

Cognitive Systems Research

Projectional Creativity Model

--Manuscript Draft--

Manuscript Number:	
Article Type:	Research Paper
Keywords:	Creativity; projection-sampling framework; search space transformation; computational creativity; problem-strategy fit; human-AI co-creativity
Corresponding Author:	Ersin Esen Esenbil Information Technologies TÜRKİYE
First Author:	Ersin Esen
Order of Authors:	Ersin Esen
Abstract:	<p>Creativity is a central capacity of human cognition and a key driver of innovation in science, art, and technology, yet most existing accounts remain descriptive, offering taxonomies without operational mechanisms that can be tested, compared, or generalised across domains. This paper introduces the Projection–Sampling framework, a mathematically grounded, simulation-ready formalism that unifies combinational, exploratory, and transformational creativity under a single process model. Within this model, creativity is defined as the intelligent transformation of a search space—through modifications to projection, sampling policy, or evaluation function—to generate outputs that are simultaneously intelligible, novel, and valuable relative to an observer’s representational frame. We instantiate the framework in six creative agent types and evaluate them in two contrasting simulation environments: symbolic word discovery and spatial maze navigation. Results reveal systematic differences in performance that align with the structural properties of each problem space, supporting the concept of creativity–problem fit as a predictive tool for selecting strategies. The framework also formalises observer-relativity, demonstrating that creativity judgments are inherently frame-dependent and arise from the interaction between generative and interpretive projections. By defining a generative design space for creative agents, the Projection–Sampling framework enables systematic exploration of projection transformations, sampling strategies, and evaluation metrics. This contributes to cognitive systems research by providing a unifying, mechanistic account of creativity that spans human cognition, artificial systems, and their interaction, offering testable principles for understanding and engineering creative behaviour.</p>

Dear Editor,

I am pleased to submit our manuscript entitled “Projectional Creativity Model” for consideration as an Original Research paper in Cognitive Systems Research.

This work introduces the Projection–Sampling framework, a mathematically grounded and simulation-ready formalism that unifies combinational, exploratory, and transformational creativity under a single process model. Creativity is defined here as the intelligent transformation of a search space, via modifications to projection, sampling policy, or evaluation function, to produce outputs that are simultaneously intelligible, novel, and valuable.

The manuscript makes three key contributions to cognitive systems research:

- A unifying formal mechanism: integrating Boden’s influential typology with a process model that can be operationalised, tested, and compared across domains.
- An explicit account of observer-relativity: formalising creativity as frame-dependent, where the same artefact may be trivial in one representational projection and transformative in another.
- Empirical validation via simulation: implementing six creative agent types and evaluating their performance in two structurally distinct problem domains, demonstrating the concept of creativity–problem fit as a predictive tool for strategy selection.

We think that this paper is directly relevant to Cognitive Systems Research because it addresses creativity as a core capacity of human-level cognition, provides a mechanistic bridge between natural and artificial systems, and establishes a generative design space for creative agents that can inform future work in cognitive architectures, grounded cognition, and human–AI co-creativity. The simulations serve to validate the theory, while the theoretical framework itself can be applied to a wide range of cognitive modelling problems beyond creativity research.

We believe this manuscript will be of interest to the journal’s interdisciplinary readership, including researchers in cognitive science, AI, philosophy of mind, and computational modelling. This work has not been published previously and is not under consideration elsewhere.

Thank you for considering our submission.

Sincerely,

Dr. Ersin Esen

Highlights

- Introduces a unifying model of creativity
- Formalises creativity via intelligibility, novelty, and value thresholds
- Demonstrates observer-relativity as a core mechanism of creative judgment
- Validates six agent types across symbolic and spatial problem domains
- Predicts creativity–problem fit for strategy selection across domains

Projectional Creativity Model

Abstract

Creativity is a central capacity of human cognition and a key driver of innovation in science, art, and technology, yet most existing accounts remain descriptive, offering taxonomies without operational mechanisms that can be tested, compared, or generalised across domains. This paper introduces the Projection–Sampling framework, a mathematically grounded, simulation-ready formalism that unifies combinational, exploratory, and transformational creativity under a single process model. Within this model, creativity is defined as the intelligent transformation of a search space—through modifications to projection, sampling policy, or evaluation function—to generate outputs that are simultaneously intelligible, novel, and valuable relative to an observer’s representational frame. We instantiate the framework in six creative agent types and evaluate them in two contrasting simulation environments: symbolic word discovery and spatial maze navigation. Results reveal systematic differences in performance that align with the structural properties of each problem space, supporting the concept of creativity–problem fit as a predictive tool for selecting strategies. The framework also formalises observer-relativity, demonstrating that creativity judgments are inherently frame-dependent and arise from the interaction between generative and interpretive projections. By defining a generative design space for creative agents, the Projection–Sampling framework enables systematic exploration of projection transformations, sampling strategies, and evaluation metrics. This contributes to cognitive systems research by providing a unifying, mechanistic account of creativity that spans human cognition, artificial systems, and their interaction, offering testable principles for understanding and engineering creative behaviour.

Keywords: Creativity, projection-sampling framework, search space transformation, computational creativity, problem–strategy fit, human–AI co-creativity

1. Introduction

What is creativity? It remains one of the most deeply valued and elusive phenomena in human cognition. It is often credited with enabling major scientific breakthroughs, artistic innovations, and problem-solving strategies across domains. Despite decades of inquiry, the question of what creativity fundamentally is—how it operates, how it can be measured, and whether it can be meaningfully replicated in artificial systems—continues to provoke debate across psychology, philosophy, and artificial intelligence (Runco & Jaeger, 2012; Boden, 2004).

Margaret Boden’s seminal typology offers a compelling foundation for addressing this complexity. She distinguishes between three major kinds of creativity: combinatorial, exploratory, and transformational (Boden, 2004). Combinatorial creativity involves novel recombinations of familiar elements. Exploratory creativity arises when one generates new outputs by traversing a structured conceptual space. Transformational creativity, by contrast, entails altering the very rules or dimensions that define that space. While Boden’s work has been enormously influential in clarifying the *kinds* of creative acts, it does not provide a formal model that allows for computational experimentation, simulation, or prediction. Consequently, it is difficult to operationalize or test the boundaries between these types or to explore the conditions under which one kind of creativity might outperform another.

In recent years, computational and cognitive approaches have begun to characterize creativity as a search process that navigates high-dimensional spaces of ideas, forms, or solutions (Schmidhuber, 2009; Liapis, Yannakakis, & Togelius, 2013). However, most of these approaches either focus on novelty alone (Lehman & Stanley, 2011) or assume fixed generative models that do not easily accommodate transformational change. This paper extends Boden’s framework by introducing a formal and computational model of creativity grounded in a generalized theory of search, projection, and sampling. Specifically, we propose that creativity is best understood as the strategic transformation of a search space in order to produce outputs that are simultaneously *intelligible* (recognizable in relation to prior knowledge) and *novel* (lacking an obvious generative path from known inputs). This duality of semantic continuity and structural divergence anchors our formal definition.

This work contributes a unified, testable foundation for computational creativity, integrates cognitive theory with formal modeling, and lays the groundwork for new applications of creativity research in artificial intelligence, education, and design. The proposed formalism is independent of domain content; it applies equally to symbolic, spatial, visual, linguistic, and scientific problem spaces.

To explore and evaluate this framework, we operationalize distinct types of creative agents and deploy them in controlled simulation environments. These environments are designed to isolate the role of structure, feedback, and representation in determining creative performance. Our results demonstrate that creative agents, when aligned with the latent topology of a problem, can significantly outperform baseline random search.

The remainder of this paper is organised as follows. Section 2 reviews key theoretical models of creativity, situating the Projection–Sampling framework within the broader cognitive and computational literature. Section 3 develops the formal foundations of the framework, defining creativity in operational terms and framing it as a process of search-space transformation. Section 4 presents a typology of creative agents derived from the framework, each instantiating a distinct strategy. Section 5 reports simulation experiments in symbolic and spatial domains, evaluating agent performance and illustrating the concept of creativity–problem fit. Section 6 discusses the implications of the framework for understanding creativity as a general cognitive capacity, emphasising observer-relativity, model interpretability, and connections to grounded cognition and active inference. Section 7 concludes by summarising contributions, outlining future research directions, and situating the framework as a foundation for a unified science of creativity.

2. Background

Creativity has long been a subject of inquiry across multiple disciplines, ranging from cognitive science and psychology to artificial intelligence and philosophy. Despite this diversity, efforts to systematize creativity often struggle to unify its various manifestations: from small acts of problem solving to transformative artistic breakthroughs. This section reviews the major theoretical foundations that inform our work, focusing first on Margaret Boden’s influential taxonomy and then situating it within a broader landscape of interdisciplinary frameworks.

2.1. Boden’s Creativity Typology

Margaret Boden’s (2004) tripartite theory remains one of the most enduring frameworks in the study of creativity. Her model distinguishes between:

- **Combinatorial Creativity:** The novel combination of familiar concepts in new ways.
- **Exploratory Creativity:** The traversal of a structured conceptual space to discover new configurations.
- **Transformational Creativity:** The alteration or redefinition of the underlying rules or dimensions that generate a conceptual space.

This taxonomy draws upon cognitive science, philosophy, and artificial intelligence, proposing that creative thought unfolds within and across structured conceptual spaces. In this framing, combinatorial and exploratory creativity operate within a fixed conceptual framework, whereas transformational creativity entails modifying the framework itself—an act often associated with major scientific or artistic revolutions.

Boden herself hinted at the limitations of this model, especially with regard to transformational creativity:

“Transformational creativity is the most profound form... but the mechanisms that allow such transformations remain elusive.” (Boden, 2004, p. 6)

This admission underscores that her framework is typological, not mechanistic. While it describes *what* kinds of creativity exist, it does not explain *how* these processes unfold in computational or formal terms. It lacks an account of the internal structure of conceptual spaces, the operators that traverse or alter them, and the conditions under which such transformations succeed. As such, the theory provides a descriptive scaffold rather than a predictive or executable model.

In this paper, we seek to extend Boden’s theory by formalizing creativity as a transformation of search spaces governed by projection and sampling processes. This approach preserves her typological distinctions while grounding them in simulation-ready mechanisms that enable computational experimentation and analysis.

2.2. Broader Theoretical Landscape

The scientific study of creativity encompasses a diverse array of disciplinary perspectives, including cognitive psychology, artificial intelligence, philosophy of mind, evolutionary theory, neuroscience, education, and sociocultural analysis. Each of these perspectives has developed its own frameworks, typologies, and methodologies for conceptualising and investigating creative phenomena, often reflecting the priorities and epistemic assumptions of their respective fields. This multiplicity has produced a rich but fragmented theoretical landscape in which models range from descriptive taxonomies of creative behaviour to formal computational frameworks and evaluation protocols. Table 1 summarises a selection of landmark contributions across this spectrum, highlighting their primary creativity types, and focal concerns. The subsequent discussion situates the projection–sampling framework within this broader context, drawing explicit comparisons with influential cognitive, computational, and evaluative models.

Table 1. Major Frameworks in Creativity Studies

Framework	Creativity Types	Focus
Boden (1990)	Combinational, Exploratory, Transformational	Cognitive modeling
Rhodes (1961)	4Ps (Person, Process, Press, Product)	Taxonomy
Guilford (1950)	Divergent, Convergent	Psychometrics
Sternberg & Lubart (1995)	Investment Theory	Personality + cognition
Weisberg (2006)	Expertise View	Problem solving
Simonton (1999)	Darwinian Blind Variation	Evolutionary psychology
Kaufman & Beghetto (2009)	4C (Mini-c to Big-C)	Developmental
Amabile (1996)	Componential Model	Motivation + skills
Runco (1991)	Divergent Thinking	Psychometrics

Baas et al. (2008)	Emotion–Creativity	Affect theory
Glăveanu (2010)	Sociocultural	Interactional
McCormack et al. (2020)	AI Creativity	Machine autonomy
Wiggins (2006)	Conceptual, Exploratory, Transformational	Formal search in conceptual and evaluation spaces
Ritchie (2007)	Novelty, Value, Typicality	Empirical evaluation criteria
Jordanous (2012)	14 creativity components	Standardised evaluation procedure
Gärdenfors (2000)	Conceptual–geometric	Representation via multidimensional conceptual spaces
Mouret & Clune (2015)	Quality–Diversity	Exploration–exploitation balance in descriptor space
Colton et al. (2011)	FACE/IDEA process & framing	Framing, evaluation, and process models of creativity

These frameworks can be broadly grouped into several categories, each contributing distinct insights into the study of creativity. Descriptive taxonomies, such as Boden’s (2004) three types and Kaufman and Beghetto’s (2009) 4C model, organise creative acts or outputs along psychological or developmental dimensions, offering conceptual clarity but little explanation of why creativity occurs or how it unfolds mechanistically. Psychological attribute and trait theories, including Guilford’s (1950) work on divergent thinking and Sternberg and Lubart’s (1995) investment theory, identify cognitive or personality correlates of creativity yet often underplay the interactional and contextual dynamics that shape creative acts. Componential or input–output models, such as Amabile’s (1996) componential theory, emphasise the interplay of motivation, domain knowledge, and environmental factors, yielding practical guidance for fostering creativity in education and industry but stopping short of deep ontological accounts of novelty. Finally, sociocultural and distributed perspectives, exemplified by Glăveanu’s (2010) interactionist model and Simonton’s (1999) Darwinian approach, view creativity as emergent from systemic interactions and situated contexts, but frequently lack formal operationalisation and remain at the level of metaphor or analogy.

Although these frameworks have each advanced our understanding of creativity from distinct disciplinary vantage points, they diverge considerably in how they formalise the underlying processes, conceptualise the role of the observer, and specify the mechanisms for generating and evaluating artefacts. The following subsections examine several influential models in greater depth—particularly those situated in computational creativity and cognitive theory—and contrast them with the projection–sampling framework, thereby clarifying the latter’s distinctive conceptual and operational contributions.

Wiggins’ (2006) Creative Systems Framework (CSF) formalises creativity as search within and between two distinct spaces: the conceptual space, defined by a set of generative rules for producing artefacts, and the evaluation space, defined by criteria for assessing those artefacts. The framework provides a meta-level formalism for describing and comparing creative systems in terms of how they generate, transform, and evaluate candidates. Similar to the projection–

sampling framework introduced here, CSF explicitly distinguishes between the generation and evaluation components of creativity and situates them within a structured representational space. However, whereas CSF primarily treats the generative rules and evaluative criteria as fixed during the search process, the projection–sampling framework embeds both generation and evaluation into a unified projectional structure, foregrounds the role of observer-relativity in defining intelligibility and novelty, and makes transformation of the underlying representational space itself a first-class creative operation.

Ritchie (2007) proposed a set of empirical criteria for evaluating the outputs of creative systems, with particular emphasis on novelty, value, and typicality relative to a reference set of artefacts. These criteria provide a practical basis for assessing the products of computational creativity in a domain-agnostic manner, enabling quantitative comparisons between systems' outputs. As in the present projection–sampling framework, Ritchie's account foregrounds novelty and value as central dimensions of creativity. However, the projection–sampling formulation replaces typicality with intelligibility, shifting the evaluative emphasis from statistical resemblance to the capacity of an observer to make sense of an artefact. This substitution makes the framework inherently observer-relative and accommodates creative acts that may be valuable and novel precisely because they break with prevailing typical forms.

Jordanous (2012) introduced the Standardised Procedure for Evaluating Creative Systems (SPECS), which identifies fourteen key components of creativity—such as originality, domain competence, and value—and provides a methodological framework for evaluating computational creativity in a structured, repeatable way. SPECS is designed to ensure that evaluations are comprehensive and comparable across systems and domains, and it draws heavily on expert consensus about what constitutes creativity. Like the projection–sampling framework, SPECS aims for domain-general applicability and emphasises multiple dimensions of creativity beyond novelty alone. However, whereas SPECS offers a checklist of descriptive components to guide evaluation, the projection–sampling framework operationalises creativity through quantitative thresholds on intelligibility, novelty, and value within an explicitly defined projectional space. This allows for direct integration of evaluation criteria into the generative process itself, rather than treating evaluation as a post hoc, external procedure.

The Quality–Diversity (QD) family of algorithms, exemplified by the MAP-Elites approach (Mouret & Clune, 2015), aims to produce a repertoire of high-performing solutions that are diverse with respect to a set of behavioural or phenotypic descriptors. Rather than seeking a single global optimum, QD methods explicitly balance exploitation of quality and exploration of the descriptor space, often leading to broad coverage of possible solution types.

Gärdenfors (2000) proposed the Conceptual Spaces framework as a geometric model of representation in cognition, where concepts are structured as convex regions within multidimensional spaces defined by quality dimensions (e.g., colour, shape, taste). This approach provides a formal bridge between symbolic and subsymbolic representations, enabling similarity, categorisation, and concept combination to be modelled as geometric relationships. Like the proposed projection–sampling framework, the conceptual spaces

approach situates creativity in relation to a structured representational space and offers a natural account of novelty as distance within that space. However, the projection–sampling framework differs in two key respects: it explicitly models observer-relativity by defining a projection that determines the accessible subspace for a given observer, and it treats transformations of this projection (not just navigation within the space) as central to creative processes. In this way, projection–sampling incorporates representational change as a first-class operation, extending beyond the static geometry of conceptual spaces.

Colton, Pease, and Saunders (2011) introduced the FACE and IDEA models as conceptual frameworks for understanding and implementing computational creativity. The FACE model emphasises the importance of Framing, Aesthetics, Concepts, and Expression, highlighting that creativity involves not only producing artefacts but also constructing narratives or “frames” that contextualise and justify them. The IDEA model (Inspire, Develop, Evaluate, Appraise) complements FACE by describing a processual view of creative activity. Both models stress that shifts in framing (how an artefact is presented and interpreted) can significantly alter perceptions of its creativity.

Taken together, these frameworks illustrate the depth and diversity of scholarly inquiry into creative behaviour, each illuminating particular facets of the phenomenon. Yet, despite their individual strengths, the theoretical landscape remains fragmented: existing models tend to address creativity from specific disciplinary standpoints and often stop short of providing a unifying, mechanistic account of creativity as a general, domain-independent process.

2.3. Limitations of Existing Frameworks

Despite their diversity, existing models of creativity exhibit several recurring limitations:

Absence of a unifying formalism

There is currently no general mathematical, logical, or topological framework capable of explaining creativity in a manner that spans domains, levels of organisation, and modalities. In the absence of such a formalism, cross-disciplinary integration remains difficult, and insights tend to remain siloed within disciplinary boundaries.

Static epistemologies

Creativity is often investigated within fixed representational spaces—static problem definitions, concept sets, or environmental parameters. Few models accommodate the transformation of the representational space itself, despite this being a defining characteristic of radical novelty. Even Boden’s influential notion of “transformational creativity” recognises the importance of such transformations but does not supply the mechanisms by which they might be realised.

Neglect of observer-dependence and processual semantics

Creativity is frequently conceptualised as an intrinsic property of artefacts rather than as a relational phenomenon emerging between an agent, a context, and an interpretive framework. This overlooks the role of semantic alignment, expectation, and ontological surprise in determining whether a given output is perceived as creative.

Limited engagement with general theories of change and emergence

Many models remain confined to specific domains and do not connect with broader theoretical accounts of emergence, self-organisation, or structural transformation. Yet such accounts are arguably essential for explaining how new forms and meanings arise in complex adaptive systems.

These limitations point to the need for a more general, formal, and process-oriented theory of creativity—one capable of subsuming, integrating, and extending existing typologies. Despite the wide influence of Boden’s framework in creativity research, there remains no operational mechanism for generating, predicting, or systematically comparing the three types of creativity she identifies. Her typology is descriptive, offering valuable conceptual distinctions, but it stops short of specifying computational or formal procedures by which combinational, exploratory, or transformational creativity could be instantiated, analysed, or tested. This absence of a mechanism has constrained the development of testable, general theories and has made it difficult to examine the conditions under which one type of creativity might outperform another.

The proposed framework in this paper addresses this gap directly. It provides a mathematically grounded, simulation-ready formalism that unifies typology and mechanism, enabling the three types to be expressed as specific operations over projections, sampling policies, and evaluation functions. In doing so, it transforms Boden’s influential but static taxonomy into a process model suitable for computational experimentation, cross-domain comparison, and predictive analysis, thereby laying the groundwork for a unifying, mechanistic account of creativity.

3. A Formal Framework of Creativity

In order to move beyond typologies and taxonomies, we require a model of creativity that is formal, processual, and domain-independent. The framework presented here builds on the projection-sampling (PS) theory of cognition and observability, which frames all observation and generation as the result of projection (contextual representation) and sampling (selective exploration within that context). We adapt this epistemic model to formulate creativity as an intelligent transformation of search space that produces outputs both novel and intelligible.

3.1. Projection and Sampling as the Basis of Creative Cognition

Let O be the total set of observable outputs in a domain (e.g., all possible images, sentences, notes, molecules, etc.). An agent never explores O directly. It is prohibitively high dimensional. Instead, it operates within a projected space:

$$P_\theta: O \rightarrow S_\theta.$$

Here, P_θ is a projection function parameterized by context θ (e.g., conceptual knowledge, cultural norms, perceptual apparatus), which transforms raw phenomena into a structured space S_θ over which search and inference are feasible. In this space, the agent performs a sampling process:

$$x_{1:n} \sim \pi(\cdot \mid P_\theta),$$

where π is a policy or strategy that selects n candidates x_i from S_θ .

All action and perception occur through projection and sampling. Creativity, under this lens, becomes a process of P_θ , modifying π , or *adapting* the goal or utility function used to evaluate the samples.

3.2. Formal Definition of Creativity

We now propose the following formal definition:

Creativity is the intelligent reduction or transformation of a search space to produce an output that is:

1. Intelligible: interpretable under a prior projection P_θ ,
2. Novel: non-trivial to generate under (P_θ, π) ,
3. Valuable: functionally useful, aesthetically coherent, or problem-relevant under some evaluation metric U .

Formally, let x^* be an output produced by an agent operating over projection $P_{\theta'}$ with policy π' . Then x^* is creative with respect to a baseline (P_θ, π) if:

$$(i) \text{ Intelligibility: } \text{sim}(P_{\theta'}(x^*), P_\theta(x^*)) > \delta$$

In simpler terms, when the output is interpreted through the agent's transformed projection, it is still recognisable and meaningful relative to the baseline projection, exceeding a minimum similarity threshold δ .

$$(ii) \text{ Novelty: } \Pr_\pi[x^*] \ll \epsilon$$

In simpler terms, the output is highly unlikely to be produced under the baseline sampling policy, that is its probability is far below a small novelty threshold ϵ .

(iii) Value: $U(x^*) > \tau$

In simpler terms, the output achieves a level of utility (such as problem-solving success or aesthetic quality) that exceeds a domain-specific value threshold τ .

Here:

- $\text{sim}(\cdot, \cdot)$ is a similarity measure between projections (e.g., structural or semantic resemblance),
- $\Pr_\pi[x^*]$ is the likelihood of sampling x^* under the baseline policy,
- $U(x^*)$ is a utility function appropriate to the domain (e.g., problem-solving success, aesthetic quality),
- δ, ϵ, τ are domain-specific thresholds.

This definition grounds creativity in three tensions:

- Between change and continuity (transforming P_θ without severing interpretability),
- Between rarity and feasibility (avoiding trivial novelty or noise),
- Between form and function (aligning generative process with meaningful evaluation).

3.3. Creativity as Search-Space Transformation

Let S_θ be the projected search space, and suppose the agent applies a transformation $T: S_\theta \rightarrow S_{\theta'}$.

This may involve a coordinate change, a conceptual reframing, or a grammar expansion, effectively redefining the rules of the generative space. The agent then explores $S_{\theta'}$ and produces candidate x^* . If x^* is intelligible under the original frame but non-trivial and valuable, it constitutes a creative act.

In this view, transformational creativity becomes a special case where the agent modifies P_θ itself. Exploratory creativity varies π while holding P_θ fixed. Combinatorial creativity performs novel recombinations within S_θ using structured policies. This unification yields a mechanistic account of all three of Boden's types as operations over projection–sampling pairs as given in Table 2.

Table 2. Typology of Boden's creativity and their corresponding mechanism in the proposed framework.

Creativity Type	Mechanism
Combinatorial	Recombination in fixed S_θ using π
Exploratory	Biased sampling via π' over S_θ
Transformational	Change of projection: $P_\theta \rightarrow P_{\theta'}$

3.4. Implications and Observability

This formalism has several immediate consequences:

1. Creativity is Observer-Relative
What is “creative” depends on the reference projection P_θ . The same output x^* may be trivial in one frame and transformative in another.
2. Creativity is Emergent, Not Enumerative
Unlike brute-force search or novelty heuristics, creative acts emerge from interactions between projectional structure, sampling strategy, and semantic priors.
3. Creativity Is Measurable in Simulations
By defining novelty, value, and intelligibility explicitly, we can simulate agents and evaluate creative behavior in controlled environments, as we demonstrate in subsequent sections.

3.5. Illustrative Examples of Creative Acts

To clarify how the proposed framework formalizes creativity across contexts, we present five illustrative examples drawn from diverse domains. Each demonstrates how novelty, intelligibility, and value emerge via projectional transformation, sampling strategy, or utility redefinition.

3.5.1. Artistic Innovation: Cubism

In early 20th-century painting, Cubism represented a radical departure from classical realism. Artists like Picasso and Braque redefined the projection P_θ of visual experience, not as a continuous 3D scene from a fixed perspective but as a multi-perspective flattening of form (Sgourev, 2013). This transformed the search space of image composition.

- Transformational Creativity: Redefined P_θ to alter spatial representation.
- Sampling: Composed images from fragmented, geometrized parts.
- Intelligibility: Viewers still recognized subjects (e.g., faces, objects) despite distortion.
- Value: Sparked an entire artistic movement and changed visual culture.

3.5.2. Scientific Discovery: Special Relativity

Einstein’s 1905 theory of special relativity can be seen as a transformation of the conceptual space underlying Newtonian mechanics. By replacing absolute time and space with the invariant speed of light, the projection $P_{\theta'}$ reorganized physical laws (Einstein, 1921/2001).

- Transformational Creativity: Shifted foundational assumptions of spacetime.
- Intelligibility: Retained core physical quantities (mass, velocity) in new form.

- Novelty: Could not be derived by local tweaks of Newtonian theory.
- Value: Resolved anomalies (e.g., Michelson–Morley) and predicted new phenomena.

3.5.3. *Engineering Design: The Suspension Bridge*

The invention of the modern suspension bridge introduced a radically new structural grammar for spanning large distances using tension instead of compression. As a prominent cultural landmark, the Brooklyn Bridge exemplified this shift (Witcher, 2022).

- Combinatorial + Transformational Creativity: Merged cable mechanics with architectural principles.
- Projectional Shift: Reframed “support” as dynamic tension.
- Novelty: No prior bridge had used suspended cables as primary structural elements.
- Value: Enabled longer spans, changing urban infrastructure worldwide.

3.5.4. *Language Play: Lewis Carroll’s Portmanteaus*

In *Through the Looking-Glass*, Carroll coined words like “slithy” (lithe + slimy) and “galumph” (gallop + triumph), which remain memorable (Carroll, 1871).

- Combinatorial Creativity: Sampled new lexical items by blending phonemes and meanings.
- Projection: Operated within English phonotactics and grammar.
- Intelligibility: Readers infer meanings via analogy to base words.
- Value: Expanded expressive capacity while preserving linguistic coherence.

3.5.5. *Machine Creativity: AlphaGo’s “Move 37”*

In its famous Go match against Lee Sedol in 2016, DeepMind’s AlphaGo played an unconventional move (Move 37 in Game 2) that shocked human experts (Silver, 2016).

- Exploratory Creativity: Exploited underexplored regions of the strategic space.
- Sampling: Derived from deep search guided by learned priors.
- Intelligibility: Move was legal and comprehensible in hindsight, but highly improbable.
- Value: Turned the tide of the game and demonstrated non-human strategic potential.

Each example satisfies the core criteria:

- A recognizable projectional lineage: they resemble earlier outputs,
- A low likelihood under prior policy: they break expectations,
- A positive functional or aesthetic outcome: they matter.

Together, they show that creativity is not confined to one modality but arises when the structure of exploration and interpretation is reconfigured.

4. A Typology of Creative Agents

We define creative agents as computational entities that produce outputs via intelligent search-space exploration and/or transformation. Each type of creativity can be instantiated as a distinct agentic strategy. These strategies are not mutually exclusive but rather represent different modes of modifying the projection P_θ , the sampling policy π , or the evaluation process U .

Below, we define six agent types, each embodying a distinct creativity mechanism.

4.1. Combinatorial Agent (ComboBot)

Core Strategy: Recombines known elements within a fixed projection.

- Projection: P_θ fixed.
- Sampling: Guided recombination of known basis elements.
- Example Behavior: Composing a hexagon by combining triangles; blending linguistic roots to coin a neologism.
- Strengths: High intelligibility; generative within constrained domains.
- Limitations: Limited novelty; confined to known dimensions.

4.2. Exploratory Agent (ExploreBot)

Core Strategy: Actively samples underexplored or sparse regions of the known space.

- Projection: P_θ fixed.
- Sampling: Biased toward novelty within S_θ ; e.g., rarity-driven or uncertainty-driven.
- Example Behavior: Making unconventional but valid Go moves; searching distant paths in a maze.
- Strengths: Discovers rare or surprising solutions.
- Limitations: Can lack coherence; novelty is not utility.

4.3. Transformational Agent (TransBot)

Core Strategy: Alters the projection $P_\theta \rightarrow P_{\theta'}$ by changing the coordinate system or generative rules.

- Projection: Actively modified.
- Sampling: Reapplied in new space $S_{\theta'}$.
- Example Behavior: Inventing non-Euclidean geometry; reinterpreting a problem in a new domain.
- Strengths: Enables radical innovation and deep shifts.

- Limitations: High risk of unintelligibility or failure.

4.4. Inferential Agent (InferoBot)

Core Strategy: Builds models of the latent structure of the environment to guide intelligent sampling.

- Projection: Remains fixed, but structured priors are learned.
- Sampling: Actively guided by an evolving internal model (e.g., via Bayesian inference or neural approximation).
- Example Behavior: Identifying high-value regions on a smooth surface; approximating reward gradients.
- Strengths: Combines efficiency with adaptivity.
- Limitations: May overfit local structures; slower startup.

4.5. Reframing Agent (ReframeBot)

Core Strategy: Alters the evaluation metric U or the problem constraints.

- Projection: May remain fixed.
- Sampling: Unchanged, but optimization is redirected.
- Example Behavior: Solving a problem by redefining success; shifting artistic evaluation from realism to emotional impact.
- Strengths: Circumvents dead ends; enables new problem definitions.
- Limitations: Difficult to quantify or justify shifts objectively.

4.6. Constructive Agent (ConstructoBot)

Core Strategy: Assembles higher-order structures from previously discovered parts.

- Projection: Hierarchical or compositional.
- Sampling: Informed by prior outputs or partial solutions.
- Example Behavior: Engineering systems from modular subsystems; composing symphonies from prior motifs.
- Strengths: Scales creativity to complex domains.
- Limitations: Requires memory, recursion, and structural representations.

This typology operationalizes creativity as agentic strategies over projection–sampling structures, enabling direct implementation in simulations or artificial systems. While many cognitive and computational models focus on the products of creativity, our typology emphasizes process structures, making it suitable for mechanistic study and cross-domain generalization.

5. Experimental Simulations

To evaluate the operational validity of our formal framework and typology, we implemented each creative agent type in controlled simulation environments. These environments were designed to reflect distinct structural challenges, allowing us to assess whether each agent's search-space strategy yields differential performance in solving, discovering, or generating novel solutions.

We conducted two major families of simulations:

1. Word Space Experiments: symbolic combinatorial generation
2. Maze Navigation Experiments: spatial exploration and planning

For each domain, we compare agent types ComboBot, TransBot, InferoBot, and ExploreBot where appropriate. As a baseline, we use Random Search that is defined as uniform sampling over the search space with no memory, modeling, or guidance mechanism.

5.1. Word Discovery Task

To evaluate the operational validity of our proposed creativity typology, we implemented each agent type in a symbolic problem-solving environment: the word discovery task. This task involves uncovering a hidden target string (either a random sequence of characters or a real word drawn from an English dictionary) without access to a lexicon or semantic priors. The agent's goal is to incrementally generate a candidate string that maximizes alignment with the target, using only global feedback: the number of character matches at correct positions.

This setup offers a high-dimensional, sparsely structured search space, reflective of creative tasks such as coining novel terms, evolving genetic sequences, or generating syntactically valid expressions. Unlike tasks where the solution landscape is smooth or continuous, the string space here is discrete, with minimal intermediate structure between candidate solutions. Thus, the environment emphasizes symbolic manipulation and structural inference as key creative mechanisms.

We evaluated four agent types consistent with our framework: Random Search (baseline), TransBot (transformational), ComboBot (combinatorial), and InferoBot (inferential). Random Search serves as a memoryless baseline, sampling uniformly from the space of all possible strings. TransBot employs simple projectional transformations, such as reversing, shifting, and substituting characters. ComboBot accumulates and recombines successful fragments from previous candidates. InferoBot updates a probabilistic model of character-position distributions using global feedback from past trials, simulating a Bayesian learning process.

Agents were tested on targets of increasing length (5, 7, 9, and 11 characters), with 1000 trials per length per condition. For each trial, the agent performed 100 steps of candidate generation

and evaluation. Performance was assessed using the match score, which is the number of correctly matched characters in their correct positions. Higher scores indicate better alignment with the hidden target string. The results are given in Table 3.

Table 3. Average match scores across 1000 trials per agent. Each entry indicates the mean number of character matches in correct positions. Higher values indicate closer alignment with the hidden target.

Agent	Random Letters				Real Word			
	5	7	9	11	5	7	9	11
Random Search	1,81	2,12	2,35	2,59	1,82	2,10	2,36	2,59
TransBot	2,75	3,08	3,46	3,71	2,73	3,02	3,46	3,71
ComboBot	1,51	1,58	1,69	1,79	1,47	1,59	1,63	1,77
InferoBot	1,91	2,26	2,50	2,77	1,93	2,24	2,50	2,79

The results suggest that TransBot outperforms all other agent types across both random and dictionary targets. Its capacity to perform projectional shifts and reversals enables it to bridge structurally distant regions of string space. InferoBot, which learns character-position likelihoods using Bayesian updates, shows moderate success but is limited by the sparsity of the feedback signal in such a discrete space. ComboBot performs poorly, likely due to the lack of reusable or meaningful substructures across random trials. Notably, even with Bayesian inference, InferoBot does not surpass the more straightforward transformation strategy employed by TransBot, underscoring the difficulty of model-based inference in symbolically sparse domains.

These findings support the notion that different creativity types yield distinct advantages depending on the structure of the problem space. In environments lacking gradient-like feedback or internal structure, transformational creativity may provide more effective heuristics than inferential or combinatorial strategies.

5.2. Maze Navigation Tasks

To further assess the operational differentiation among agent types, we devised a spatial problem-solving environment involving maze navigation. In this task, each agent must discover a valid path from a randomly assigned start point to a goal location within a two-dimensional grid maze of increasing size (from 10×10 to 40×40). The maze includes randomly placed obstacles (walls), and agents are restricted to four-directional movement (up, down, left, right). Critically, agents have no prior knowledge of the maze topology and receive only minimal feedback on progress: success or failure upon reaching the goal, and the total number of steps taken.

This task captures essential aspects of spatial reasoning and planning, including pathfinding under partial observability, sparse rewards, and the need for exploration versus exploitation trade-offs. We compare five agent types: Random Walk (baseline), TransBot, ComboBot, InferoBot, and ExploreBot. Each agent is permitted a fixed number of steps proportional to the maze size and is initialized from a random starting cell different than the goal. The results are given in Table 4.

Table 4. Maze navigation performance across different maze sizes. Success: number of trials (out of 100) reaching the goal. Steps: average number of steps taken (including failures).

Agent	Maze Size							
	10		20		30		40	
	Success	Mean Step	Success	Mean Step	Success	Mean Step	Success	Mean Step
Random Walk	24	78.65	10	361.49	3	873.99	1	1584.03
TransBot	12	89.71	3	388.20	3	873.31	1	1584.03
ComboBot	18	84.83	8	369.05	2	882.29	2	1568.12
InferoBot	55	49.08	42	237.03	25	679.01	16	1347.05
ExploreBot	76	55.15	72	232.30	51	644.46	54	1065.55

ExploreBot emerges as the most successful agent across all maze sizes, significantly outperforming others in both success rate and path efficiency. Its strategy (greedy hill-climbing on a latent utility surface) proves highly effective in identifying promising movement directions, even without a global map. InferoBot also achieves strong performance, especially in smaller mazes, by updating probabilistic movement models based on success feedback. However, its performance degrades in larger mazes, possibly due to slower convergence of its internal model in expansive environments.

By contrast, TransBot and ComboBot demonstrate limited adaptability in this task. Their projectional transformations and recombinations offer little utility without structural reuse or semantic landmarks, making them more susceptible to local loops or inefficient paths. Random Walk predictably performs the worst, highlighting the difficulty of uninformed search in sparse, high-dimensional spatial environments.

These results reinforce the framework's central hypothesis: different creativity strategies yield variable utility across structurally distinct domains. While inferential modeling provides a learning advantage, it may be outpaced by novelty-seeking exploration strategies in environments where local cues do not generalize well. The superior performance of ExploreBot in maze navigation suggests that exploratory creativity (biased toward underexplored regions) can be more effective than structured inference when spatial uncertainty dominates the search landscape.

6. Discussion

6.1. Creativity as a Generalization Mechanism

The Projection–Sampling framework positions creativity not as a mysterious cognitive leap but as a general mechanism for generating adaptive behaviour under novel or changing conditions. By transforming the search space via projectional shifts, altering sampling policies, or redefining evaluation metrics, a creative agent can generate outputs that go beyond prior exemplars while remaining intelligible to a given observer. In this sense, creativity operates as a *generalization mechanism* that extends learned or inherited structures to contexts that were not directly encoded in the agent’s prior experience. This view bridges the gap between theories of creativity as “domain-specific expertise” and those that see it as a “domain-general cognitive capacity.”

6.2. Creativity vs. Brute-Force Exploration

A central implication of this framework is that creativity is distinct from exhaustive search or purely stochastic novelty-seeking. Brute-force methods may produce surprising outputs, but without projectional alignment and evaluative coherence, such outputs are typically unintelligible or irrelevant. The formal criteria in Section 3.2 explicitly reject trivial novelty by requiring outputs to meet intelligibility and value thresholds. Creative acts emerge when exploration is guided by structural insight (encoded in P_θ , π , U) rather than by unbounded enumeration.

6.3. The Centrality of Projections and Interpretability

The projection function P_θ is the core of the proposed framework. It determines what an agent can represent, manipulate, and evaluate, thereby shaping both the scope of novelty and the conditions for intelligibility. By explicitly modelling this mapping, the framework integrates interpretability into the generative process itself. This stands in contrast to output-only definitions of creativity, which judge artefacts in isolation. Here, the meaning of an output is always situated relative to the projection through which it is generated and perceived.

6.4. Observer-Relativity as a Defining Novelty

A distinctive contribution of this work is the formal incorporation of *observer-relativity* into the definition of creativity. What is judged as “creative” is not an intrinsic property of the artefact but a relation between the artefact, the projection that generated it, and the projection through which it is interpreted.

For instance, in the domain of chess, a particular move sequence may be considered routine by an expert grandmaster operating under a projection P_{expert} that encodes deep tactical patterns. The same sequence, however, might appear startlingly original to a novice whose projection

P_{novice} lacks those embedded strategies. In our formalism, the move’s low novelty under P_{expert} but high novelty under P_{novice} demonstrates that creativity is frame-dependent.

This perspective sets the framework apart from output-only definitions and aligns it with theories of grounded cognition, in which meaning and novelty emerge from the interaction between representational context and sensory–motor engagement.

6.5. Creativity–Problem Fit as a Predictive Tool

The experimental results in Sections 5.1 and 5.2 show that different agent types excel under different structural conditions of the problem space. This suggests that the framework can serve as a *predictive tool*: given known or inferred structural properties of a problem space, it can recommend the most effective creativity strategy. An illustrative mappings between agent types and tasks are given Table 5.

Table 5. Agent and task association.

Problem Space Structure	Best-Fit Agent Type
High Regularity, Rich Feedback	InferoBot (model-based inference)
Sparse Feedback, Weak Regularity	TransBot (projectional transformation)
Spatial/Topological Exploration	ExploreBot (novelty-biased search)
Symbolic/Discrete Search	ComboBot or TransBot (structural recombination or transformation)

Such mappings could be expanded into a two-dimensional map where axes represent problem-space smoothness and reusability of substructures, with agent performance plotted accordingly. This approach could support adaptive creativity systems that select or blend strategies dynamically based on problem diagnostics.

6.6. Implications for Cognitive Systems Research and Other Fields

The Projection–Sampling framework offers a general mechanism for adaptive, intelligent behaviour that is directly relevant to cognitive systems theory. By defining creativity as transformations in projection, sampling, and evaluation functions, it formalises how (human or artificial) agents can restructure their representational spaces to address novel challenges. This formulation bridges low-level generative mechanisms with high-level cognitive capacities, which is often absent in domain-specific models. The explicit treatment of observer-relativity incorporates perspective-dependence into the architecture itself, enabling richer accounts of meaning, interpretation, and frame-dependent decision-making.

The projection function P_θ operationalises an agent’s “view” of the world, making it possible to trace how representational structure influences the generation and evaluation of candidate solutions. This capability connects naturally with grounded cognition, in which concepts and affordances are shaped by perceptual and motor experience, and with active inference, where

agents act to minimise surprise relative to generative models. Projection–Sampling extends these traditions by formalising representational change itself as a first-class, creative operation.

Beyond the cognitive systems community, the framework supports concrete applications:

- AI: Provides a unified basis for incorporating novelty, intelligibility, and value into generative systems, improving relevance and coherence of outputs.
- Art: Enables formal analysis of style shifts, genre emergence, and framing changes, supporting adaptive human–AI co-creativity.
- Science: Models the conditions under which conceptual breakthroughs occur, enabling simulation-based exploration of theory change.
- Education: Offers a structure for teaching creativity as a set of transferable strategies, with an emphasis on matching strategies to problem types.

7. Conclusion

This paper has advanced a formal, process-oriented account of creativity grounded in the interplay of projection, sampling, and evaluation. We have defined creativity as the generation of outputs that are intelligible, novel, and valuable relative to a given projection–policy–utility baseline. This formalism subsumes Boden’s influential typology (combinational, exploratory, and transformational creativity) by expressing each type as a specific transformation of the projection function, sampling strategy, or evaluation criterion. Furthermore, we enrich this typology by three additional creativity types.

Through simulation experiments in symbolic word discovery and spatial maze navigation, we demonstrated that different creativity strategies excel under different structural properties of the problem space. These findings support the framework’s predictive potential: by diagnosing the topology and feedback properties of a task environment, one can anticipate which creative strategy will yield the highest performance. The concept of creativity–problem fit thus emerges as both an explanatory and prescriptive tool.

This framework defines a generative design space for creative agents, enabling systematic exploration of projection transformations, sampling policies, and evaluation functions. Future work can extend this design space in several directions:

- Testing new agent types, including hybrids that dynamically switch between creativity modes.
- Mapping creativity–problem fit across domains, from visual art to scientific theory change to engineering design.
- Applying the framework to human–AI co-creativity, enabling adaptive collaboration where strategies shift in response to human intent and contextual cues.
- Developing richer and more compositional environments in which agents must combine creativity types to solve multi-stage, cross-domain challenges.

By grounding creativity in projection–sampling transformations, this work lays the foundation for a unified science of creativity that spans human cognition, artificial systems, and their interaction. Such a science would enable creativity to be studied, simulated, and engineered under common, testable principles, bridging the conceptual divide between descriptive theory and operational mechanism. In doing so, it has the potential to reframe creativity not merely as an artistic or cognitive phenomenon, but as a general property of adaptive, intelligent systems.

References

- Amabile, T. M. (1996). *Creativity in context*. Westview Press.
- Baas, M., De Dreu, C. K., & Nijstad, B. A. (2008). A meta-analysis of 25 years of mood-creativity research. *Psychological Bulletin*, 134(6), 779–806.
- Boden, M. A. (2004). *The creative mind: Myths and mechanisms* (2nd ed.). Routledge.
- Carroll, L. (1871). *Through the Looking-Glass, and What Alice Found There*.
- Einstein, A. (1921/2001). *Relativity: The special and the general theory*. Routledge.
- Gärdenfors, P. (2000). *Conceptual spaces: The geometry of thought*. MIT Press.
<https://doi.org/10.7551/mitpress/2076.001.0001>
- Glăveanu, V. P. (2010). Principles for a cultural psychology of creativity. *Culture & Psychology*, 16(2), 147–163.
- Guilford, J. P. (1950). Creativity. *American Psychologist*, 5(9), 444–454.
- Kaufman, J. C., & Beghetto, R. A. (2009). Beyond big and little: The four c model of creativity. *Review of General Psychology*, 13(1), 1–12.
- Lehman, J., & Stanley, K. O. (2011). Abandoning objectives: Evolution through the search for novelty alone. *Evolutionary Computation*, 19(2), 189–223.
- Liapis, A., Yannakakis, G. N., & Togelius, J. (2013). Sentient sketchbook: Computer-aided game level authoring. *Proceedings of the 8th Conference on the Foundations of Digital Games*.
- McCormack, J., Gifford, T., & Hutchings, P. (2020). Autonomy, authenticity, authorship and intention in computer generated art. In *Proceedings of the 11th International Conference on Computational Creativity*.
- Mouret, J.-B., & Clune, J. (2015). Illuminating search spaces by mapping elites. *arXiv preprint arXiv:1504.04909*. <https://doi.org/10.48550/arXiv.1504.04909>
- Rhodes, M. (1961). An analysis of creativity. *Phi Delta Kappan*, 42(7), 305–310.
- Runco, M. A. (1991). *Divergent thinking*. Ablex Publishing.
- Runco, M. A., & Jaeger, G. J. (2012). The standard definition of creativity. *Creativity Research Journal*, 24(1), 92–96.
- Schmidhuber, J. (2009). Simple algorithmic principles of discovery, subjective beauty, selective attention, curiosity & creativity. In *Proceedings of the Tenth International Conference on Simulation of Adaptive Behavior* (pp. 17–22).
- Sgourev, S. V. (2013). How Paris gave rise to Cubism (and Picasso): Ambiguity and fragmentation in radical innovation. *Organization Science*, 24(6), 1601–1617.

Silver, D., Huang, A., Maddison, C.J., Guez, A., Sifre, L., Van Den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M. and Dieleman, S., 2016. Mastering the game of Go with deep neural networks and tree search. *nature*, 529(7587), pp.484-489.

Simonton, D. K. (1999). *Origins of genius: Darwinian perspectives on creativity*. Oxford University Press.

Sternberg, R. J., & Lubart, T. I. (1995). *Defying the crowd: Cultivating creativity in a culture of conformity*. Free Press.

Weisberg, R. W. (2006). *Creativity: Understanding innovation in problem solving, science, invention, and the arts*. Wiley.

Witcher, T. R. (2022). Bridge of the Century. *Civil Engineering Magazine Archive*, 92(4), 26-29.

Declaration of interests

☒The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Projectional Creativity Model

Ersin Esen

Esenbil Information Tehchnologies

Acknowledgements

No funding is received for this study.

Declaration of Interest statement

Author has no interest to declare.

Corresponding author address

Atabey Cd. No:2 Palma Doro Sitesi E-12 Cekmekoy Istanbul Turkey

Corresponding author email address

ersinesen@gmail.com