizes comparable to those in the psychology literature.

This path is feasible because it builds on existing psychometric infrastructure rather than requiring de novo methodological invention. Its limitation is that it measures individual-level psychological states, whereas the Inspiration Economy framework aspires to capture collective socio-economic change (Buheji, 2021) [6]. Individual-level scales alone cannot substantiate the framework's macro-level claims.

Figure (6) captures the core existential dilemma of the AI era by contrasting "Generation" with "Creation." On the left, "Generation" is depicted as the distinct domain of AI capability: a mechanistic, data-driven funnel that perfectly optimizes stimulus-response loops by recombining historical data to produce an endless stream of novel outputs. On the right, "Creation" represents the human necessity—a deeply organic and intentional process rooted in lived experience and the search for meaning, as emphasized by Brainard (2026) [2]. The graphic issues a critical warning: if we allow the algorithmic ease of "generation" to outsource our capacity for genuine inspiration, we risk eroding the uniquely human judgment required to determine what is actually worth creating.

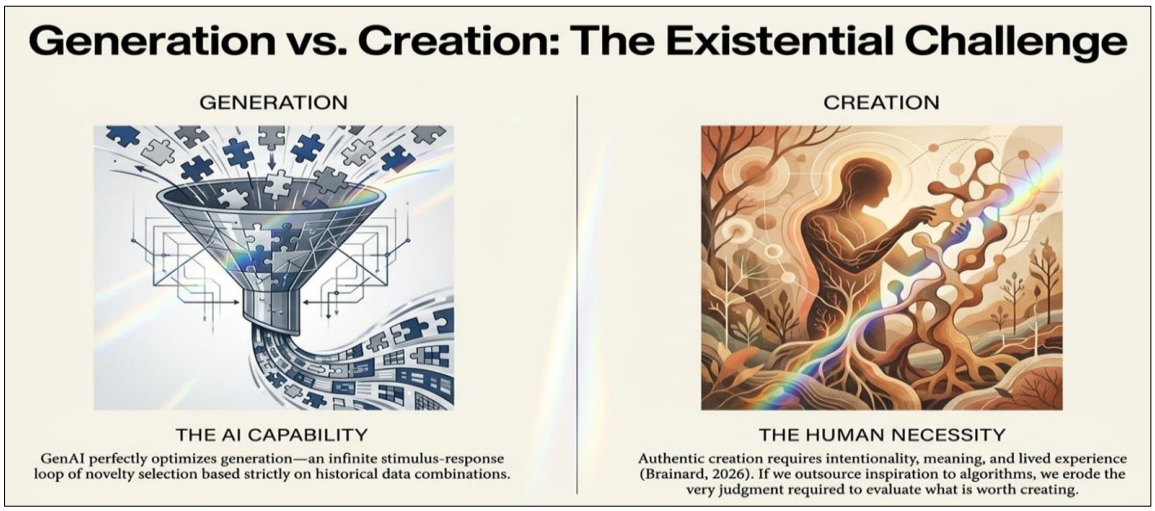


Fig 6

4.4.2. Path Two: Upgrade Case Studies to Quasi-Experimental or Pre–Post Designs

The Inspiration Economy literature currently relies primarily on narrative case reports (Buheji, 2019; Al-Muhannadi & Buheji, 2024) [5]. To generate effect sizes, future Labs would need to incorporate at minimum a pre–post measurement design, and ideally a comparison condition. Three designs are feasible:

Pre–post comparison. Measure key indicators—household income, employment status, psychological resilience scores, community participation—before and after Lab implementation. Calculate standardized mean change. This design does not establish causality but provides preliminary quantitative evidence of change.

Quasi-experimental design. Identify a comparable community or group that does not receive the Lab intervention and compare outcomes between groups. Propensity score matching could strengthen comparability where randomization is infeasible.

Waiting-list control. Where resources are limited, assign participants to immediate intervention or delayed intervention (waiting list). Compare outcomes at the same time point before the delayed group receives the intervention. This design is ethically defensible because all participants eventually receive the intervention.

It is noteworthy that Buheji's Poverty Lab research claims to have employed "advanced randomised controlled trials" in some applications (Buheji, 2019, as cited in Buheji & Choubani, 2026) [5]. If this claim is accurate, the data infrastructure for effect sizes may already exist; the critical question is whether these data are publicly available and reported in standardized form. The framework needs standardization of reporting that would make such data commensurable across studies.

4.4.3. Path Three: Systematic Coding of Case Data and Calculation of Proportion Effect Sizes

Where controlled designs are infeasible in the short term, a compromise approach is to conduct systematic coding of existing Inspiration Economy case reports. Each case would be coded for: whether the intervention occurred, number of participants, direction of outcome change (improvement / no change / deterioration), and whether a pre-specified goal was achieved. From these codes, researchers could calculate proportion effect sizes (e.g., proportion of cases showing improvement) or risk ratios comparing intervention and comparison conditions where available.

This approach is analogous to single-case experimental design (SCED) meta-analysis, which is well-established in special education, clinical psychology, and social work. It does not produce the same precision as randomized trials, but it is quantifiable, comparable across cases, and capable of synthesis. For a framework whose evidence base is currently narrative, systematic coding would represent a significant methodological advance—transforming anecdotal case reports into a structured database amenable to quantitative summary.

4.4.4. Path Four: Establish a Core Outcome Measures Set (COS-IE)

A fundamental reason the Inspiration Economy literature cannot currently produce comparable effect sizes is that different Labs measure different things: one Lab examines women's employment, another youth resilience, another community knowledge sharing (Buheji, 2019; Al-Muhannadi & Buheji, 2024) [5]. Without a minimum common set of indicators, data from different studies cannot be pooled and effect sizes cannot be meaningfully compared.

The framework would benefit from establishing a Core Outcome Measures in Inspiration Economy (COS-IE)—a minimum set of indicators that all Inspiration Lab studies commit to reporting. Candidate domains include: individual inspiration level (measured by the Inspiration Scale; Thrash & Elliot, 2003) [20], community participation, household economic status change, and subjective well-being. The COS-IE need not be exhaustive; its purpose is to ensure a common core that enables cross-study synthesis while allowing Labs to add context-specific measures.

This path is structurally demanding because it requires consensus across the framework's research community—a community currently concentrated around a single founder and affiliated outlets (Buheji, 2015; CEEMAN, 2018) [3, 15]. Establishing a COS-IE would require the framework's leadership to prioritize comparability over the autonomy of individual Labs. Whether this is achievable is an open question.

4.4.5. The Fundamental Tension: Effect Sizes and the Framework's Epistemology

An honest assessment must acknowledge a core tension. The epistemology of the Inspiration Economy framework is participatory, context-dependent, and process-oriented (Buheji, 2021; Buheji & Choubani, 2026) [6, 12]. Its strength lies in documenting complex social change processes that resist decontextualization. The logic of effect sizes, by contrast, requires standardization, comparability, and abstraction from context.

Even if the four pathways above are pursued, Inspiration Economy effect sizes will likely be highly heterogeneous, with limited generalizability. They may answer "whether it worked in this context" but not "how large the effect is across contexts." This is not a failure; it is a characteristic of the phenomenon under study. Complex socio-economic interventions are not pharmaceuticals, and the expectation that they should produce uniform effect sizes may itself be inappropriate.

The most realistic recommendation, therefore, is to treat effect sizes as a supplementary tool for the Inspiration Economy framework, not as its sole evidentiary standard. The framework can retain its qualitative case narratives as its primary evidence form while systematically collecting standardized indicators in projects where feasible—particularly those with comparison conditions. These indicators should be reported as preliminary effect size evidence, explicitly framed as context-dependent and hypothesis-generating rather than definitive.

This approach preserves the methodological integrity of the Inspiration Economy framework while establishing a bridge for dialogue with evidence-based research paradigms. It also creates a clear research agenda: the framework's claims about "inspiration optimization" need not remain normative assertions. They can become testable hypotheses, provided the framework's research community commits to the measurement infrastructure that testability requires.

Figure (7) illustrates a structured, four-tiered stairway representing a methodological roadmap to achieve empirical rigor for the Inspiration Economy framework. Ascending from foundational steps to more complex institutional demands, the first "Immediate" step suggests adapting validated psychological instruments, such as the Thrash & Elliot Inspiration Scale, for lab participants. The next "Feasible" step involves upgrading current narrative case studies into pre-post or quasi-experimental measurement designs to capture baseline data. Moving higher, the "Systematic" tier calls for the rigorous coding of qualitative case data to calculate standardized proportion effect sizes across different projects. Finally, the most "Demanding" apex requires the field to establish a Core Outcome Measures Set (COS-IE) to ensure cross-study comparability and enable statistical pooling. This progression provides a clear, actionable agenda for moving the Inspiration Economy from normative case narratives toward a quantifiable, evidence-based paradigm.

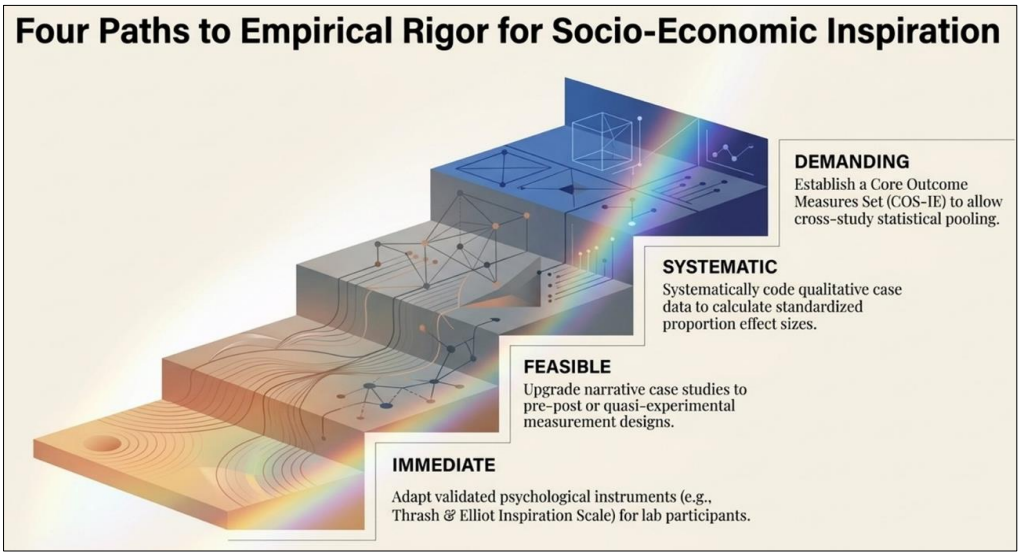


Fig 7

5. Limitations

Track A. The meta-analytic evidence is drawn primarily from design and creative cognition tasks with university student samples. Generalizability to other domains and populations is uncertain. The Zhang *et al*. (2026) [23] meta-analysis is the most comprehensive available, but it does not resolve all moderator questions. Research on AI-generated stimuli is nascent; the studies reviewed here (Mahmud, 2025; Hou & Wang, 2025) [17, 18] are small-scale and require replication.

Track B. While Google Scholar is not a conventional bibliometric database, its broader coverage makes it the most practical source for capturing this corpus, much of which appears in outlets beyond Scopus's indexing.

Integrative. The two-track design cannot produce a single "pooled conclusion" about inspiration. This is a deliberate limitation. Readers seeking a unified statistic will not find one here.

6. Conclusion

This study makes three contributions. First, it consolidates the quantitative evidence on example exposure and creative performance, confirming a dimension-specific pattern that resists blanket "inspiration works" claims: examples improve quality, not quantity or variety, and a single uncommon example is most effective (Sio *et al*., 2015; Zhang *et al*., 2026) [19, 23]. Emerging evidence on AI-generated stimuli

extends this pattern: GenAI increases perceived inspiration but may introduce new fixation mechanisms and does not reliably enhance ideational fluency (Mahmud, 2025) [18].

Second, it provides the first systematic appraisal of the Inspiration Economy literature's evidentiary structure, documenting its authorial concentration (Buheji, 2016, 2021, 2026) [4, 6, 8].

Third, it demonstrates that the two literatures are incommensurable but comparable—comparable in the sense that comparing them reveals what each can and cannot claim, and incommensurable in the sense that neither can borrow legitimacy from the other. In an era where GenAI increasingly mediates access to inspiration, this distinction is not merely academic. It determines whether "inspiration optimization" becomes a meaningful, evidence-based practice or a marketing slogan.

The practical implication is straightforward: "inspiration optimization" is a meaningful empirical claim only when the outcome, comparison condition, falsification criterion, and independence of evidence are specified. The psychology strand meets these criteria, albeit with modest effect sizes and domain-specific findings (Zhang *et al*., 2026) [23]. The deeper challenge, however, is not methodological but existential. If AI can generate infinite stimuli optimized for measurable output, the question becomes: what kind of inspiration do we want to preserve? The answer will determine not only the future of creativity research but the future of human creative life.

Figure (8) illustrates the necessity of synthesizing the two distinct literatures—Track A's experimental psychology and Track B's Inspiration Economy—to achieve a unified maturity for inspiration research. The central graphic, featuring the precise, geometric structures of psychology (in blue) intertwining with the organic, collective nodes of the Inspiration Economy (in orange), represents the required synthesis. As the text explains, "Why Track A?" is essential because we need the rigorous empirical bounds of experimental psychology to safeguard against AI hype and the hidden traps of algorithmic fixation. Conversely, "Why Track B?" is equally vital, as we need the normative ambition of the Inspiration Economy to ensure that inspiration remains a social good—one that builds collective human capacity rather than merely accelerating machine output. Together, these complementary tools provide the mature framework required to navigate the complex realities of the generative AI era.

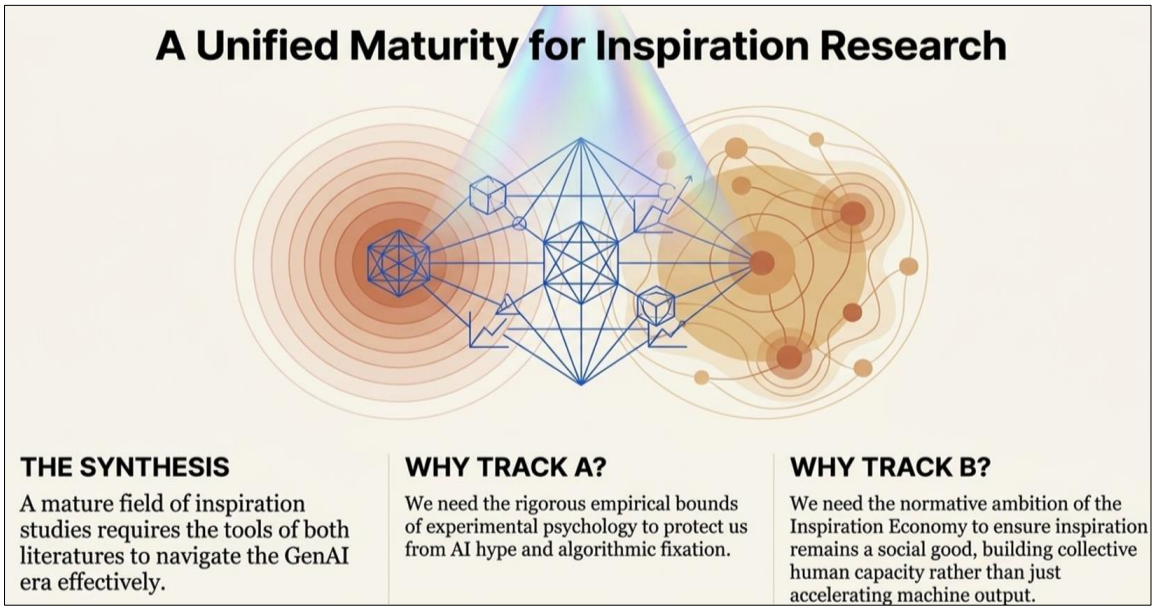


Fig 8

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