Scaling Serendipity: A S.M.A.R.T Framework for AI-Augmented Innovation

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Despite record investments in R&D, scientific and technological breakthroughs are becoming less frequent, and ideas are getting harder to find. One of the most pervasive barriers is *cognitive fixation*: as experts become increasingly specialized, this can paradoxically narrow creative vision and make it difficult to look beyond low-hanging fruit. Even when teams manage to identify a promising inspiration, *transferring* its underlying principles to developing concepts in a new context presents a second major obstacle. Finally, bold ideas frequently die in the so-called "fuzzy front end" of R&D because they are not *systematically de-risked*. A failure at any of these stages can block the entire pipeline of innovation, leading to missed opportunities and eroded market leadership.

History consistently shows that the most transformative innovations emerge not from deeper digging within a single field, but from unexpected connections across domains. To fit a massive solar array into a narrow rocket, NASA engineers turned to the principles of origami to design a compact, self-deployable structure. In Japan, engineers studying the streamlined beak of a kingfisher discovered the key to eliminating the sonic boom of high-speed trains. And in medicine, a car mechanic adapted a party trick found on YouTube for removing a cork from a wine bottle to create the Odón device, a life-saving tool for difficult childbirths.

Despite its power, analogical reasoning remains one of the most underutilized tools in innovation. Because the process is cognitively demanding and highly sensitive to fixation, it too often depends on chance—emerging from rare moments of serendipity rather than systematic discovery. This white paper introduces **SMART**, a human-AI collaborative framework that turns analogical discovery from serendipity into a systematic, end-to-end process. SMART—which stands for **Search, Map, Adapt, Refine, and Test**—accelerates innovation from sourcing distant inspirations to developing and validating novel, viable solutions.

The impact of our framework has been validated in peer-reviewed research, enterprise collaborations, and global innovation challenges, including multiple awards in top-tier HCI and machine learning venues (CHI, CSCW, KDD) and publications in top journals such as Proceeding of the National Academy of Sciences. Across controlled studies, systems built on this framework have demonstrated measurable gains in idea quality, novelty, and feasibility with practicing designers and R&D professionals, and have been reported on in venues including NPR, Forbes, Axios, GeekWire, and more. Beyond the lab, this framework is shaping real-world innovation in global challenges run by organizations like Conservation X Labs, where our approaches have been used in more than a dozen challenges distributing over $12 million in funding and supporting startups that have raised over $500 million in follow-on investment; and by R&D teams at Toyota. Below we describe the SMART framework in order to provide a clear, evidence-based roadmap for building a more resilient and transformative innovation engine.

The SMART Framework: Accelerating Analogical Breakthroughs with AI

1. Search at Scale

Experts face a fundamental challenge in searching for analogical solutions from distant fields: the same expertise that fuels insight can trap them in familiar approaches. Existing computational approaches face similar challenges: keyword or embedding-based search methods rely on surface co-occurrences, while analogies require looking beyond to deep structural similarities. Meanwhile, LLM-based approaches suffer from *mode collapse*, resulting in homogeneous ideas over time. We introduced a new way of learning analogous structure at scale through *purpose–mechanism schemas*: learning different vector embeddings for *the purpose* a system is trying to achieve versus *the mechanism* it uses achieves that purpose [2]. For example, a yogurt maker's purpose is to *make yogurt* while its mechanism involves using a *vacuum cooled drum*. Looking for other ideas with similar purposes but different and diverse mechanisms results in analogous inspirations like *sharkskin microgrooves* for "reducing friction without lubricants." In controlled studies, this method doubled the number of high-quality ideas generated, and can unlock the value of millions of unstructured ideas functionally relevant to a target problem, whether in a company's own internal knowledge or in papers, patents, or online websites [3, 5].

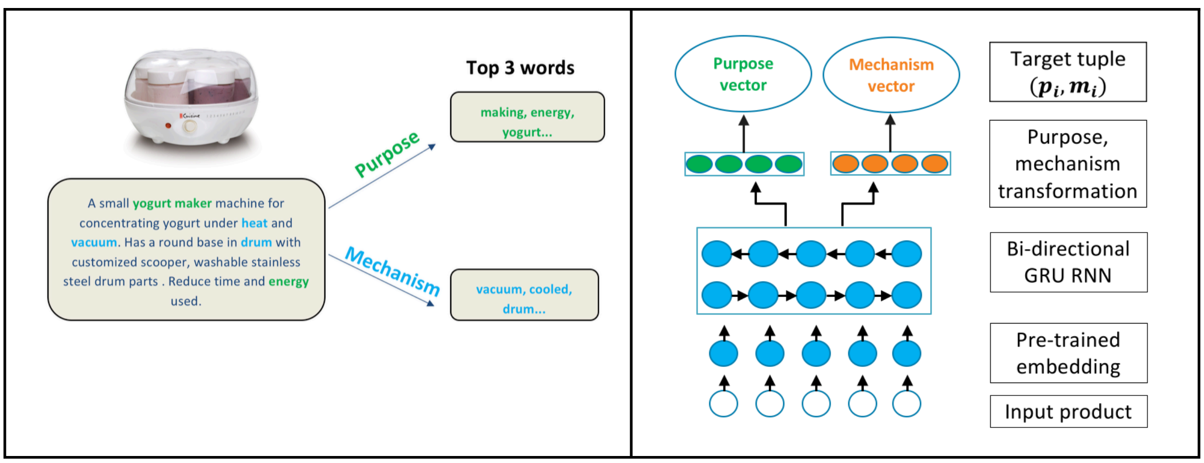


Figure 1. The Purpose-Mechanism Schema. The system breaks down ideas into dual vector embedding representations (left) using deep learning with siamese networks (right). Given a Purpose (e.g., "reduce friction without lubricants") the system can search for diverse, analogous Mechanisms (e.g., "Sharkskin Microgrooves," "Self-Healing Coatings") from outside their domain to break cognitive fixation.

2. Map to Target Domain

Simply finding a novel analogy is not enough; R&D teams often struggle to "map" the abstract concept to their specific, real-world problem. This cognitive gap is where most analogical innovation fails. For example, a designer working on a bike rack will struggle to find an actionable path from the inspiration of "snail mucus." We developed a system called **BioSpark** that computationally bridges this gap [7]. It not only finds inspirations but automatically *transfers* them to the target domain, generating specific application scenarios (e.g., how the snail's adaptive adhesion translates to a hydrogel-based clamp for varied bike frames) and suggesting concrete, manufacturable materials (e.g., specific hydrogels that remain pliable in winter conditions). In studies, designers using this system explored a wider design space and produced **significantly more creative ideas** than those using standard generative AI, demonstrating that mapping is a critical step in making inspiration actionable.

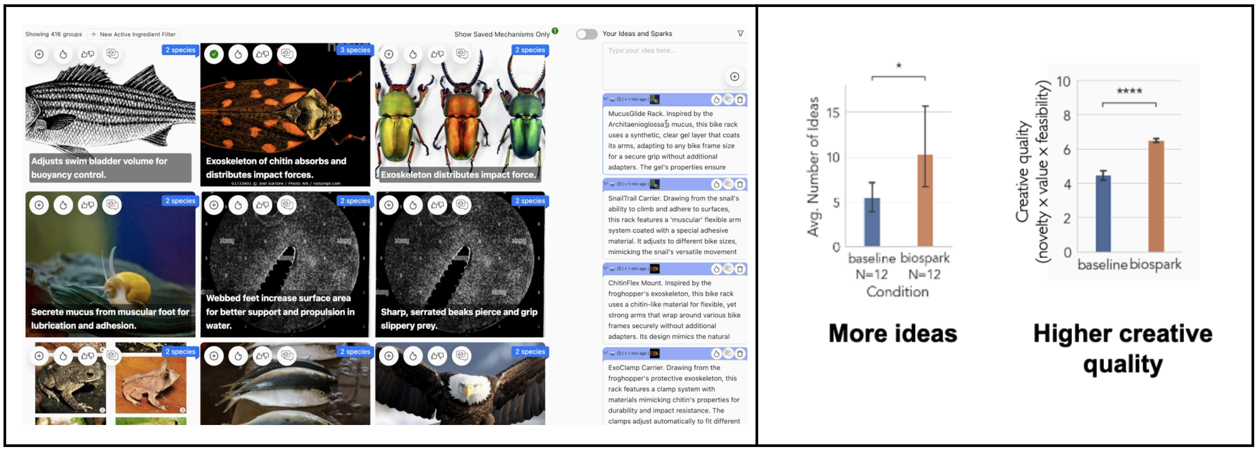


*Figure 2. The **BioSpark** system (left) bridges the "transfer gap" by translating an abstract biological inspiration (e.g., snail mucus) into a concrete, "mapped" engineering concept (e.g., an adaptive hydrogel bike rack). Users generated more ideas and ideas with creative quality than a generative AI baseline.*

3. Adapt with Human Expertise

Breakthroughs rarely come from adopting an external idea wholesale; they come from **experts adapting an idea's core principle** using their deep domain knowledge. The Wright brothers, for instance, adapted the *principle* of shear from a cardboard box, not the material itself. Our research focuses on computationally facilitating this expert adaptation. We found that feeding experts targeted analogical ideas (e.g., a "fin structure") prompts creative leaps (e.g., to "nanoscale fins" for chip cooling) [5]. We also applied this in collaborative settings with organizations like Conservation X Labs, developing algorithms to match teams from diverse domains (e.g., drone-based poacher tracking and ocean microplastic detection) that share a **deep structural problem**. After refining our matching algorithm to find this "sweet spot" of cognitive distance, teams showed **significant improvements in idea novelty and usefulness** [6].

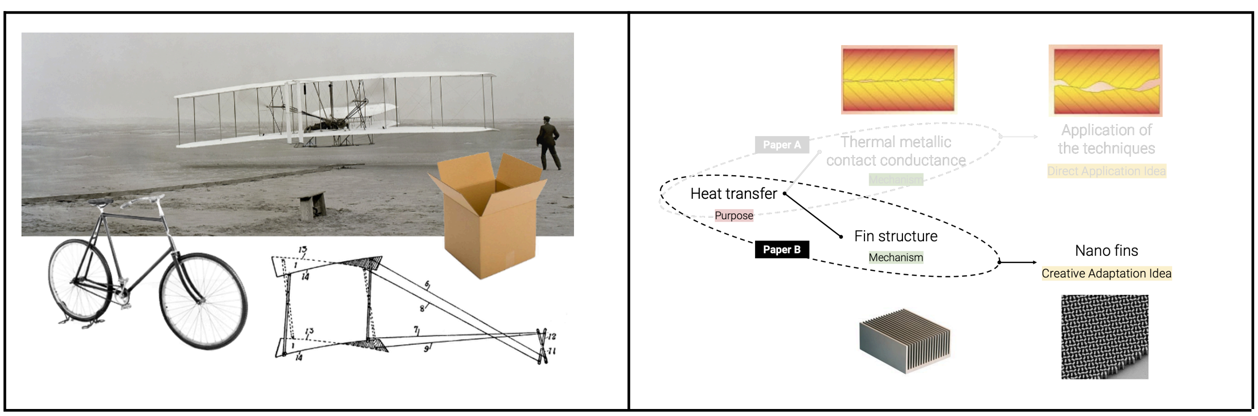
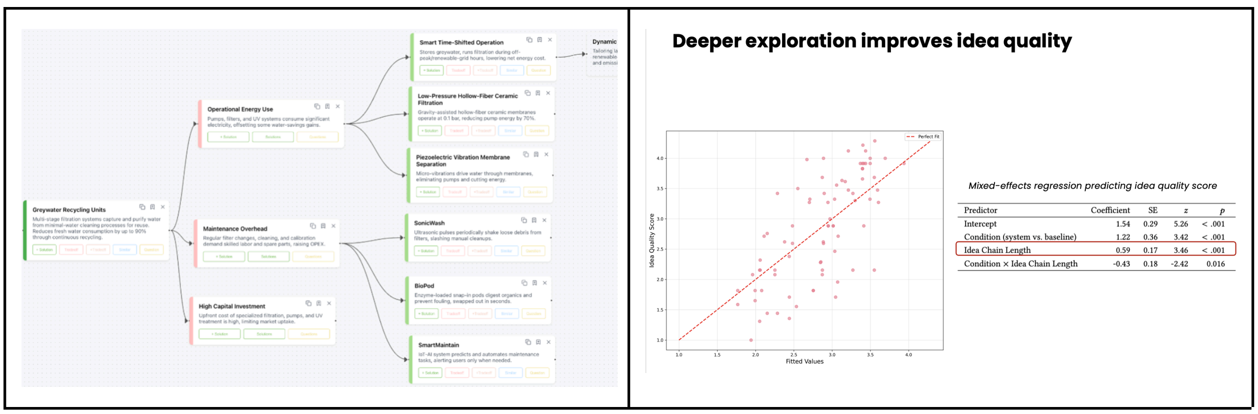


Figure 3. Creative adaptation in analogical search relies on bringing in expert tacit knowledge, such as the Wright brothers translating the shearing of a cardboard box to a pulley system for controlling the wings. Our systems lead to 5x+ more frequent creative adaptations (e.g., using the idea of a fin structure to generate nanoscale "fins" that translate heat into motion) versus traditional approaches.

4. Refine and Iterate

Innovation is not a single "lightning strike" but a complex, branching process of refinement. Dyson's vacuum, for example, required **5,000 iterations** to solve the cascade of sub-problems. Standard AI tools, with their linear, conversational interfaces, are fundamentally mismatched to this non-linear exploration, causing users to abandon paths prematurely. We developed **Flexmind**, a system that provides a non-linear canvas where an AI partner actively helps the user explore and solve emergent sub-problems [9]. This "tool for thought" mirrors the branching nature of R&D. We found that users of Flexmind explored **many more solutions in greater depth**, and statistical analysis confirmed that this deeper exploration **statistically significantly leads to higher-quality ideas**, as rated by senior R&D leaders.



Predictor	Coefficient	SE	z	p
Intercept	1.54	0.29	5.26	$< .001$
Condition (system vs. baseline)	1.22	0.36	3.42	$< .001$
Idea Chain Length	0.59	0.17	3.46	$< .001$
Condition × Idea Chain Length	-0.43	0.18	-2.42	0.016

*Figure 4. The **Flexmind** system (left) enables the deep, branching exploration required for real R&D. Unlike a linear chat interface, Flexmind's visual canvas encourages users to pursue and solve multiple sub-problems, resulting in the richer idea structures that lead to breakthroughs (right).*

5. Test Viability

Turning inspiration into impact requires more than imagination—it demands evidence that an idea can work and a path to prove it. Our latest work-in-progress, Inspyral, extends this capability by mapping early ideas to analogous solutions across domains to help teams evaluate viability, identifying potential collaborators and implementation partners who could help bring them to life, and estimating technology readiness and potential impact if realized. For example, when exploring novel flossing technologies, Inspyral surfaces analogs in soft-robotic cleaning systems that use magnetic actuation to navigate and dislodge buildup in confined spaces—offering concrete cues about materials, control strategies, and feasible validation steps. It then connects these insights to potential partners and next-step experiments, helping teams see not only whether an idea can work, but how, where, and with whom it can advance toward proof-of-concept.

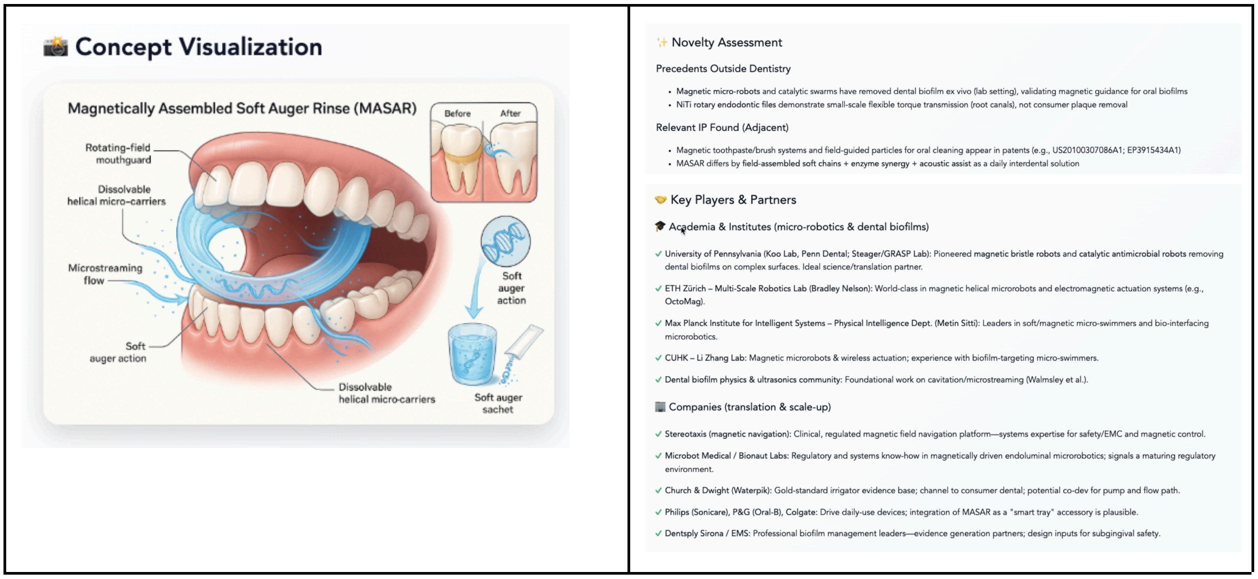


Figure 5. For a novel concept ("Magnetically Assembled Soft-Auger Rinse"), our system auto-generates a preliminary diligence report. This dashboard allows R&D teams to quickly test an idea's viability by assessing predicted outcomes, safety, Impact x Readiness Level (IRL), potential partners, and more.

Building Your Innovation Pipeline

Our research has established a computational framework for making innovation a scalable, evidence-driven process. We are now operationalizing this work into an end-to-end, human-AI collaborative platform that accelerates the full journey from idea to impact.This system unites systematic **Search**, guided **Mapping**, expert **Adaptation**, iterative **Refinement**, and rapid **Testing** into a cohesive ecosystem.

At its core, the platform is designed to **augment—not replace—human expertise,** while leveraging AI in a way that avoids the risk of linear thinking and homogeneity to enable your organization to uncover high-potential solutions, de-risk them faster, and bring transformative ideas to life with greater confidence. We are now inviting forward-looking R&D partners to collaborate on pilot deployments, helping shape the next generation of innovation systems. These partnerships offer a unique opportunity to shape and validate the next generation of innovation systems—driving faster iteration, higher-quality ideas, and measurable impact across industries.

Collaborative User Study with R&D Teams

To tailor this transformative engine to your specific needs, one way of engaging may include a "white glove" co-design partnership. This would allow us to work closely with your R&D experts, understand their unique challenges, and deliver immediate, tangible value. Our proposed collaboration follows a structured, multi-phase approach:

- **Phase 1: Discovery and Scoping (2 weeks)** We begin with deep-dive discussions to map your current innovation pipeline and workflows. Together, we will identify a high-impact R&D problem and define clear success metrics—what constitutes a "win" for your team. This phase involves approximately 6 hours of engagement across three focused sessions to map practices, scope problems, and run initial validation sessions.

- **Phase 2: High-Touch Co-Design & Iteration (2 weeks)** Our team will work directly alongside your experts as co-design partners. We will deploy our engine on the selected problem and rapidly iterate based on your team's real-time feedback. We propose 2-hour working sessions every 2–3 days to maintain momentum and ensure the platform's outputs are tailored to your needs.
- **Phase 3: Rigorous Pilot and Validation (2 weeks + follow-up)** We will run a structured pilot study, observing your team members as they use the platform on real R&D tasks. Using rigorous methods (think-aloud protocols, surveys, interviews), we will experimentally measure the impact on your innovation process. This is followed by a month-long deployment for application to ongoing challenges, allowing us to assess the sustained impact and long-term value of the concepts generated.

The Outcome: A successful pilot will demonstrate a clear return on investment and establish you as a key partner in transforming the future of innovation.

Team

Our team has been at the forefront of computational analogical innovation, contributing to its development as a rigorous, evidence-based discipline. Backed by over a decade of peer-reviewed research and 40+ years of combined expertise across HCI, AI, design, and cognitive science, our interdisciplinary team is now focused on translating this deep foundation into real-world impact.

- **Dr. Aniket Kittur** is a Professor in CMU's Human-Computer Interaction Institute whose research on AI-augmented cognition aims to accelerate innovation. His work has received numerous accolades, including an NSF CAREER award, induction into the CHI Academy, and 17 best paper or honorable mention awards. His research has led to significant real-world impact, including founding a VC-funded startup, influencing features used by 150 million Mozilla Firefox users, and co-creating a tool deployed by AI2 to over 200,000 scientists monthly. His Ph.D. at UCLA focused on computational models of analogy.
- **Dr. Nikolas Martelaro** is an Assistant Professor in CMU's Human-Computer Interaction Institute. His research develops novel computational tools to support designers and engineers, from co-creative human-AI sketching interfaces that use analogies to conversational AI partners for design. He has extensive experience collaborating with industry partners such as Toyota, Autodesk, and Adobe to ground his research in real-world innovation needs.
- **Dr. Vikram Mohanty** is a Postdoctoral Fellow in CMU's Human-Computer Interaction Institute specializing in building interactive AI systems for complex, real-world sensemaking. During his Ph.D., he led the development of Civil War Photo Sleuth, an AI-powered platform he grew to over 20,000 users and co-founded as a 501(c)(3) nonprofit foundation, demonstrating his ability to manage the full lifecycle of a translational project. He also brings direct industry R&D experience from Bosch Research and the Toyota Research Institute.

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