DISSERTATION

ENGINEERING IMPACTFUL SCIENCE IN A RESEARCH ENTERPRISE BY DYNAMIC MODELING OF INNOVATION LIFE CYCLE AND EVOLUTION

Submitted by

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ABSTRACT

ENGINEERING IMPACTFUL SCIENCE IN A RESEARCH ENTERPRISE BY DYNAMIC MODELING OF INNOVATION LIFE CYCLE AND EVOLUTION

Despite record-high global R&D investments, we are witnessing an "Innovation Paradox" where research outputs are yielding diminishing returns. This national innovation slowdown is evidenced by the United States falling to No. 6 in the 2023 Global Innovation Index. This crisis is particularly acute in the Department of War's S&T enterprise, where the Secretary of War has explicitly identified that the traditional "linear model" of R&D management is "dangerous to mission accomplishment." Recently, at a Reagan Institute event on the National Security Innovation Base, the Fourth Annual National Security Innovation Base Report Card was published. It stated that, “America has the resources it needs to achieve technological superiority over global adversaries, and Washington has signaled its intent to transform and modernize the National Security Innovation Base, but amid encouraging progress, roadblocks remain,” Traditional frameworks for managing and measuring scientific progress are failing, treating innovation as a static, linear process. This linear assembly line perspective is in direct conflict with the reality of complex research ecosystems, such as that of the Department of War (DOW). Innovation systems are governed by dynamic feedback loops, emergent properties, and evolutionary pressures that linear models cannot capture. Not treating innovation as evolutionary leads to flawed forecasting and perpetuates systemic organizational failures, such as policies that favor low-risk exploitation over the exploration required for true breakthroughs. This is a classic representation of the "Innovator's

Dilemma." The main question that persistently exists for governments, industries, and academia is, “how do we balance risk with the probability of innovation”.

This dissertation develops and validates a new computational systems model that reconceptualizes innovation as a Complex Adaptive System. It posits that breakthrough ideas do not merely appear; they evolve. To model this, the research integrates principles of biological evolution with a multi-model simulation environment. It utilizes a rigorous suite of systems thinking tools, including agent-based modeling (ABM) to simulate the competitive and adaptive interactions between researchers, and genetic algorithms to model the "natural selection" and procreation of ideas.

The primary contribution of this research is a dynamic, six-level framework that provides a more accurate method for forecasting the structured temporal progression from incremental to breakthrough innovation. The model demonstrates how small refinements categorized as incremental, cumulatively build toward larger advances that are categorized as modular and architectural. These advances in turn can trigger disruptive and radical paradigm shifts.

Ultimately, this dissertation establishes a robust, systems-aware methodology for strategic R&D investment. By providing new quantitative metrics for classifying and measuring innovative potential, such as the proposed Innovation Procreation (IP^{o}), this work provides a dynamic framework for investment strategies aimed at fostering the high-impact, transformative research essential for national and economic security.

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DEDICATION

To my mother (Clara), brother (Terrence), offsprings (Natasha and Lawrence), and Sarwat Chappell for always supporting me.

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NOMENCLATURE AND KEY DEFINITIONS

Mathematical Symbols & Indices

- IP^0: Innovation Procreation (Base) – The fundamental metric representing the generative potential of an idea to influence subsequent innovations.
- $P(x)$: Probability Distribution Function – Often referring to the Power Law or Generalized Pareto Distribution (GPD) in the context of "Black Swan" breakthroughs.
- ξ (xi): Shape Parameter – In Extreme Value Theory (EVT), determines the "heaviness" of the tail (the likelihood of breakthrough vs. incremental change).
- σ (sigma): Scale Parameter – Defines the dispersion or "stretch" of the innovation impact distribution.
- R_e: Exploration Rate – The ratio of resources allocated to high-uncertainty, high-impact research versus incremental refinement.
- K_s: Knowledge Stock – The cumulative, non-depreciating "reservoir" of scientific understanding within the enterprise.

Acronyms

- ABM: Agent-Based Modeling
- CAS: Complex Adaptive System
- DOW: Department of War
- EVT: Extreme Value Theory
- GPD: Generalized Pareto Distribution
- S&T: Science and Technology
- SD: System Dynamics

- Vensim: Visual Enumeration and Simulation (The software platform for SD modeling)

Key Definitions

Systems & Modeling

- Complex Adaptive System (CAS): A system in which a perfect understanding of the individual parts does not convey a perfect understanding of the whole system's behavior. In this dissertation, the research enterprise is modeled as a CAS where researchers (agents) and ideas (entities) interact to produce emergent breakthroughs.
- Feedback Loop (Balancing/Reinforcing): The basic structural element of System Dynamics. Reinforcing loops (R) drive exponential growth or collapse, while Balancing loops (B) provide stability or resistance to change (e.g., organizational inertia).
- Agent-Based Modeling (ABM): A bottom-up computational modeling paradigm where individual "agents" (researchers) follow simple rules that lead to complex, aggregate patterns (innovation trends).

Innovation Taxonomy

- Incremental Innovation: Small, continuous improvements to existing technologies or processes that do not fundamentally change the underlying system.
- Modular Innovation: Technological change where the core design concepts of a product’s individual components are significantly altered.
- Architectural Innovation: A reconfiguration of existing systems or components that links them together in a new way, creating a novel functional outcome.
- Radical Innovation: An innovation that creates a new market or value network, eventually displacing established market leaders or technologies (per Clayton Christensen).

- Disruptive/Breakthrough Paradigm Shift: A fundamental change in the basic concepts and experimental practices of a scientific discipline; a "Black Swan" event in the research ecosystem.

Evolutionary Dynamics

- Innovation Procreation: The conceptual framework where ideas are treated as biological entities that "procreate" through recombination, mutation, and selection within the research environment.
- Genetic Algorithm (GA): A search heuristic used in this model to simulate the "Natural Selection" of ideas, where the most "fit" (impactful) concepts survive and mutate into next-generation innovations.
- The Innovator's Dilemma: The paradox where successful organizations fail because they focus on meeting current customer needs (exploitation) at the expense of developing the next wave of disruptive technology (exploration).

Probability Theory and Statistical Foundations

- Extreme Value Theory (EVT): A branch of statistics dealing with the extreme deviations from the median of probability distributions. Used here to model the "tails" of innovation where high-impact breakthroughs reside.
- Power Law: A functional relationship between two quantities where a relative change in one quantity results in a proportional relative change in the other, regardless of the initial size of those quantities (e.g., the 80/20 rule in R&D impact).
- Bayes Theorem: Mathematical formula used to determine the conditional probability of an event based on prior knowledge of conditions that might be related to the event.

- Stochastic Uncertainty: The inherent randomness or variability in a system that cannot be reduced by collecting more data.
- Determinism: The philosophical and scientific concept that every event, action, and decision is the inevitable result of preceding causes.
- Epistemic probability (also known as subjective probability: A measure of the degree of belief or certainty that an individual has in a particular proposition or hypothesis, based on the information currently available to them.
- Aleatory probability (also known as statistical or stochastic probability): refers to the inherent randomness or "chance" in a physical process.
- Prior Probability P(H): The initial probability assigned to a hypothesis before any new evidence is observed.
- Posterior Probability P(H|E): The updated probability of the hypothesis after taking the new evidence into account.
- Likelihood P(E|H): The probability of observing the specific evidence (E), if the hypothesis (H) is true.
- Sensitivity: Sensitivity is the probability that the test is positive (T+) given that the condition is present.
- Specificity: Specificity is the probability that the test is negative (T-) given that the condition is absent. 1 – (Specificity) is the false positive rate.
- S-Curve (Sigmoid Function): The mathematical signature of a system transitioning from one stable state to another through a process of feedback and constraint

CHAPTER 1: INTRODUCTION

1.1 The Stagnation of Linear Innovation: Why current R&D is failing to produce Breakthroughs in short time periods.

While innovation is universally recognized as the lifeblood of technological and economic advancement, the frameworks used to understand it are fundamentally flawed (Christensen et al., 2018). Traditional models treat scientific progress as a static, linear process, failing to capture the dynamic feedback loops, emergent properties, and evolutionary pressures that truly govern discovery (Björk & Magnusson, 2009). This analytical gap leaves the innovation process appearing chaotic and unpredictable. It sometimes leads to accepting risk without knowing what the probability of innovation is. A Unified Multi-Model framework with dynamic causal feedback is researched in this dissertation to quantify risk with the probability of innovation.

Present metrics for predicting innovation involve statistical correlations that are non-dynamic. These non-dynamic correlations and linear data analytics fail to account for the temporal components and interdependencies that are theorized for innovation. Our current innovation theories are decoupled from the actual, time dependent processes of discovery. We are essentially trying to manage the future using a rearview mirror. Current frameworks rely almost exclusively on lagging indicators like patent counts, citation counts, and past expenditures. These metrics tell us what happened one to five to ten years ago, they provide a retrospective, static snapshot rather than a predictive measure of systemic impact. This research seeks to bridge this gap by moving from these lagging indicators to a more dynamic, predictive modeling approach. A dynamic based innovation model (DBIM) was created for deducing the cause of innovation from citation patterns.

This DBIM gives probabilities of innovation from changes in purpose, structure, behavior or use of previous scientific research innovations. Causal analysis is used to quantify the direct and indirect effect of changes in purpose, structure, behavior, or use for creating new innovations.

Systems Thinking, Systems Dynamics, and Bayesian Analytics are used for quantitative analysis of the complex interplay of variables, feedback loops, and time delays that influence innovation. These techniques show the cause of innovations, and their emergence. The result of this investigation shows that small changes in purpose, structure, behavior, or use of previous innovative research can cause new innovations. These small changes can be simulated, quantified, and used for prediction from observational studies of publication, citation patterns, and research requests. This technique can be used by academia, industry, and government agencies to give insights into potential influences, outcomes, and hindrances within an innovation ecosystem. Because traditional approaches ignore the complex, non-linear interactions between different categories of innovation, researcher information, resources, and policies, their ability to reliably measure or forecast progress is severely limited. This dissertation argues that innovation is not a simple, linear path but a Complex Adaptive System (CAS), and it must be modeled as such (Ahmad et al., 2024). Today's environment of rapid technological change and global competition makes the ability to innovate effectively an advantage and a strategic imperative. Knowing how to balance risk of investments is also essential. Many organizations find themselves in an "innovation crisis," constrained by old management frameworks that are fundamentally misaligned with the complex, non-linear nature of new modern discovery (Zeng et al., 2017). Traditional linear models of the Department of War's (DOW) research and development (R&D) management treat innovation as a predictable sequence of inputs and outputs. This is no longer sufficient to deliver next generation capability to warfighters. This failure creates a critical need for a more dynamic, predictive, and systemic framework to guide strategic investment and manage R&D portfolios for sustained high-impact results (*War Department Overhauls Innovation Ecosystem*, n.d.).

Dynamic models from this dissertation have shown that small refinements in products or processes, known as incremental innovations, build toward larger advances such as modular improvements, architectural redesigns, and radical paradigm shifts. These, in turn, may lead to disruptive innovations that displace established systems, and ultimately, breakthroughs that redefine entire fields through new standards and unforeseen behaviors (Christensen et al., 2018). Innovation is cumulative and recursive: each stage absorbs and transforms prior developments, creating increasingly complex and impactful outcomes. Feedback in innovation shows that innovations are not linear endpoints but part of a continuous cycle, where new changes reshape ideas and renew the process of innovation. Innovation is a dynamic system of progression in this dissertation, where incremental changes can eventually trigger transformative breakthroughs. A Systems Thinking approach was used to frame the coupling associations of the multi-model approach to innovation.

Systems Thinking leads to Systems Principles that are the framework of the concepts and methods used to understand how parts of a system interact to produce the behavior of an enterprise system (Schlüter et al., 2023). Instead of looking at elements in isolation, systems thinking emphasizes interconnections, feedback loops, delays, and patterns that shape outcomes over time. Research activity is represented as a dynamic system in which researching contains many elements that evolve over time, respond to inputs, generate outputs, and contain feedback processes that shape its trajectory. Because of the dynamics of research activities, Systems Thinking principles were used to see beyond linear cause-and-effect relationships and recognize that certain actions in a research enterprise can have unintended consequences when viewed in the broader system.

Systems Thinking principles are also used for analyzing complex problems, improving decision-making, and designing more effective solutions in areas such as technology engineering, business management, health, policy, and war fighting. By applying systems thinking, individuals and organizations can better anticipate ripple effects, adapt to change, and create sustainable improvements. This dissertation presents a new model, based on five Systems Principles that are more representative of reality because they explicitly incorporate feedback loops and evolutionary mechanisms that show how earlier innovations are absorbed and transformed into higher-order frameworks.

1.2 Problem Statement and Research Gap: The Innovation Crisis and the Failure of Linear Models

The evidence of a national innovation slowdown is compelling. After holding the top position, the United States fell to No. 6 in the 2023 Global Innovation Index (GII), with nations like Switzerland, Sweden, and Singapore now ranking higher (Nasir & Zhang, 2024). This decline signals a systemic challenge that requires more than increased spending; it requires a new way of thinking.

This challenge is particularly acute within complex ecosystems like the Department of War's Science and Technology (S&T) enterprise (*War Department Overhauls Innovation Ecosystem*, n.d.). In a recent memorandum that fundamentally restructured the DOW innovation ecosystem, the Secretary of War identified the traditional "linear model" of R&D management as being "dangerous to mission accomplishment," which is a direct indictment of the old paradigm.

This move to deliver "warfighting advantage faster than our adversaries can adapt" is an acknowledgment that the previous approach was failing its mission.

As stated before, traditional metrics used to measure innovation, such as the number of patents filed or the percentage of revenue allocated to R&D, are often misleading and do not balance risk of investment with the probability of innovation (ter Haar, 2018). They fail to capture the true impact of an innovation, which may manifest as a novel business model, a transformative new process, or a creative method of engaging customers, rather than just a new product.

The failure of existing linear frameworks is evident in several critical research gaps that impede accurate foresight and cultivation of impactful research, particularly for breakthrough advancements:

1. Inadequate Traditional Metrics: Conventional measures such as Technology Readiness Levels (TRLs), patent counts, citations, or R&D expenditures are lagging indicators that capture only a limited, static snapshot of the innovation process. They fail to account for the dynamic, intangible contributions of collaboration, knowledge assimilation, or systemic context (Trump et al., 2025).
2. Limitations of Static Categorization: Models like the Henderson-Clark framework offer useful but static classifications (Incremental, Architectural, Radical). They do not model the evolutionary progression between these stages or adequately define the "Breakthrough" innovation required to guide basic research investment (Almgren & Skobelev, 2020).
3. The Innovator's Dilemma: Static frameworks offer no practical, dynamic guidance for navigating the "Innovator's Dilemma," where organizations systematically fail to adopt new innovations (Henderson, 2006). This problem is amplified in today's volatile and complex environments.

4. Lack of Predictive Metrics for Basic Research: A significant gap exists in metrics for predicting or measuring the success of innovative basic research. This absence leads stakeholders, such as those in the Department of Defense, to question the efficacy of foundational science investments.

These shortcomings demonstrate that a new framework is required. This framework must transcend linear thinking and embrace a complex adaptive systems approach to capture the non-linear, emergent, and evolutionary behavior of innovation.

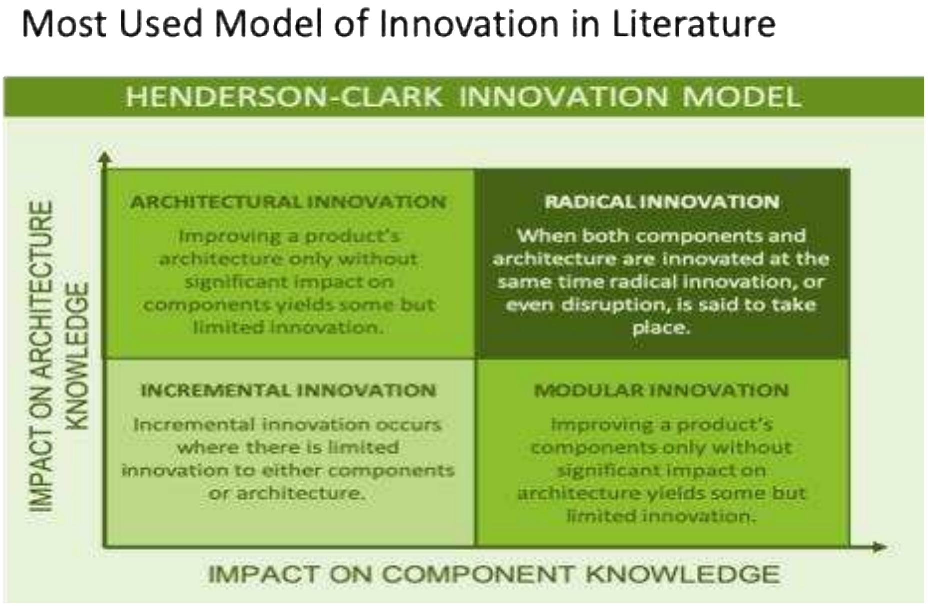
1.3 The Innovator's Dilemma in Modern R&D

Established organizations consistently face what Clayton Christensen famously termed "The Innovator's Dilemma": the tendency to optimize for present needs and exploit existing competencies at the expense of exploring the disruptive capabilities that will define the future (Christensen et al., 2018).

This is not simply a cognitive failure of senior management. As Rebecca Henderson's work clarifies, this dilemma is deeply rooted in organizational competencies. The very structures and processes that make an organization successful today become rigid barriers that prevent it from seeing and seizing the next wave of innovation. High levels of technological uncertainty make existing knowledge obsolete faster, forcing firms into a difficult balancing act between exploitation of maximizing short-term returns and exploration by expanding their knowledge base for the future.

The dilemma faced by organizations within an innovation ecosystem is identifying and choosing between making a good thing even better like a phone company adding a slightly better camera and a faster chip or developing something that needs lots of research that might be a game changer in the future. Large organizations usually ignore these because they don't think their near-term availability is cost effective.

Innovation today is seen as the process of turning an idea or invention into a product or service that creates value or attracts customers. Measuring innovation involves various methods, both traditional and modern (Tahamtan & Bornmann, 2019). Traditional metrics include the number of patents filed, research and development (R&D) spending as a percentage of revenue, and the number of new products created. While useful, these metrics often miss the broader impact of innovation (Huang et al., 2022). True innovation might involve a new process, a novel business model, or a creative way of engaging customers. It is noted that Greg Satell's contributions to the field of innovation have been widely recognized, making "Mapping Innovation" a seminal piece for those looking to drive transformational change within their organizations (Satell, 2017). One present innovation model, shown in Figure (1), is static and fails to represent innovation's nonlinear evolution.



Improving a product's architecture only without significant impact on components yields some but limited innovation.

When both components and architecture are innovated at the same time radical innovation, or even disruption, is said to take place.

Incremental innovation occurs where there is limited innovation to either components or architecture.

Improving a product's components only without significant impact on architecture yields some but limited innovation.

Figure (1). Henderson-Clark framework for innovation.
This is a static model of innovation used by industry.

The Henderson-Clark Model is widely used in literature to categorize innovation into four quadrants. This model's framework is used to describe the types of innovations shown in the figure. In her work, she highlights these primary types as the "Four Horizons of Innovation." These categories help organizations think strategically about their innovation efforts and how they can balance short-term and long-term goals. The four types of innovation are:

- Incremental Innovation: This type of innovation focuses on making incremental improvements to existing products, processes, or services.
- Architectural innovation: Architectural innovation occurs when new products or services use existing technology to create new markets and/or new consumers that did not purchase that item before.
- Radical Innovation: When new products or services are developed using new technology that open new markets, the result is called radical innovation.
- Disruptive Innovation: Disruptive innovation is about creating entirely new and groundbreaking solutions that may disrupt existing markets or industries.

These categories provide a framework for business organizations to manage their innovation portfolios (Henderson, 1994). They do not capture breakthrough innovations as a category desired from organizations seeking game changing advancements. These four categories also fail to address the "The Innovator's Dilemma", as investigated in the paper published by Clayton Christiansen in 1970. The innovator's dilemma refers to the challenge faced by established firms in responding to disruptive innovations (Henderson, 2006). Rebecca Henderson does discuss this dilemma and explains Christiansen's concept by indicating that the dilemma is not just due to cognitive failures or decision-making issues at senior management levels, it is also rooted in organizational competencies.

This dissertation attempts to redefine the categories and understand the dynamic complexities of innovation moving between categories to help resolve the innovation dilemma of Clayton Christiansen. This is partially accomplished by giving a causal explanation of where basic and high-level innovations evolve from in a quantifiable representation.

This different model of innovation proposed in this dissertation may lead to government and industrial decisions that better understand where to invest for future growth to avoid the mistakes as documented in the Kodak corporations continued investments in camera film technology instead of investing in digital camera technology, even though digital cameras were invented at Kodak. Financial adjustments focused on exploration rather than exploitation are particularly beneficial for financial performance during periods of technological turbulence (*The Innovator's Dilemma When New Technologies Cause Great Firms to Fail - Book - Faculty & Research - Harvard Business School*, n.d.).

1.4 Dissertation: A Systems-Based Approach to Innovation

The thesis of this research puts forth a new concept and framework for understanding, measuring, predicting, and managing innovation. Innovation must be framed as a complex dynamic system that exhibits life cycle and evolution. Innovation eco-systems, within research and development, should be characterized by dynamic, emergent, and evolutionary interactions of their constituent parts. Linear, cause-and-effect thinking is insufficient to predict or manage their behavior.

This dissertation introduces a unified, dynamic multi-model framework that provides a robust methodology for strategic R&D investment and portfolio management. By integrating

Systems Thinking, principles of biological evolution, and a suite of computational and statistical models, this framework moves beyond static metrics to capture the dynamic lifecycle of how ideas are born, mutate, compete, and evolve into breakthroughs.

This new framework is built upon a re-characterization of innovation not as a singular event, but as an evolutionary, multi-stage process driven by a core engine of discovery.

To ground this concept with a realistic foundation, five distinct research questions were developed for this dissertation. The five questions are:

- RQ1: Which systems thinking principles and Systems Engineering paradigms match the life cycle transition and evolutionary nature of the innovation process?
- RQ2: Can a predictive model of the life cycle transition and evolutionary nature of innovation be developed to enable better R&D policy decisions?
- RQ3: Can this model reproduce the known dynamics of well-known innovations?
- RQ4: How can we gain confidence in the practical value of the integrated model of innovation (i.e. validation)?
- RQ5: How can we practically implement this model in large organizations to improve the culture and mental models to make better R&D policies & decisions?

These research questions were used to identify the intersection of systems thinking and innovation. (RQ1) establishes a robust conceptual framework that acknowledges innovation as a non-linear, evolutionary process rather than a simple pipeline. RQ2 and RQ3 transition this theory into a measurable tool, ensuring the work is not just abstract but capable of recreating and predicting real-world dynamics. RQ4 and RQ5, bridges the academic understanding to ensure the research results in a high-fidelity model that can transform a R&D enterprise culture decision-making in complex environments. The answers to these dissertation research questions demonstrate theoretical alignment, methodological rigor, and practical utility. They are:

- RQ1: Which systems thinking principles and SE paradigms match the life cycle transition and evolutionary nature of the innovation process?

  RA1: Based on reviewing literature on existing mental models, categorization methods, innovation metrics, patterns of behavior of major innovations and 85 years of combined professional experience with all major real-world aspects of the innovation process: there are 5 systems principles that offer excellent qualitative explanations of innovation transitions as a function of a change in Purpose, Structure, Behavior, or Use of a System. The Enterprise Systems Engineering (ESE) paradigm is used with the systems principles as the most appropriate for an R&D Enterprise.
- RQ2: Can a predictive model of the life cycle transition and evolutionary nature of innovation be developed to enable better R&D policy decisions?

  RA2: Yes, we discovered it is possible to use the MBST method to model the flow of information between the six main phases of the innovation process that allows us to move away from binary success/failure technology decisions towards dynamic resource allocation decisions that adapt with the innovation life cycle.
- RQ3: Can this model reproduce the known dynamics of well-known innovations?
  RA3: Yes, using the integrated model approach, we were able to document and match the dynamic response of highly cited research on communities of interest and the influence of Noble Prize-winning innovations.
- RQ4: How can we gain confidence in the practical value of the integrated model of innovation (i.e. validation)?

RA4: We used triangulation approach combining Historical Back-Testing, Monte-Carlo Sensitivity Analysis and 80 Years of S&T Expert feedback on simulated behavior matching real-world response.

- RQ5: How do you practically implement Dissertation findings in large organizations to improve the culture and mental models to make better R&D policies & decisions?
  RA5: I have started implementing the better way of thinking about innovation in my organization. Early indications are positive due to upper-level organizational collaborators requests for my research. It will not be possible to share most details of my real-world implementation for obvious reasons, but some abstract reflections in a last chapter of dissertation will give guidance to others who may want to put my method into practice.

The answers to the research questions demonstrates that innovation is not a stochastic accident, but a systemic process that can be modeled, predicted, and managed through the lens of Enterprise Systems Engineering. By synthesizing systems thinking principles with evolutionary dynamics, this research moves beyond descriptive theory to provide a functional, validated toolkit for R&D leadership.

1.5 Systems Thinking Framework

Systems Principles (SPs) were critical for constructing Unified Models for Innovation Forecasting and Strategy because they necessitate viewing innovation not as a linear event, but as a complex, evolving, and highly interconnected phenomenon (Rousseau, 2017). The multi-model approach, which aims to create Unified Innovation Models, explicitly uses Systems Thinking as its foundation. Specifically, the Systems Thinking Principles capture the necessary contexts of innovation by encapsulating the change in purpose, structure, behavior, use, and external events that effect various elements within a system of innovation (Shahroudi et al., n.d.). This holistic perspective counters the limitations of traditional, linear, and compartmentalized thinking, which often relies on the misguided belief that improving parts in isolation will improve the whole. Instead, the complexity of innovation requires recognizing the entirety of complex relationships, dynamics, and interdependencies that foster new ideas. The Architecture Principle reinforces this approach by stating that the purpose, structure, behavior, and use of systems mutually influence each other, implying that interfering with one factor will ripple through the others, guiding strategists to identify the best leverage points for stimulating innovation. By implementing tools rooted in SPs, such as Dynamic Causal Models and agent-based simulations that track system components like purpose, structure, behavior, and use, the Unified Model approach is a powerful tool to connect cause and effect, enabling prediction of outcomes like increased citations (the effect) by analyzing shifts in knowledge systems (the cause), thus significantly enhancing strategic foresight and optimizing resource allocation for future technology development.

1.6 Dissertation Statement and Major Contributions

As stated previously, innovation must be modeled from multiple computational systems models that frame innovation as a Complex Adaptive System to find a balance of risk of investing in science or technology from an innovation ecosystem with the probability that new innovations will be created. Innovation creation can be modeled by integrating principles of biological evolution with agent-based and dynamics system simulations. This provides a more accurate method for forecasting the progression from incremental to breakthrough and establishes a robust, systems-aware methodology for strategic R&D investment.

Innovation outcomes across science, engineering, and technology consistently exhibit behavior that is incompatible with linear models and smooth bell-shaped normal distribution statistical assumptions. Empirical evidence shows that most innovations, incremental progress, produce modest or marginal impact, while a very small number of innovations, breakthroughs, generate orders-of-magnitude changes in capability, performance, or value (Capponi et al., 2022). These rare breakthrough events dominate cumulative outcomes. This means that the average innovation is not the strongest factor in how a field of science, technology or engineering progresses. The property of heavy-tailed behavior or Black-Swan events in innovation can be observed in citation distributions, patent values, economic returns, and historical technological discontinuities (Anderson et al., 2017). Complex systems with heavy tailed distributions show that variance is not noise, it is a defining structural feature. Normal Gaussian models, of innovation citation patterns, fail to accurately predict black-swan events because they assume symmetry and finite variance, with rapidly vanishing probabilities for extreme events. Complex innovation systems violate these assumptions due to upside deviations being far larger than downside deviations in which extreme events matter more than typical ones and effects compound multiplicatively in feedback rather than additively. If innovation outcomes were Gaussian, breakthroughs would be predictable around a mean trend, and incremental improvements would dominate long-term impact. Historical evidence shows the opposite. Breakthroughs are not anomalies; they are the mechanism through which scientific, technological, and engineered systems advance.

Because of this empirical evidence, this research introduces several major contributions to Systems Dynamics to build a Unified Innovation Model approach which encompasses the probabilities of fostering and predicting Breakthrough innovations:

- A Six-Level Evolutionary framework: This dissertation proposes a novel six-level hierarchy that defines innovation as an evolutionary continuum: Incremental → Modular → Architectural → Radical → Disruptive → Breakthrough. This framework models innovation as a cumulative sequence, where early-stage innovations create the necessary conditions for the emergence of more complex, advanced forms.
- The Dynamic Multi-Model CAS Framework: The research integrates multiple computational lenses to model innovation *as* a Complex Adaptive System, exhibiting irregularities, competition, and selection. This framework blends the following components:
    - Biological Evolution (Genetic Algorithms): Innovation is modeled as an evolutionary process. Genetic Algorithms (GAs) simulate the "natural selection" of ideas based on measurable attributes (e.g., rigor, innovativeness, validity, impact) to determine which "innovations" survive, combine, and evolve.
    - Causal Inference and System Dynamics: The work uses causal inference (including Directed Acyclic Graphs) to move beyond correlation and isolate the specific systemic feedback drivers (e.g., changes in purpose, structure, and behavior) that propel innovative outcomes.
    - Agent-Based Modeling (ABM): An ABM is utilized to simulate the emergent behavior of innovation diffusion, modeling how ideas (from incremental to

breakthrough) spread through a population of interacting researchers and how adoption dynamics change over time.

  - Probabilistic and Time Series Analysis: The framework integrates quantitative tools, including the Bass diffusion model (S-curve adoption archetypes), Granger Causality (to confirm the temporal cascade of innovation types), and Monte Carlo simulations (for uncertainty analysis), into a single, dynamic system.
  - Innovation Motive Force (IMF): A dynamic systems-causal framework integrating EMF analogy, Bayesian learning, Diffusion, Divergence, and Dynamic Causal Inference for Modeling innovation in an enterprise system (Efron, 2013).

This research in Enterprise System Engineering postulates and uses the concept of Evolving Probability Distributions (EPDs) as dynamic states which represents a paradigm shift from viewing uncertainty in probability theory as random static noise to treating it as a time-varying feature of a system's internal structure (Eberle & Marinelli, 2013).

1.7 Impact and Dissertation Structure

This dissertation provides evidence for a deep structural parallel in how information and influence propagate through a population to be used for engineering an R&D enterprise system. The mathematical formulation of Bayes' Theorem about belief revision and the Bass Model about market adoption is presented. They both describe a transition from "unknown" to "known" mediated by the weight of evidence. This understanding is needed for Enterprise System Engineering to determine the best levers to balance risk and probability of innovation in a R&D ecosystem. In this dissertation, a R&D enterprise is treated as a knowledge-processing engine. In this framework, citations and patents are not just administrative markers; they are used as evidence that reduce the uncertainty of a research contribution or a technology's viability.

The main component in understanding the patterns of citations, patents, or research requests is recognition and utilization of the S- Curve or Sigmoid function. In the context of this dissertation, the Sigmoid Function is more than just a shape; it is the mathematical signature of a system transitioning from one stable state to another through a process of feedback and constraint. The S-curve emerges in both dynamic Bayes models and Bass Innovation diffusion models due to how they handle the rate of change as more information enters a system over time.

The standard Sigmoid function, often called the Logistic Function, is defined by the following formula:

$$S(t) = \frac{L}{1+e^{-k(t-t_0)}} \tag{1}$$

The variable L is the Carrying Capacity. It is the maximum value of the curve. It is the 100% adoption or a probability of 1.0 for adoption. The variable k is the Growth Rate and is the steepness of the curve. The variable t_0 is the Inflection Point which is the horizontal center of the S-curve, where the rate of change shifts from acceleration to deceleration.

A linkage was developed with the Sigmoid function for system processes of a research enterprise and the output of a Pareto distribution power law function. By integrating a new metric developed in this dissertation, the Innovation Procreation number ($IP^{0)}$, the procreative potential, it is possible to recreate the S-curve pattern and thus calculate a Pareto distribution for recognizing Breakthrough research. IP^0 is defined as the ratio of citations generated by innovative research or technology projects to the initial research or technology project over time. IP^0 is essentially the reproductive number of an innovation. An IP^0 below 1.0 means the idea is stagnant. It will eventually disappear. An IP^0 above 1.0 indicates a "viral" spread and adoption of the innovation. Different levels of innovation carry different procreative potentials. Incremental changes have low IP^0. Breakthroughs have large procreative potential as analyzed from citation patterns of Nobel Prize research. They can create thousands of imitators of research from a single innovative research publication.

The equation for IP^0 is:

$$IP^0 = \frac{citations\ of\ inital\ \ research}{initital\ research \times time} \tag{2}$$

The linkage to the Sigmoid function S-curve is shown as:

$$S(t) = \frac{L}{1+e^{-IP^0(t)}} \tag{3}$$

where k (The Growth Rate) for the sigmoid function defines the steepness of the curve, is now driven by IP^0.

The output of an enterprise system is defined in terms of a Pareto distribution in which, from observations of citation patterns, 80% of citations generated within a specified community of interest, is done by 20% of impactful research. This exhibits a power law behavior that can be used to simulate extreme events that have high impacts such as the creation of a "Breakthrough" innovation as defined in this dissertation. The relation of IP^0 to the power law is shown as:

$$\mathrm{y} = Ax^{-\alpha} \tag{4}$$

where the relationship between the scaling exponent α and the procreative rate IP^0 can be derived from the "Master Equation" of network growth in which the nodes of connectivity are researchers and their papers (Zhou & Mondragón, 2004). Defining η as the efficiency of knowledge transfer, a Bayesian Likelihood, the relation is:

$$\alpha = 1 + \frac{1}{\eta \times IP^0} \tag{5}$$

The Power Law states that the more followers an idea has, the easier it is to get even more. If an idea has a high IP^0, the research idea is adopted at a high rate to create a large "Following" in a network of researchers in a community of interest.

This is seen as the desired output of a R&D enterprise designed to create and deliver game changing disruptive innovations in a timely manner. A requirement for Enterprise Systems Engineering of a R&D ecosystem is to create the environment for "Impactful" research, you don't need lots of small ideas. You need idea's with very high IP^0s that flatten a Power Law's heavy tail and turn into advancements that change the paradigm of a desired capability.

By integrating the S-curve from Bass diffusion, Bayesian updating, 80/20 Pareto distribution analysis, and Power Law behavior, this dissertation shows how groups of people change their minds in relation to new information. This S-curve validates that Bayesian agents behave realistically. They are being convinced by the cumulative weight of the evidence of innovation.

This dissertation's findings confirm that breakthroughs are not isolated events but are the result of an evolutionary progression, emerging from systemic complexity and spreading through networks. The integration of these methodologies provides a powerful lens for understanding innovation as a dynamic, interrelated system, moving beyond mere frequency counts to explore causality, timing, and structural emergence. Ultimately, this research provides a foundation for more robust investment strategies and a vital decision-support tool for policymakers. By quantifying the evolutionary behavior of research and identifying key systemic leveraging points, this framework enables organizations to strategically manage their research portfolios, balance exploration with exploitation, and foster the sustained breakthroughs that drive technological progress.

This dissertation develops a suite of six management simulators to assist with this endeavor that are derived from the analytical framework presented in three papers submitted for publication. These are the 5 management simulators:

1. Innovation Portfolio Resource-Allocation Simulator
2. Idea Mutation & Evolution Trajectory Simulator
3. Citation-Based Early Breakthrough Detection Simulator
4. Scientific Method Cycle Efficiency Simulator
5. Innovation Motive Force (IMF), Return on Investment (ROI), Risk–Reward Simulator

These original models integrate idea mutation dynamics, Bass diffusion processes, Bayesian learning, Kullback–Leibler (KL) divergence, and citation-based empirical anchoring (Impraimakis, 2024). This work operationalizes theory into applied decision-support tools designed for research management, policy planning, and strategic investment across science and technology (S&T) ecosystems. Each simulator is presented with its purpose, mathematical foundation, operational interface, and decision-making advantages. Collectively, the simulators demonstrate how system-dynamics–based innovation theory can be translated into real-time, interactive tools for optimizing research portfolios and forecasting emerging scientific opportunities.

CHAPTER 2: LITERATURE REVIEW AND THEORETICAL FOUNDATIONS

2.1 Theoretical Framework and Methodological Approach: Innovation as a Complex Adaptive System

To effectively manage the risk and prediction of innovation, innovation must be reframed. Instead of using a simple predictable production line mentality to understand innovation, innovation should be understood as a dynamic, living ecosystem where ideas evolve in response to their environment. This perspective is essential for understanding how a series of minor, incremental improvements can cascade into transformative, paradigm shifting breakthroughs. Understanding innovation as dynamic allows us to see the hidden connections and feedback loops that govern the entire innovation lifecycle. This dissertation adopts this perspective, combined with a multi-faceted theoretical framework rooted in biological evolution, to model and predict breakthrough innovations. By recognizing that innovating is a dynamic, complex process rather than a linear or isolated event, this research integrates five computational and theoretical lenses into a Unified Innovation Multi Model concept (Durán, 2020).

2.2 The Unified Innovation Multi-Mode Concept: An Integrated Systems Approach

The core motivation for this approach is the recognition that existing conventional models such as citation counts, patent counts, financial spread sheets, or frameworks like the Henderson-Clark model, often fail to capture the holistic, non-linear dynamics of innovation, especially breakthrough advancements. The complex nature of innovation creation involves human behaviors, resource availability, organizational capabilities, and researcher economic factors, interacting dynamically in nonlinear ways.

To address this challenge, a “Unified Dynamic Innovation Multi-Model concept” was created in this dissertation that systematically blends:

1. Bass Diffusion Models: Which are used to model the adoption rate of innovations and map the acceptance archetypes of innovative research using S-curves derived from citation patterns.
2. Causal Inference Models: Employed to establish causation over correlation by isolating the non-linear systemic factors, quantified by changes in research purpose, structure, and behavior, or use that truly drive the adoption of an innovation.
3. Genetic Algorithms (GAs): Utilized to model innovation as an evolutionary process and optimize measurable attribute like chromosomes of innovative research for fitness (Whitley, 1994).
4. Agent-Based Models (ABMs): To formalizes the rules from other models into a simulation environment to observe the adoption, life cycle, and evolution of innovation through the dynamic, emergent behaviors of interacting agents in a community of interest (Antelmi et al., 2023).
5. Monte Carlo Methods: Executed with MATLAB simulations to give stochastic scenario analysis, sensitivity tests, and the quantification of uncertainty and potential return on investment (ROI).
6. System Dynamic Models: To simulate a innovation ecosystems, framed as a voltage-based metaphor that is used to draw a systems analogy between Innovation Motive Force

(IMF) and electric potential or Electromotive Force (EMF), and the flow of ideas, knowledge, and inventions in a research and development enterprise innovation ecosystem (Durán, 2020).

7. Bayesian Probabilistic Inference: Applying Bayes' Theorem allows the move beyond simple citation counts to the quantification of the predictive power of citation patterns. This means not looking at how many citations an idea has, but calculating the probability that an idea represents a true innovation based on the evidence provided by its citation performance over time (Berrar, 2018).

This systematic workflow, using archetypal analysis to causal modeling, evolutionary optimization, and dynamic simulation, ensures a full-spectrum evaluation of innovation performance, attribute sensitivity, and predicted investment returns.

2.3 The Six-Level Evolutionary Framework of Innovation

A central component of this research is the definition and application of a six-level model of innovation that structures the continuum of idea, technological, and research advancement. This model proposes that innovations follow a sequential, cumulative, and hierarchical life cycle, where earlier stages form the necessary groundwork for later, more complex breakthroughs.

The six defined levels of innovation are:

1. Incremental Innovations: Characterized by small, continuous improvements made to existing research, products, processes, or technology paradigms. These tend to be easier to implement, require fewer resources, and face less resistance.

2. Modular Innovations: Involve significant changes to one or more components of previous research or elements of technology without altering the overall architecture.

3. Architectural Innovations: Focus on the reconfiguration of the way various mathematical models are used in, how they interact, or how technology components of a system fit together. This marks a shift toward system-level changes.

4. Radical Innovations: Represent a paradigm shift of research scientific models or the development of entirely new models that revolutionize a field. These introduce fundamentally new technologies or approaches.

5. Disruptive Innovations: Challenge and eventually displace established research or drastically alter existing system models. These often begin modestly, targeting niche areas of science and technology advancement.

6. Breakthrough Innovations: Represent monumental leaps that redefine the theoretical landscape of the understanding of a research area, driving entirely new scientific models, technologies and transformative game changing capabilities.

This six-level framework moves beyond models typically focused solely on business, like Henderson-Clark's, by specifically incorporating the need for Breakthrough science and technology that are desired in sectors like the Department of War. This new model of innovation evolution and life cycle is the underpinning of balancing risk of innovation investment with the probability of innovating and is based on these Systems Principles:

- Principle 1: Foundation of Change

  Systems principle: Emergence

  Innovations arise when a system’s purpose, structure, behavior, or use shifts. These changes create emergent properties, outcomes that cannot be reduced to their parts, providing the spark for the next step in the innovation cycle.

- Principle 2: Path Dependence and Cumulative Building

  Systems principle: Interconnectedness & Path Dependence

  Each stage of innovation is built upon earlier stages. Incremental improvements form the basis for modular advances, which enable architectural restructuring, radical change, and eventually disruptive or breakthrough transformations. This reflects the way system elements are path-dependent and cumulative.

- Principle 3: Feedback and Recursion

  Systems principle: Feedback Loops

  Innovation evolves through recursive feedback, not linear progression. Later stages influence earlier ones, with breakthroughs reshaping incremental refinements and disruptions cascading back through the system. This mirrors how reinforcing and balancing loops regulate system behavior. This intrinsic evolution produces emergent behaviors that cannot be anticipated from earlier stages alone, reflecting the tendency of complex systems to grow in scope, connectivity, and unpredictability as they develop.

- Principle 4: Intrinsic Evolution due to Complexity

  Systems principle: Hierarchy & Expanding Boundaries

  As innovation advances, the scope and complexity of research grow. Higher stages draw on lower stages creating more research elements, thus producing unpredictable interactions, consistent with the systems principle that hierarchies expand, and boundaries shift as complexity grows. Boundaries widen to encompass broader ideas with the number and diversity of research areas increasing. This means previous research can become interdependent in new ways.

- Principle 5: Human-Centered Drivers as Sources

  Systems principle: Mental Models & Purpose

  At every stage, innovation is powered by human drivers, ideas, needs, and wisdom. These provide purpose and renewal for the system, while breakthroughs reset and redirect the cycle. This ties to the systems principle that all systems are shaped by human intentions and mental models. The five Systems Principles are the foundation on which a new model of innovation evolution and life cycle is based shown in Figure (2).

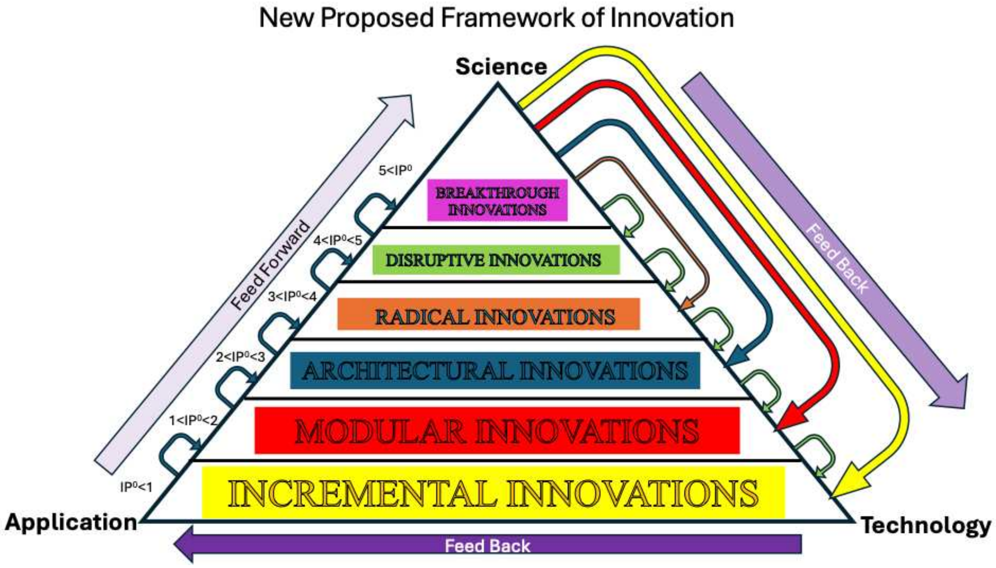


Figure (2). This is the Pyramid of Innovation. IP^0 is a theoretical concept. It is labeled “Innovation Procreation”. The higher the number, the more people adopt the Innovation. It is like R^0 in epidemiology.

The figure illustrates a conceptual model and is proposed as a new thinking framework of innovation. It uses a triangular pyramid structure to represent the foundation and structure of innovations based on innovation types with their relationship to Science, Technology, and Application. Most existing innovation models with categories tend to present innovation as a linear or static progression that moves from one stage to another without accounting for feedback or evolution. Traditional frameworks of innovation often treat incremental, modular, architectural, radical, disruptive, and breakthrough innovations as distinct and independent types. Most, if not all present frameworks of innovation do not consider these types of innovation as interconnected phases within a dynamic system. This oversimplification misses how real-world innovation unfolds, through cycles of refinement, feedback, and adaptation, where new developments reshape the conditions for future change.

It has been shown that in practice, innovation rarely follows a one-way path; it evolves through recursive learning, integration of past advances, and the reconfiguration of ideas to meet emerging needs. The most common type of innovation is small, steady improvements to existing components. As an example, the difference between a 2.8 GHz Pentium 4 processor and a 3.0 GHz Pentium 4 processor is a classic incremental innovation. It's the same basic component and architecture, just made slightly faster and more efficient. A modular innovation is when a core component is changed, but the system's linkages, i.e. the architecture, stay the same. The internal technology of a solid-state drive (SSD) is completely different from a spinning-platter hard disk drive (HDD). However, it was designed to fit the same architecture of a personal computer. Architectural innovation is when existing components are linked together in a new way, changing the system's architecture. IBM's innovation was architectural when they created an open standard architecture that defined how non-proprietary components would link together. This new architecture spawned the entire "PC clone" industry and established the Wintel (Windows-Intel) dominance that has lasted for decades. Disruptive innovations are when a technology or scientific paper enters science or engineering discipline and displaces present known capabilities. The PC was a disruptive innovation that first captured the low-end hobbyists and small businesses. As the

PC improved, it eventually replaced the minicomputer market that was dominated by Digital Equipment Corporation (DEC). The breakthrough was connecting all PC's together on an internet. This changed the world we live in.

The takeover by the PC could have been predicted from models that incorporated the incremental, modular, architectural, and radical improvements that are governed by Moore's Law. Heavy-tailed rare breakthrough events should be modeled as emergent outcomes of system structure rather than as arbitrary randomness. In a dynamically modeled innovation system, stochasticity becomes consequential when an innovation eco-system is primed through accumulated knowledge, institutional readiness, and reduced structural resistance. Random variation alone does not generate breakthroughs. Instead, randomness acts as a trigger that can amplify accumulated disruptive knowledge into transformational change when conditions are favorable. This distinction reframes uncertainty as conditional rather than ubiquitous. Pareto or power-law distributions which exhibit heave-tailed predictive behavior, provide a mathematically appropriate representation of this. Unlike Gaussian distributions, Pareto distributions have no characteristic scale and assign non-negligible probability to extreme outcomes. In such distributions, a shape parameter governs tail thickness, determining how likely large events are relative to small ones. In the IMF framework of this dissertation, this parameter is endogenous and linked to institutional resistance. Resistance can eliminate breakthroughs and reshape their probability distribution. Lower resistance thickens the tail, increasing both the likelihood and magnitude of extreme events without guaranteeing them. This aligns with empirical observations that organizational reforms do not produce breakthroughs on demand, but they can significantly alter the odds in their favor.

Modeling breakthroughs with heavy-tailed distributions is essential for realistic decision-making and calculating the risk of investing in innovative activities. In heavy-tailed R&D systems, averages are misleading, diversification behaves differently, and small structural changes can produce outsized consequences in the future. Gaussian assumptions bias management toward predictability and incremental optimization, encourages risk aversion and underinvestment in exploratory work. Pareto heavy-tailed assumptions can highlight the value of optionality, variance management, and structural readiness. It shifts the managerial objective from forecasting specific outcomes to shaping the distribution of possible futures.

The six-stage innovation pipeline provides the structural backbone that allows heavy-tailed breakthroughs to emerge in a disciplined and causally interpretable way. Innovation is treated as an evolutionary process rather than a sequence of isolated projects. Each stage represents a qualitative shift in knowledge integration, uncertainty, institutional resistance, and potential impact. These stages are not arbitrary labels; they correspond to increasing levels of systemic coupling, which fundamentally change how ideas behave and are adopted as they mature.

The new model of innovation could reshape innovation theory. It is important to state that these innovation categories of classification are not a linear evolutionary path that a single product follows. This innovation framework implies innovation evolve from being incremental into being modular, then architectural, and so on with feedback at each stage of innovation. A technology platform will experience all these different types of innovation at various points in its life cycle. A comparison of this evolutionary model with the standard literature model is as follows:

- The Henderson-Clark model gives us Incremental, Modular, Architectural**,** and Radical. These describe the technological nature of change at a single point in time, not cause of change or evolution of where the change came from.

- Disruptive innovation, from Clayton Christensen, is a market phenomenon. It describes how an innovation enters a market and displaces incumbents. This model does not explain the cause of the disruptive innovation or the possible life cycle on improving the innovation into a breakthrough.
- In present literature, Breakthrough innovations are a more general term for innovations with a very high, game-changing impact, often synonymous with Radical and Disruptive innovations in literature. Breakthroughs are not listed in the Henderson-Clark or Clayton Christensen models of innovation.

One way to justify the efficacy of this dissertation's new model of innovation is to take a technology and identify how it experienced each of these types of innovation. Once again, the personal computer is a classic and clear example.

To illustrate the feed forward and feedback nature between innovation levels, a causal model was developed from recognizing innovation as a cumulative, iterative, and regenerative process. This model provides a more accurate and system-oriented understanding of how breakthroughs emerge from feedback on previous innovations. The causal loop diagram depicting the new model is shown in Figure (3). This causal loop diagram illustrates the evolution and life cycle of innovation as a dynamic system. The process begins with Ideas, Needs, and Wisdom, which generate Incremental innovations. These progress forward (green arrows) into Modular, Architectural, Radical, Disruptive, and Breakthrough innovations, each representing increasing levels of novelty and systemic impact. Breakthrough innovations complete the cycle by feeding back into the pool of new ideas, restarting the process. Alongside this forward progression, feedback loops (red arrows) show how higher-level innovations influence or revert to earlier stages, ensuring that learning and knowledge are recycled rather than lost. Together, the forward and feedback loops create a self-reinforcing cycle where innovation is both evolutionary and recursive, balancing progress with continuous adaptation. The causal loop diagram was used as a foundation of how to build a dynamic model that incorporates the Bass Diffusion framework for innovation adoption and replication over time.

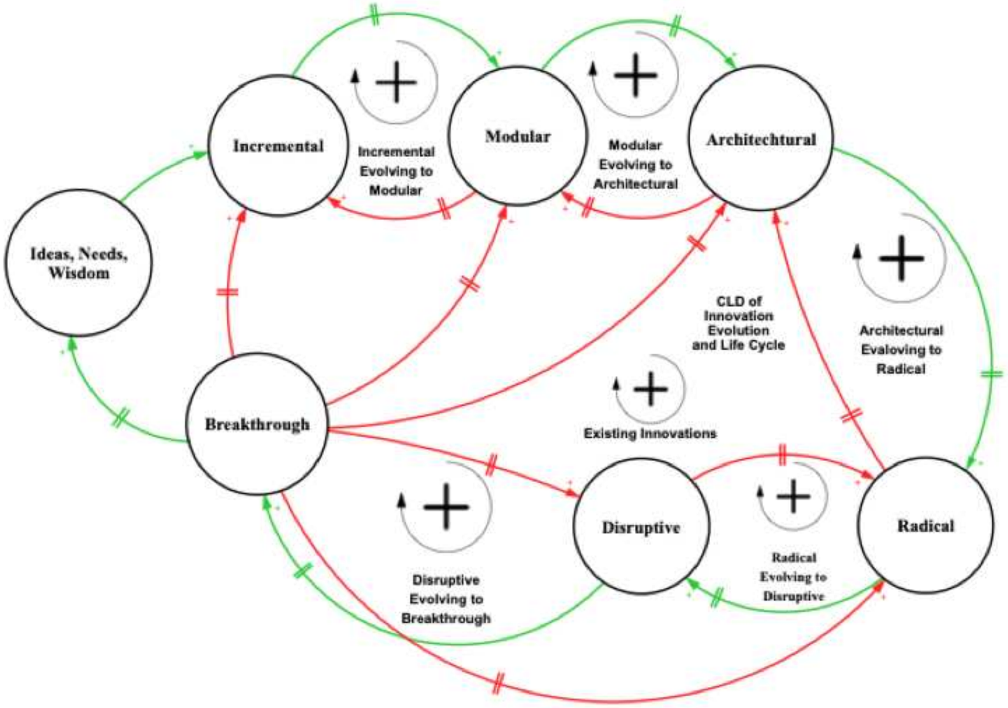


Figure (3). This diagram is a Causal Loop Diagram (CLD) showing the life cycle of innovation across six stages.

Unlike the linear Innovation models, this visualization highlights the reinforcing loops (+) that drive the evolution from one level to the next.

An innovation diffusion model, developed by Frank Bass, was used to describe adoption as the result of two key forces, innovation and imitation (Orbach, 2016). The innovation effect, represented by the coefficient *p*, captures adoption driven by external influences such as marketing, media, or policy, where individuals adopt without relying on prior adopters. The imitation effect, represented by the coefficient *q*, reflects adoption driven by social contagion, where potential adopters are influenced by those who have already adopted. Together, these forces generate the characteristic S-shaped adoption curve, seen in Figure (4), where early adoption starts slowly, accelerates as imitation spreads, and eventually tapers off as the market saturates. The Bass model is widely used in technology management, marketing, and policy to forecast product diffusion, evaluate innovation strategies, and inform investment decisions (Horvat et al., 2020). Its strength lies in its balance of simplicity and explanatory power, making it a bridge between theoretical models of innovation and practical forecasting tools.

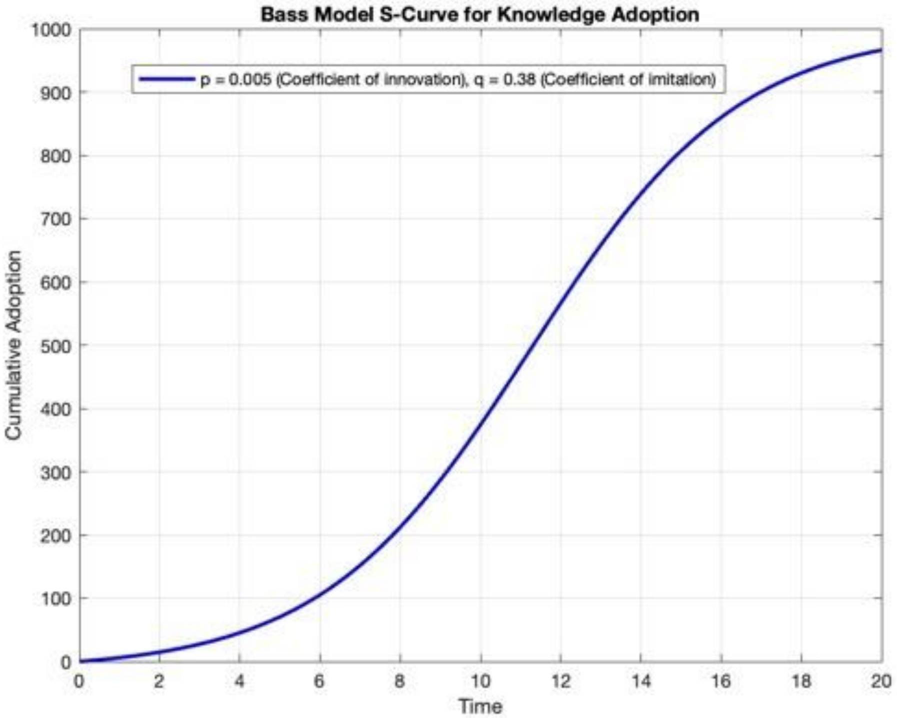


Figure (4). The plot illustrates the Bass Model S-curve for knowledge adoption over time. The x-axis represents time, while the y-axis shows the cumulative adoption.

The Bass Diffusion model shown in Figure (4) was used as the foundation for mathematically simulating adoption across the six stages of innovation, Incremental, Modular, Architectural, Radical, Disruptive, and Breakthrough. By embedding Bass dynamics within each stage, the pipeline became a structural representation of innovation flow and a dynamic adoption system. This allowed simulation of stage-specific adoption, delays, and feedback, where p and q act as tunable parameters linked to absorptive capacity, policy pressures, amount of change in purpose, structure, behavior, or use, and external drivers. The result is a multi-layered diffusion process capable of capturing both the cumulative path dependent nature of innovation, innovation evolution, and the nonlinear adoption dynamics that is seen in real-world innovation ecosystem environments. An example of this process as seen in real world innovation ecosystems is the adoption and continuous evolution of the smart phone.

2.4 Innovation as Biological Evolution

As mentioned previously, in this dissertation, innovation is conceptualized as an evolutionary process akin to nature, exhibiting irregularities, competitiveness, and adaptive qualities (Stewart, 2003). This perspective views technological advancement as driven by iteration and natural selection, where beneficial ideas survive and spread while less useful one's fade.

This dissertation conceptualizes innovation as:

- Mutation and Selection: Innovation is modeled as a series of iterative mutations, like those observed in viruses, where modification leads to shifts in functionality and competitive advantage.
- Genetic Algorithms: To simulate this evolution, Genetic Algorithms (GAs) apply natural selection concepts to quantifiable innovation characteristics. Eight core attributes of innovation, Clarity, Relevance, Rigor, Innovativeness, Validity, Reliability, Transparency, and Impact, are encoded as chromosomes. The GA optimizes these traits based on the dual

objectives of maximizing the total attribute score (performance) and controlling the variance (differences).

The intrinsic evolution process produces emergent behaviors from earlier stages. This results in new research element connectivity, and unpredictability. The framework that innovation is an evolutionary process, where modifications in existing research are incremental through breakthrough and drive entirely new forms of innovations, was used. The representation of innovation as an evolution model allowed for the application of genetic algorithms as a computational tool (Katoch et al., 2021). Genetic algorithms have been developed to mimic biological evolution in complex systems. The genetic algorithm computational workflow, shown in Figure (5), was used. The genetic algorithm simulates the spread of successful organisms due to their strengths for survival that incorporate mutation of the organism. This evolution theory was extended to the concept of the spread of ideas or innovative published research. As proven by the Bass diffusion model, successful products or technologies spread rapidly through populations. This is akin to how some very contagious viruses spread through a host population.

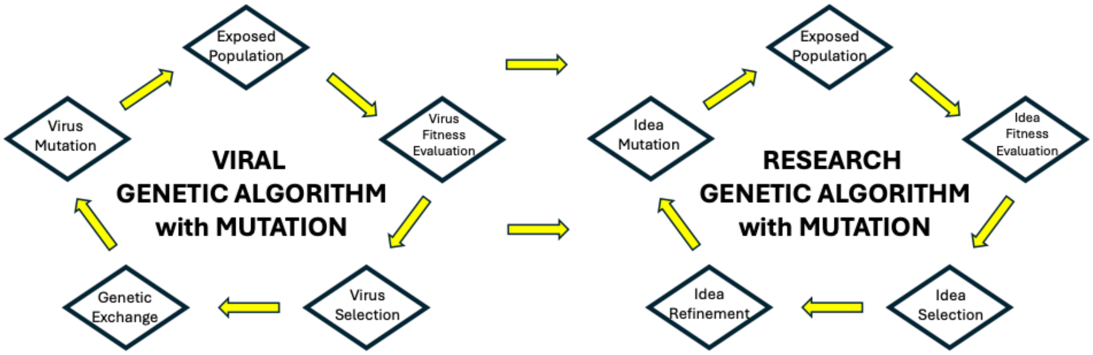


Figure (5). This is the framework for mimicking research mutation with viral mutation. This is a correlation of Viral Genetic Algorithm with Research Ideas Genetic Algorithm.

The genetic algorithm used for this dissertation, simulated the adoption of research due to the strength of the research adoptability within a community according to the evolutionary process of mutation of the research and its replication probability. Figure (6) shows the categorical distribution of each of the six categories of innovation from initial research that has high adoptability for Incremental innovative advancements. Figure (7) shows the computed adoption percentages, modeled in MATLAB, from a population of one thousand researchers working in the same field as the innovative research. The algorithm calculated that most of a population's adoption occurs at the incremental level. The genetic algorithm's values are only at one instant in time and represent feed forward mutation and adoption of research. The percentages for each category of innovation were used as the conditional probability values for a dynamic innovation diffusion model that incorporated feed forward and feedback causal relationships.

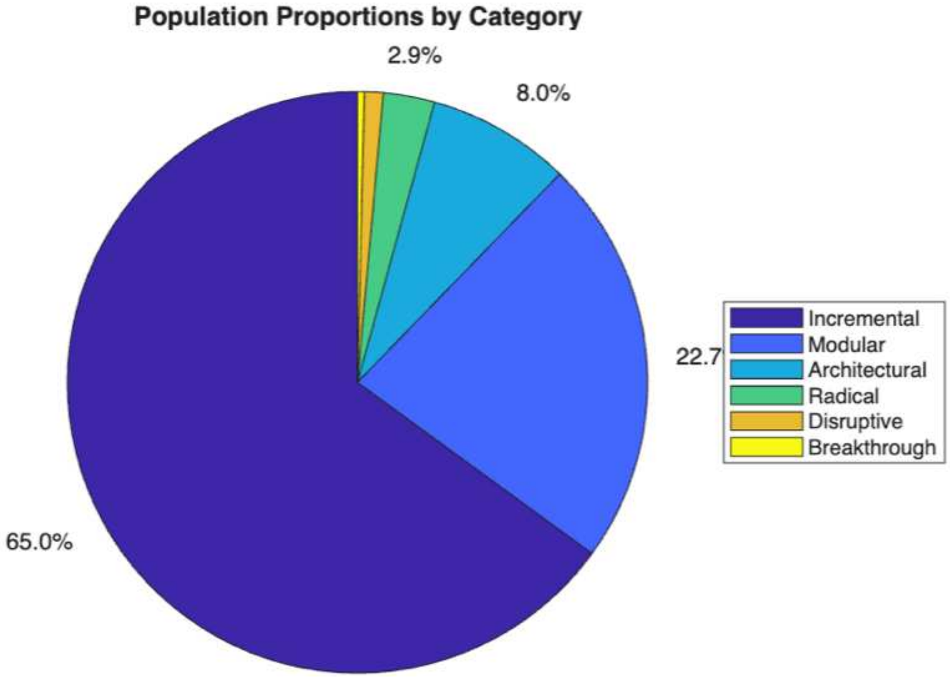


Figure (6). Genetic Algorithm calculations of innovation distributions in a population of adopted research spread.

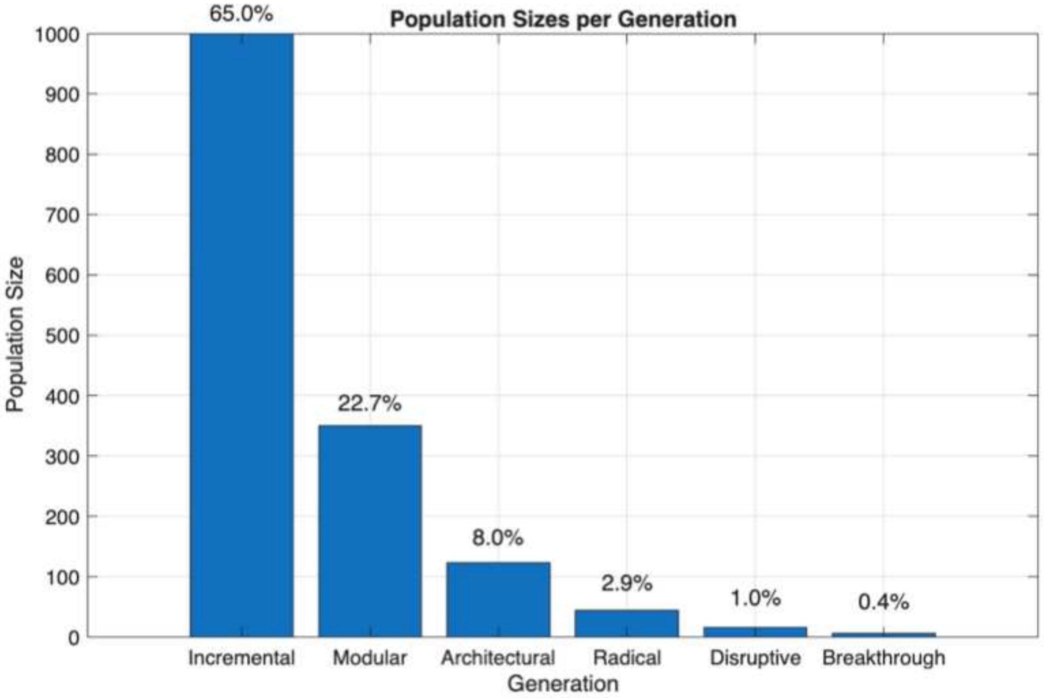


Figure (7). Genetic algorithm output of percentage of population adopting new innovative research that started as a incremental innovative idea.

Figure (7) shows the population sizes thinning of innovation. While 65% of ideas remain at the Incremental level, only a tiny fraction (0.4%) possesses the fitness required to evolve into a Breakthrough.

The new framework of innovation with evolution from idea mutation feed forwards and feedback was structured into the six progressive categories, Incremental, Modular, Architectural, Radical, Disruptive, and Breakthrough. Genetic modeling frames innovative ideas as emerging from Needs, and Wisdom, which are then filtered through four dimensions of present ideas, changes of Purpose, Structure, Behavior, and Use. These dimensions form the basis of how innovations are assessed and modified. Any transformation in these areas can lead to different categories of innovation. A diagram of the evolution and life cycle of innovation, driven by the mutation of ideas, is shown in Figure (8).

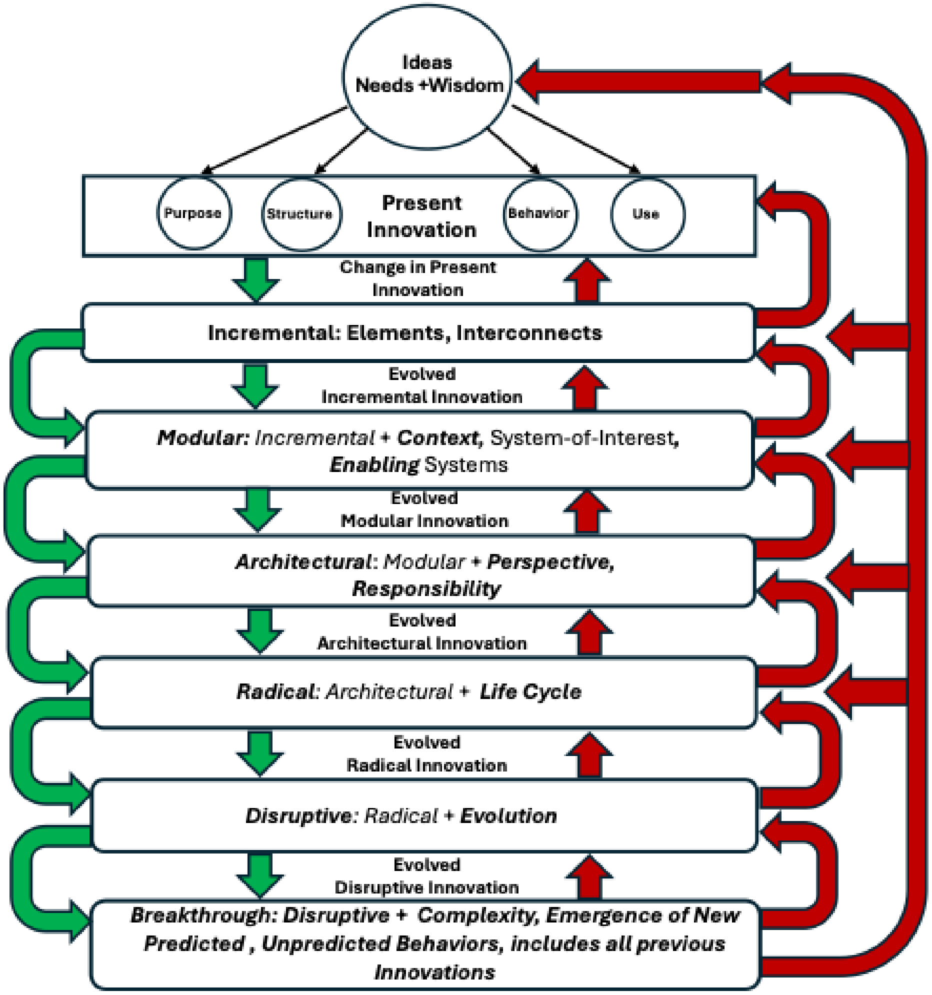


Figure (8). Diagram of innovation as a dynamic systems-driven evolutionary cascade with feedback.

Figure (8) illustrates the innovation pathways and feedback mechanisms, showing how incremental refinements progressively lead to higher levels of innovation. Incremental innovation begins with small improvements to existing products and processes, often realized through continuous refinements, which in turn lay the foundation for modular innovation. At the modular stage, these improvements are expanded by introducing context, system-of-interest considerations, and enabling systems, with emphasis on recombining components and modular upgrades.

Architectural innovation advances this further by altering the overall design and configuration of systems, enabling new functionalities and requiring shifts in perspective and responsibility. Radical innovation emerges when fundamental principles or paradigms are transformed, creating life cycle changes and groundbreaking advancements. Disruptive innovation then reshapes entire industries or research areas by introducing new principles or technologies that displace established systems and norms. Ultimately, breakthrough innovation evolves from disruptive forces, producing entirely new standards and paradigms characterized by complexity, unpredictability, and novel behaviors not previously envisioned. Together, these pathways demonstrate how innovation is cumulative and dynamic, building layer by layer toward transformative change.

Feedback loops are a continuous process by which the results of one stage can influence and shape a previous stage of innovation. The feedback Loops in Figure (8), illustrate the essential feedback within the innovation cycle. This demonstrates that innovation is never a one directional or finite process. Each stage of innovation from incremental, modular, architectural, radical, disruptive, and breakthrough, feeds the broader system of change in purpose, structure, behavior, and use. This feedback mechanism highlights innovation as a nonlinear, iterative process where progress at one level reshapes the conditions for future advancements. As innovations mutate and evolve, they generate new ideas, redefine needs, and shift perspectives, which in turn stimulate the next wave of development. Rather than closing a cycle, each feedback loop ensures continuity, adaptability, and renewal, allowing the system to learn from past changes and integrate them into future pathways. This recursive dynamic underscores that innovation is both cumulative and regenerative, with every advancement contributing to the evolution of ongoing transformation.

2.5 Causal Mechanisms and System Dynamics

To understand why innovation occurs, this dissertation moves beyond traditional correlation metrics like citation counts, which capture a limited aspect of adoption, toward establishing causality.

The causal methods used in this dissertation are:

- Causal Inference: The dissertation utilizes Causal Inference theory, which is instrumental in isolating variables that truly drive innovative output. This methodology employs techniques like observational studies and statistical methods to manage confounding variables.
- Mediation**:** A central causal model, framed using Systems Thinking principles, posits that the relationship between research publication and their adoption, measured by citation patterns, is mediated by changes or mutation of previous research. Specifically, the factors causing innovation are framed as the change in purpose, structure, behavior, or use of the research from individuals or organization ecosystems.
- Dynamic Modeling: Dynamic models incorporate changes in variables and their relationships over time, capturing the temporal aspects necessary for effective innovation forecasting and planning. The use of tools like Bayesian Structural Time-Series (BSTS) models (e.g., implemented in the R package CausalImpact) allowed for counterfactual prediction, simulating what the adoption trajectory of citations, would have been in the absence of a specific innovative intervention.

A causal model was theorized for this article in which the change in structure, purpose, and behavior are all mediators of research and the citations the research receives. The Directed Acyclic

Graph (DAG) is shown in Figure (9) where the adoption of research is mediated by the change in purpose, structure, or behavior of previous research. Mediation analysis was used to explore the direct effect of publishing research on citation patterns and the indirect effect of the change in the published research purpose, structure, or behavior on citation patterns as a cause of innovation (Pearl, 2012).

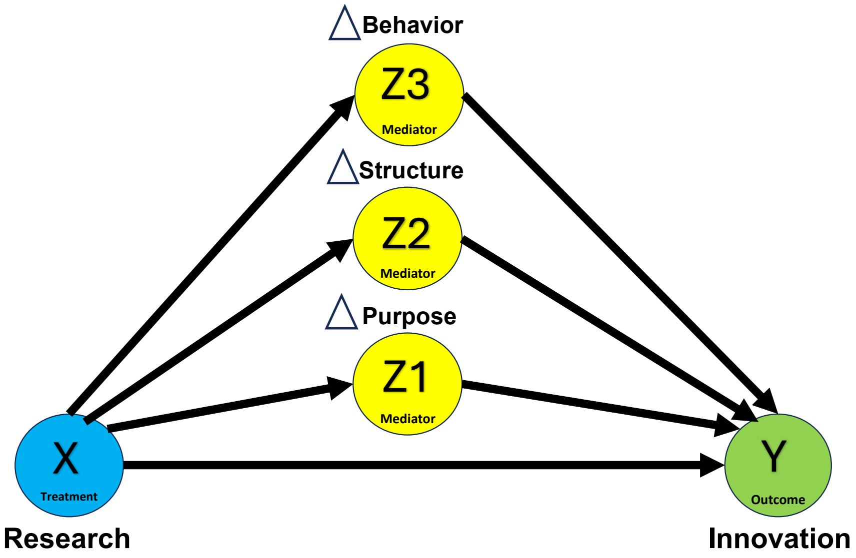


Figure (9). DAG model of Innovation: A system is more than the sum of its parts: Elements, Interconnects and Behavior with change in Purpose, Structure and Behavior the cause of Innovation.

It has also been shown that the mediation analysis shown in Figure (9) can be used as a statistical approach to explore how an independent variable can influence a dependent variable through a mediator variable (Tingley et al., 2014). This analysis helped in understanding both the direct effects of the independent variables on the dependent variable and the indirect effects that operate through the mediator. This type of analysis is used in fields like medical testing, pharmaceutical trials, psychology, sociology, and economics, where complex relationships between variables are common. For instance, a researcher might be interested in not only whether a training program (independent variable) improves employee productivity (dependent variable) but also how it affects productivity through changes in employee morale, the mediator. By using mediation analysis, a researcher can quantify the direct impact of the training on productivity while also assessing the indirect impact via morale. This comprehensive approach provides a deeper insight into the causal mechanisms of innovation to inform more accurate assessments of the probability of inventing.

A Structural Equation Model (SCM) was made to represent the causal diagram shown in Figure (9). The SCM is shown as:

$$X := f_X(U_x) \tag{6}$$

$$Z_1 := f_{Z1}(X, U_{z1}), \tag{7}$$

$$Z_2 := f_{Z2}(X, U_{z2}), \tag{8}$$

$$Z_3 := f_{Z3}(X, U_{z3}), \tag{9}$$

$$Y := f_Y(X, Z_1, Z_{2,} Z_{3,} U_Y) \tag{10}$$

$where\ U_x, U_{z1}, U_{z2}, U_{z3}, U_y$ are unobserved and unconfounded variables.

The counterfactual definition for the indirect effect of the mediators represented by change in Purpose, Structure, or Behavior is shown in Equation (11):

$$IE_{x,x'}(Y) = E[f_Y(X, f_{Z1}(x', U_{z1}), f_{Z2}(x', U_{z2)}, f_{Z3}(x', U_{z3}), U_y] - E[f_Y(X, f_{Z1}(x, U_{z1}), f_{Z2}(x, U_{z2}), f_{Z3}(x, U_{z3}), U_y] \tag{11}$$

The causal indirect formula, shown in Equation (12), is used for estimating the mediation effects of change in Purpose, Structure, and Behavior because it provides a structured approach to defining direct and indirect effects in nonlinear settings, ensures a causal interpretation of effect measures, allows for nonparametric estimation, enables sensitivity analysis, offers flexibility in implementation, and provides a clear target quantity for capturing indirect effects in nonlinear systems (Pearl, 2012). Additionally, it is preferred for its applicability to nonlinear models, evaluation of path-specific effects, avoidance of distorted results, distinction between necessary and sufficient interpretations, and effectiveness in estimating components in nonlinear systems. The formula is accessible, bias-free, estimable by ordinary regression, and valid under standard linear analysis assumptions, making it a versatile and reliable tool for causal analysis in various fields (Pearl, 2012).

$$IE_{x,x\prime}(\mathrm{Y}) = \sum_z E(Y|x,z)[P(z|x') - P(z|x) \tag{12}$$

By using mediation analysis and dynamic models as a metric for innovation, it was discovered that simulated values of citations over time could be closely correlated with data of citations over time of Nobel Prize winners. The DAG models allow for counterfactual examination of different scenarios, such as greater or lesser change in purpose, structure, and behavior on innovation, manifesting as greater or lesser citations over time. Another advantage of using a mediation analysis and dynamic models for innovation is that the models developed for this paper generate different citation patterns as possible innovation outcomes for hypothesized scenarios of amounts of change that need to be innovative.

2.6 Agent-Based Modeling and Behavioral Dynamics

To translate the abstract causal and evolutionary theories into observable system dynamics, Agent-Based Modeling (ABM) was employed:

- Agent Interaction: ABM for studying the evolution of innovation as it captures the dynamic and emergent behaviors of individual agents (researchers or organizations) interacting within an evolving environment. This simulates how ideas emerge, spread, and coalesce into transformative advancements.
- Behavioral Modeling and Uncertainty: Models the spread of innovation Ideas (from incremental to breakthrough) based on rules involving the agent's research attributes.

The model incorporated behavioral elements like Prospect Theory, shown in Figure (10), which recognizes that people do not evaluate risk logically, often overvaluing losses and undervaluing gains. Integrating this behavioral reality helps dynamic models achieve more accurate predictions of investment outcomes and market confidence shifts.

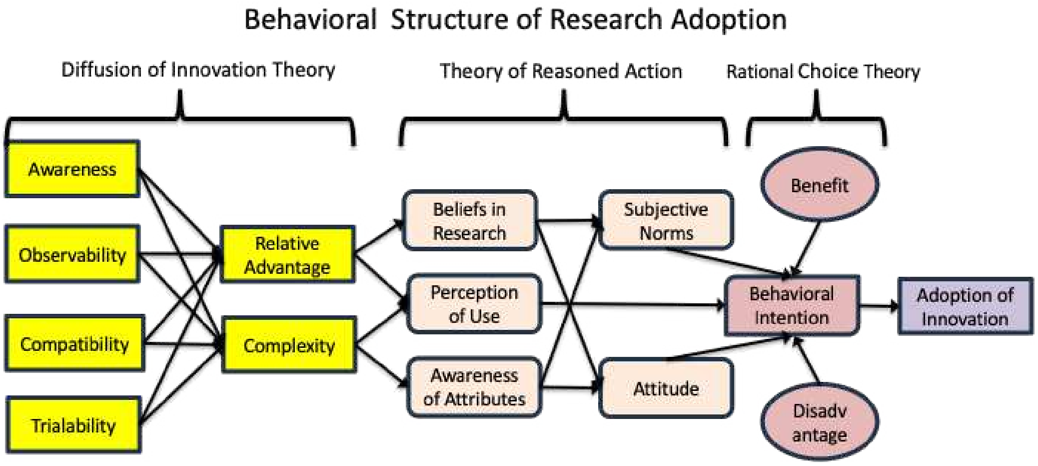


Figure (10). This is the Behavioral model used for the Agent-Based simulation.

CHAPTER 3: THE MULTI-MODEL FRAMEWORK METHODOLOGY

3.1 A Multi-Model Approach to Quantifying Innovation

Because innovation is a multifaceted phenomenon, no single analytical model can capture its complexity. A multi-model approach is therefore necessary to analyze it from different perspectives. This section details how this framework integrates probabilistic, causal, and systemic models to create a unified and quantitatively rigorous methodology for understanding and managing the innovation process.

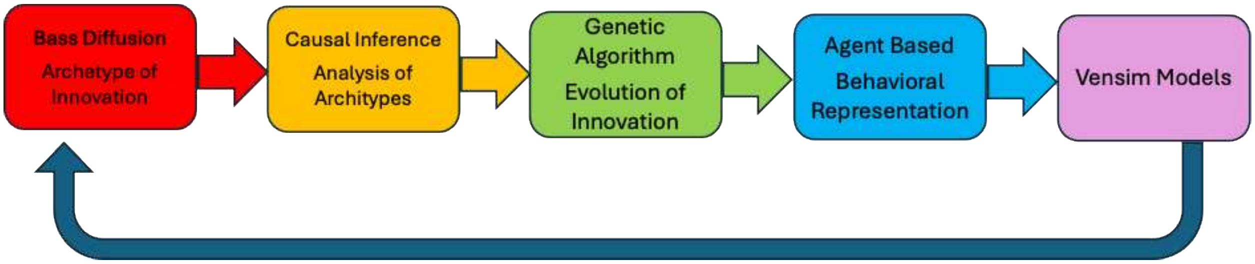


Figure (11). This is the Multi Model flow framework. It integrates Bass Diffusion, Causal Inference, Genetic Algorithms, Agent-Based Modeling, Dynamic Causal Loop Simulations.

Figure (11) is a conceptual workflow diagram cyclic methodology for modeling innovation. This dissertation uses this conceptual framework as the basis to explore, model, and simulate the properties of the dynamic systemic nature of innovation. The workflow components in the figure show the process moving from left to right through the following stages, Bass Diffusion, Causal Inference, Genetic Algorithms, Agent-Based Modeling, and Dynamic Causal Loop Simulations.

The Bass Diffusion module with sublabel "Archetype of Innovation", represents the starting point that focuses on how new products or ideas spread through a population. The Causal Inference module with sublabel "Analysis of Architypes", represents the use of statistical methods to determine the cause-and-effect relationships within the diffusion patterns. The Genetic Algorithm module with sublabel "Evolution of Innovation", represents the use of evolutionary heuristics to refine the innovation models. The Agent Based Behavioral moves the analysis into Agent-Based Modeling (ABM), simulating the individual actions and interactions of autonomous agents. The Vensim Models module is the final stage for simulation software used for conceptualizing, documenting, simulating, and analyzing models of dynamic systems.

3.2 The Probabilistic Nature of Innovation Success

There is a deep structural parallel in how information, as updated by Bayesian probabilities, and technology adoption, as modeled by the innovation diffusion developed by Frank Bass in 1969, is used for forecasting and reducing uncertainty (Massiani & Gohs, 2015). Bayes' Theorem is about belief revision, and the Bass Model is about market adoption. They both describe a transition from unknown to known mediated by the weight of evidence. The S-curve emerges in both models because of how they handle the rate of change as more information enters a system (Adner & Kapoor, 2016).

In the dynamic Bayesian model created for this dissertation, posterior probabilities are being updated over successive time steps. The early stage when the prior probabilities are low and evidence is sparse; the posterior grows slowly. The inflection point occurs as evidence accumulates, each new data point provides a relative boost to certainty. This is the steep part of the S-curve. The saturation stage occurs when the posterior probability approaches a probability of one and additional evidence has diminishing returns. You can’t get more certain than certain, so the curve levels off.

The Bass Model defines adoption through two forces: Innovation (external influence) and Imitation (internal influence). During the early stage when "Innovators" adopt an idea based on external factors, growth is slow. The inflection point occurs when "Imitators" see the innovators have produced something innovative and replicate the innovation. This creates a feedback loop in which the more people who adopt, the faster others are convinced. The saturation stage occurs when the pool of potential adopters shrinks, causing the growth rate to drop.

The reason a dynamic Bayes model looks like a Bass curve is because evidence is acting as the "imitation" factor. A population adopting a product is mathematically similar to a person adopting a belief when continuously being updated with new information. In both cases, the first half of the process is driven by discovery, and the second half is constrained by the remaining room to grow. This is shown in Figure (12) and Figure (13) respectfully.

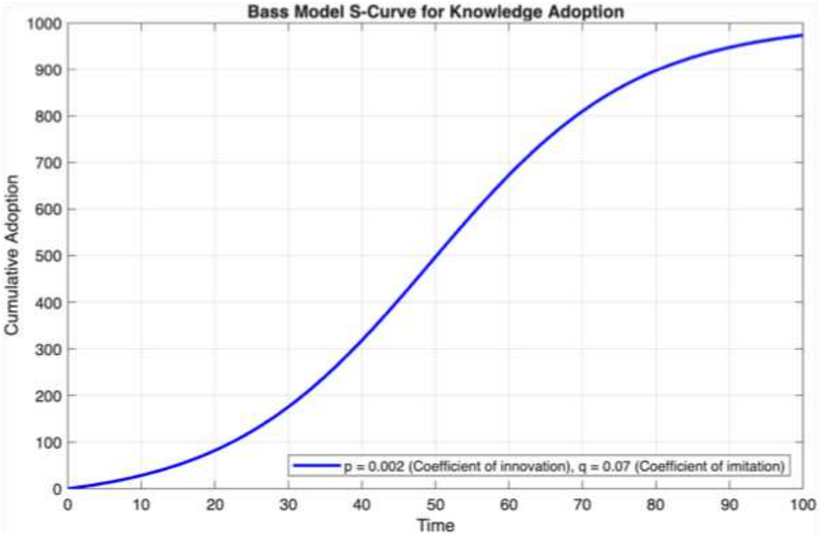


Figure (12). MATLAB Model of Bass Innovation Diffusion of Technology Adoption.

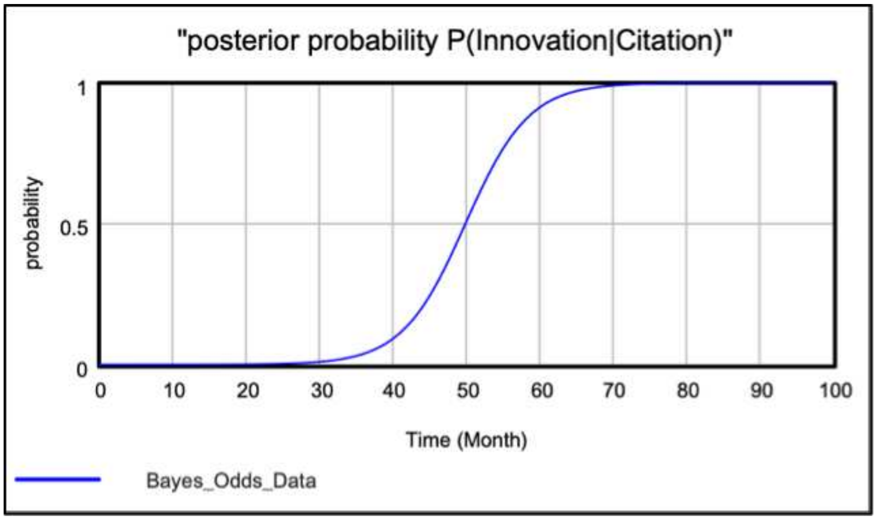


Figure (13). Vensim Dynamic Bayes Theorem Model of Probability of Innovation Given Citations.

Figure (12) and (13) are indicative of a Research Enterprise where a paper's citation count follows a dynamic Bayesian update. Each new citation acts as a "likelihood ratio" that increases the scientific community's belief in the validity of that research.

A mathematical bridge between these two models was developed. How they both treat the rate of change as a function of information versus how much is unknown was formulated.

By applying a system engineering, systems thinking context, it was found that this is a study of information entropy reduction versus saturation in a relevant community of interest.

The Bass model describes the probability that an individual will adopt at time t, given that they haven't adopted yet. The fundamental equation for the cumulative fraction of adopters F(t) is:

$$\frac{dF(t)}{dt} = (p + qF(t))(1 - F(t)) \tag{13}$$

where:

- p (Coefficient of Innovation): The external influence (constant discovery).
- q (Coefficient of Imitation): The internal influence (network effect).

- (1 - F(t)): The remaining potential.

When q > p, the interaction between F(t) and (1 - F(t)) creates the classic S-shaped logistic growth. In the dynamic Bayesian model, evidence arrives as a continuous stream of information or data that is modeled as a Log-Likelihood Ratio. The posterior probability P(t) is calculated as a ratio. If L(t) is the likelihood ratio of the evidence, the posterior odds evolve. When converted back to probability, the "velocity" of your belief P(t) can be expressed as:

$$\frac{dP(t)}{dt} = s \times P(t)(1 - P(t)) \tag{14}$$

where:

- s is the signal-to-noise ratio or the "strength" of the evidence.
- P(t) (1 - P(t)): This is the variance of a Bernoulli distribution.

The reason both generate a sigmoid function is that the Bass Model is effectively a Bayesian update of a population's collective belief in a product. Mathematical this arises do to the (1 - X) term in both equations where growth must slow down as you approach the limit of 100% certainty or 100% market share. This creates the upper curve of the sigmoid function.

The adoption or imitation term in the Bass model, q F(t) represents people convincing each other. In Bayes, P(t) represents the current weight of the prior belief. Both act as accelerators of the more you know, the faster you learn, until you run out of new information. The information threshold in System Engineering is often seen this as a State Transition. This is when a person moves from State A (Unaware/Disbelieving) to State B (Adopted/Certain).

This mathematical overlap can be used to show that Innovation Adoption is a Bayesian Learning Process. Instead of using “researchers imitate good innovations”, you can imply that researchers are “updating their belief of the innovation's value”, based on the observed evidence of others' success. This also grounds the empirical Bass model in cognitive decision theory.

3.3 Uncovering the Causal Drivers of Innovation

To effectively manage and foster innovation, we must understand its causal drivers, not just its correlations. This framework employs a causal mediation model to identify the mechanisms through which actions lead to innovative outcomes. The analysis reveals that innovation is primarily mediated by systemic changes in three key areas: Purpose, Structure, and Behavior. The results from the Causal Mediation Analysis were statistically significant, yielding an Average Causal Mediated Effect (ACME) of 71.2 and an Average Direct Effect (ADE) of 362.3 ($p < 0.001$), confirming that these mediators are powerful causal pathways to innovation. By targeting these factors, leaders can design policies that have a predictable and significant impact on innovative output.

Counterfactual analysis of the Bass diffusion model was used for causal inference by simulating what adoption trajectories would have looked like under alternative scenarios (Varian, 2016). This was done by holding all other factors constant and systematically varying one input to estimate the marginal impact of innovative research on cumulative adoption. A MATLAB script model was written to simulate increasing of (p) by 0.01 which led to a 15% rise in total adoption over 30 periods. This meant that the change in adoption of innovative research could be attributed directly to the intervention of publishing an innovative research paper, assuming model validity. Causal impact analysis was used to validate this counterfactual analysis (Ellis, 2005). By employing techniques such as observational studies or natural experiments, researchers can identify the specific factors that cause an increase in innovative output. Initial investigations were carried out using Causal Impact analysis of highly cited researchers' publications on the relevant population in their respective field.

The CausalImpact package in R Studio is a tool for conducting observational studies on time series data when randomized experiments are not feasible (Brodersen et al., 2015). It employs Bayesian structural time-series models to estimate the causal effect of an intervention on a time series. The package constructs a counterfactual prediction of what would have happened without the intervention, allowing for a comparison with the actual outcome. This is achieved using a control time series not influenced by the intervention to model the expected evolution of the response metric. The influence on relevant population citations was analyzed for many different fields. An example of analysis is shown for Nobel prize winner Dr. Anton Zeilinger. His Nobel prize was for experiments with entangled photons, establishing the violation of bell inequalities and pioneering quantum information science." His Nobel prize research paper is titled "Experimental Quantum Teleportation"(Bouwmeester et al., 1997). From 1997 to 2023, this paper received 4177 citations as referenced from Web of Science data. The impact of this research, measured by citation patterns in the field of Entanglement Physics, was performed using R Studio's CausalImpact statistical analysis tool and is shown below in Figure (14).

The three graphs in Figure (14). visually represent the process of inferring the causal impact of the research paper "Experimental Quantum Teleportation" through counterfactual predictions in citations in entanglement Physics. The top graph is the simulated trajectory showing treated and untreated citation patterns with counterfactual predictions. The dashed line shows what would have happened if the Nobel Prize research paper had not been published, and the solid line shows what happened after the Nobel Prize research was published. The middle graph, pointwise, shows the inferred causal impact, illustrating the difference between observed data and counterfactual predictions. The bottom graph, the cumulative impact plot, demonstrates the summed effect of the Nobel prize research over time. Additional elements of shaded areas are for uncertainty, and vertical bars time. The results of the causal impact analysis are shown in Table (1). Posterior tail-area probability p:0.00103 and the Posterior prob. of a causal effect: 99.89723%. The causal impact analysis indicates that Nobel Prize research influences research within its field.

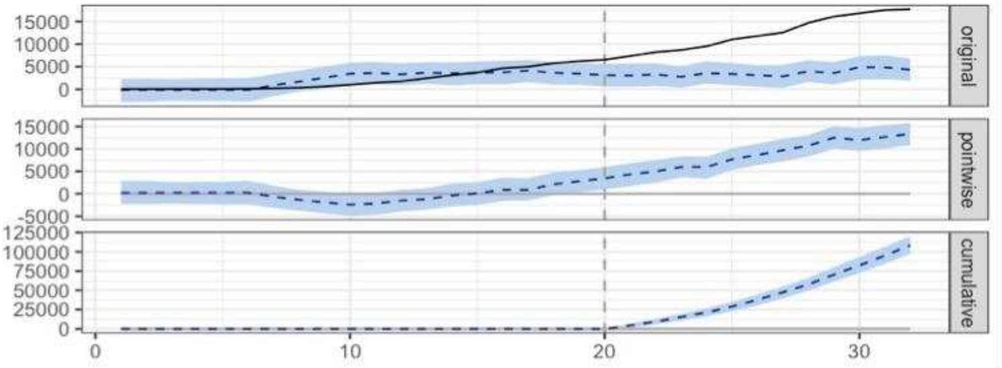


Figure (14). Causal Impact analysis of “Experimental quantum teleportation” in the field of Entangled photon research. Dash line shows what the com citation pattern would have looked like if not for the landmark Nobel prize research.

Table (1). Statistical analysis from the CausalImpact simulation of the effect of Nobel prize research.

Posterior Inference Results {CausalImpact}		
	Average	Cumulative
Actual	12672	152061
Prediction (s.d.)	3635 (495)	43624 (5940)
95% CI	[2687, 4644]	[32250, 55724]
Absolute effect (s.d.)	9036 (495)	108437 (5940)
95% CI	[8028, 9984]	[96337, 119811]
Relative effect (s.d.)	254% (52%)	254% (52%)
95% CI	[173%, 372%]	[173%, 372%]

3.4 A System Dynamics Analogy: Innovation Motive Force (IMF)

To model the flow, potential, and constraints within an innovation ecosystem, this framework introduces a structured analogy between Electro Motive Force (EMF) in electrical circuits and a newly defined Innovation Motive Force (IMF) in socio-technical systems. IMF represents the systemic "push" that drives ideas and knowledge through an organization or research community. This analogy provides a powerful and intuitive vocabulary for diagnosing the health of an innovation system:

Table 2: Electro Motive Force (EMF) in electrical circuits and a newly defined Innovation Motive Force (IMF) in a R&D enterprise system.

Electrical System	Innovation System
EMF (ε): Power source	IMF (ψ): Innovation drivers (funding, policy, vision)
Voltage (V):	Innovation Potential (stored potential for change)
Current (I):	Knowledge/Idea Flow rate
Resistance (R):	Bureaucratic friction, inertia, culture
Capacitance (C):	Learning systems, absorptive capacity, institutional memory

This framework of representing the forces that drive innovation allowed the modeling of an innovation ecosystem as a conservation-based system, enabling the diagnosis of bottlenecks (resistance), the evaluation of organizational learning (capacitance), and the prediction of knowledge flow based on systemic potential (voltage). The model is shown in Figure (15). These theoretical and analytical frameworks provide the grammar for describing innovation. They are validated and brought to life through computational simulations.

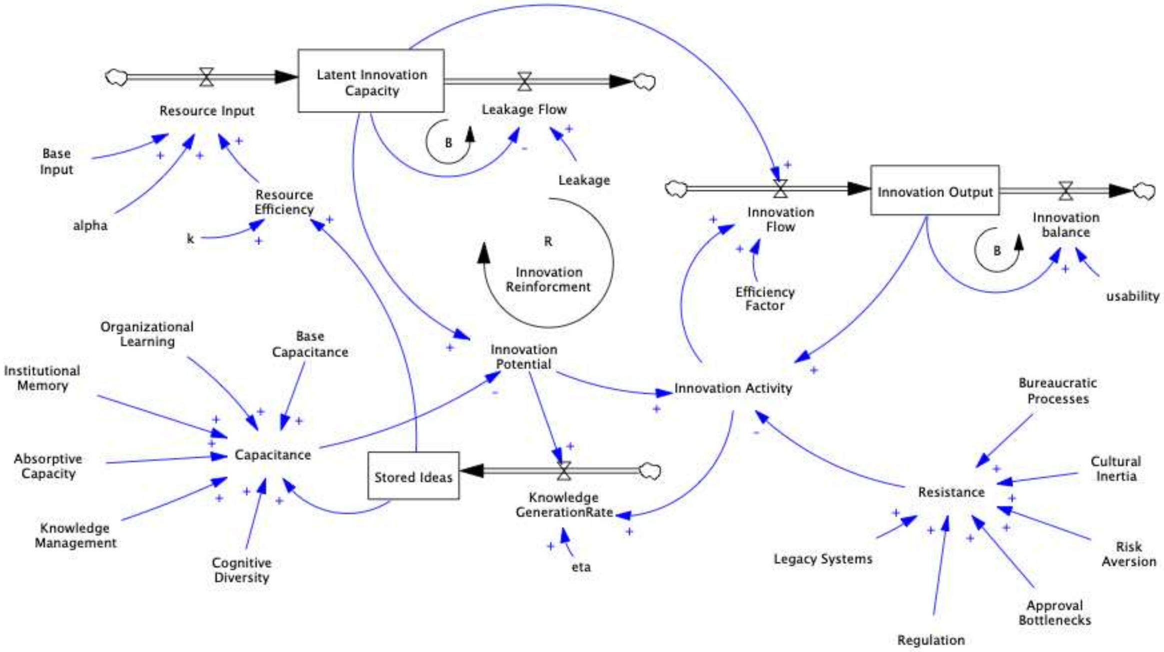


Figure (15). Dynamic Model of Electromotive Force Representation of an Innovation Ecosystem with Capacitance for Storing Research and Resistance to Innovative Actions.

Figure (15) represents the System Dynamics architecture of the Innovation Motive Force (IMF) model. This is how we map the electrical engineering analogies, Potential, Capacitance, and Resistance, into the causal loops of a research enterprise. The model visualizes how Resource Inputs accumulate into Latent Innovation Capacity, which is then converted into Innovation Potential. The system's ability to generate innovative research is not just a function of funding, it is governed by the interplay between an organization's ability to absorb and store knowledge through Cognitive Diversity, Institutional Memory, Resistance from Bureaucratic Processes, Risk Aversion, and Legacy Systems. A limitation to this model is that it requires the quantification of inherently qualitative organizational traits, such as "cultural inertia" or "cognitive diversity" for capacitance and resistance. This is totally subjective and would require years of experience to do.

CHAPTER 4: COMPUTATIONAL MODELING AND EMPIRICAL VALIDATION

4.1 The Six-Level Taxonomy of Innovation Evolution

The 80/20 Pareto distribution serves as a fundamental signature of recognizing the creation of innovations in a R&D innovation enterprise system (Bernardara et al., 2014). It describes how impact is distributed within a community of interest. Most observations of citations from an innovation systems yield low values. A small number of extreme citation observations produce incredibly high values. These outliers represent the innovative research of the enterprise.

In a Pareto-distributed system, the "average" becomes a misleading metric (Nortey et al., 2015). The extreme outliers pull the mean significantly far from the median. Standard statistical measures often fail to capture the true behavior of the system because they assume a normal distribution that does not exist if we examine innovation history. Success in innovative research is not incremental. It is concentrated in these rare, high-impact events.

Empirical data across diverse domains confirms this scarcity. In the fields of Brain-Computer Interface, Hypersonic Weapons, and High Energy Lasers, the distribution of citations follows a consistent power-law pattern. A tiny fraction of papers accounts for the majority of total citations. This concentration remains stable regardless of the specific technical or scientific discipline. This is shown in Figure (16), Figure (17), and Figure (18) respectfully.

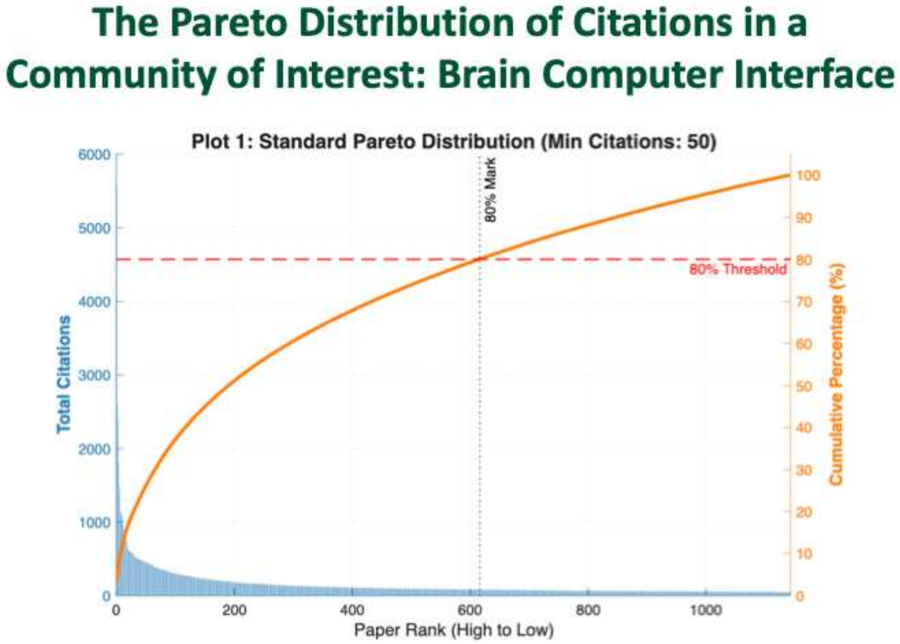

The Pareto Distribution of Citations in a Community of Interest: Brain Computer Interface

Figure (16). Shows a Pareto Distribution with the 80% of citations coming from 20% of the population of the community. This shows distinct Power Law behavior.

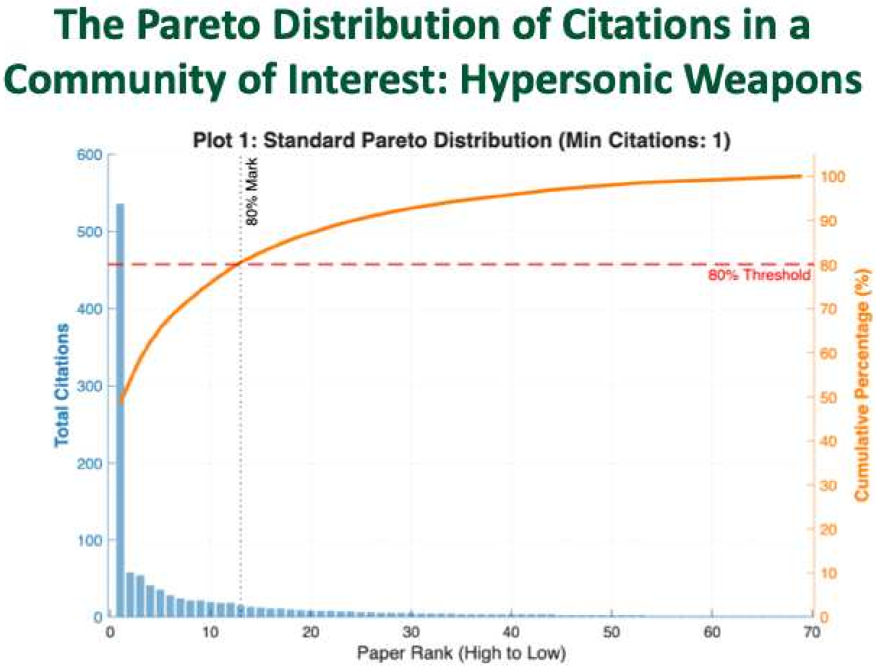

The Pareto Distribution of Citations in a Community of Interest: Hypersonic Weapons

Figure (17). Shows another Pareto Distribution with the 80% of citations coming from 20% of the population of the community. This shows distinct Power Law behavior.

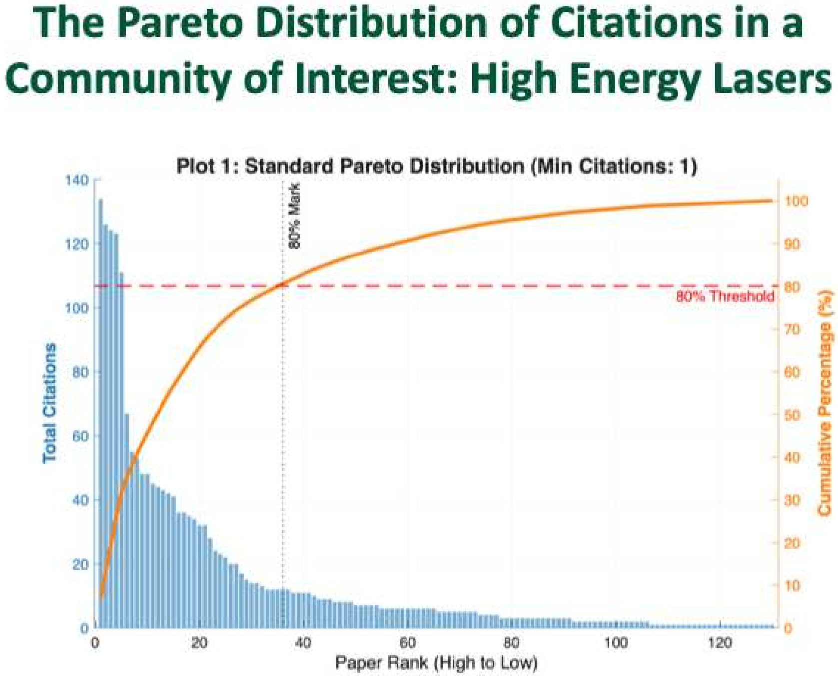


Figure (18). This another example of a Pareto Distribution with the 80% of citations coming from 20% of the population of the community. This shows distinct Power Law behavior.

Innovation can be categorized by its magnitude and probability. Incremental improvements form the "Long Tail" of the distribution as shown in Figures (16), (17), and (18). These represent steady-state progress with a high probability of occurrence but relatively low citation counts. As we move toward the "head" of the distribution, we find modular, architectural, and radical innovations. These events are increasingly rare and impactful.

At the far extreme of the distribution lie disruptive and breakthrough innovations. Breakthroughs represent the top 1% of events, often requiring over 600 citations to reach this threshold. These are the "Superstars" or extreme-value events that redefine entire sub-fields. While they occur with a probability of less than 1%, they drive the primary evolution of the research community.

Visualizing this data on a log-log scale reveals a linear relationship characteristic of power laws shown in Figure (19). This perspective allows for the precise mapping of innovation categories to specific citation magnitude thresholds. It provides a mathematical framework to differentiate between steady-state improvements and radical shifts in knowledge.

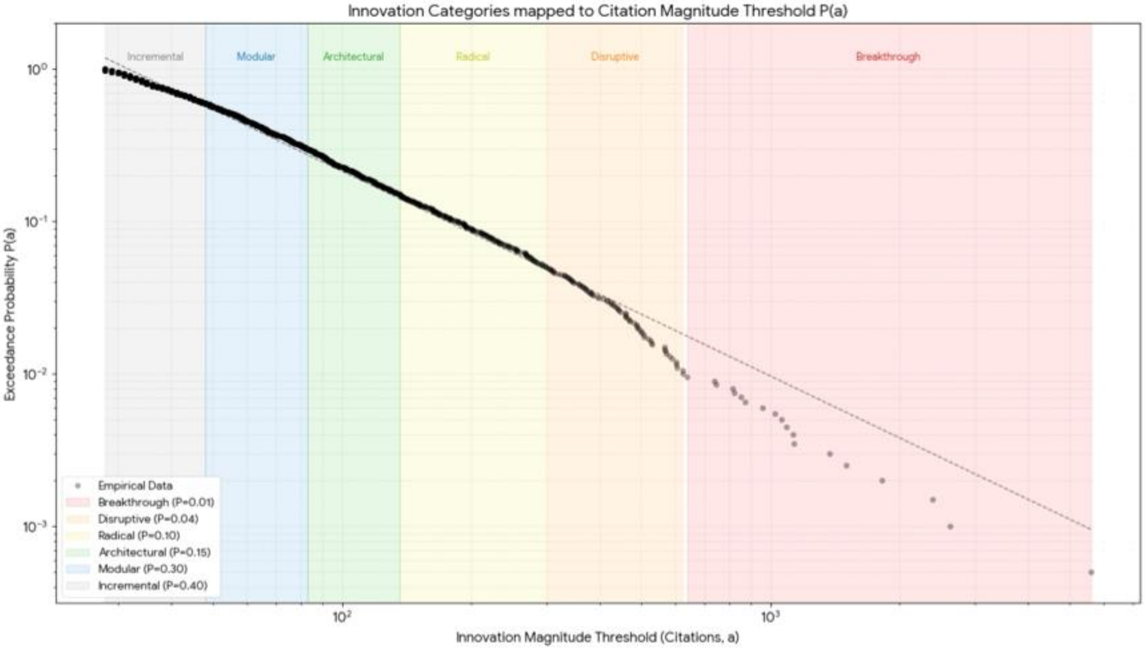


Figure (19). This figure shows the six categories of innovation magnitude defined by a Log-Log plot of the Pareto distribution. A true power law distribution is a straight line on a log-log scale. This verifies the use of a Pareto distribution for detecting the extreme event of Breakthroughs.

The Exceedance Probability P(a) shown in Figure (19) is the likelihood of a paper achieving a certain citation threshold. This mapping illustrates how the "Community of Interest" filters and amplifies innovation magnitude.

This research integrates System Dynamics, Extreme Value Theory (EVT), and Bayesian Inference with the Pareto distribution acting as the mathematical bridge connecting these three domains. This is shown in Figure (20) using observational data from Web of Science (*Clarivate*, 2026).

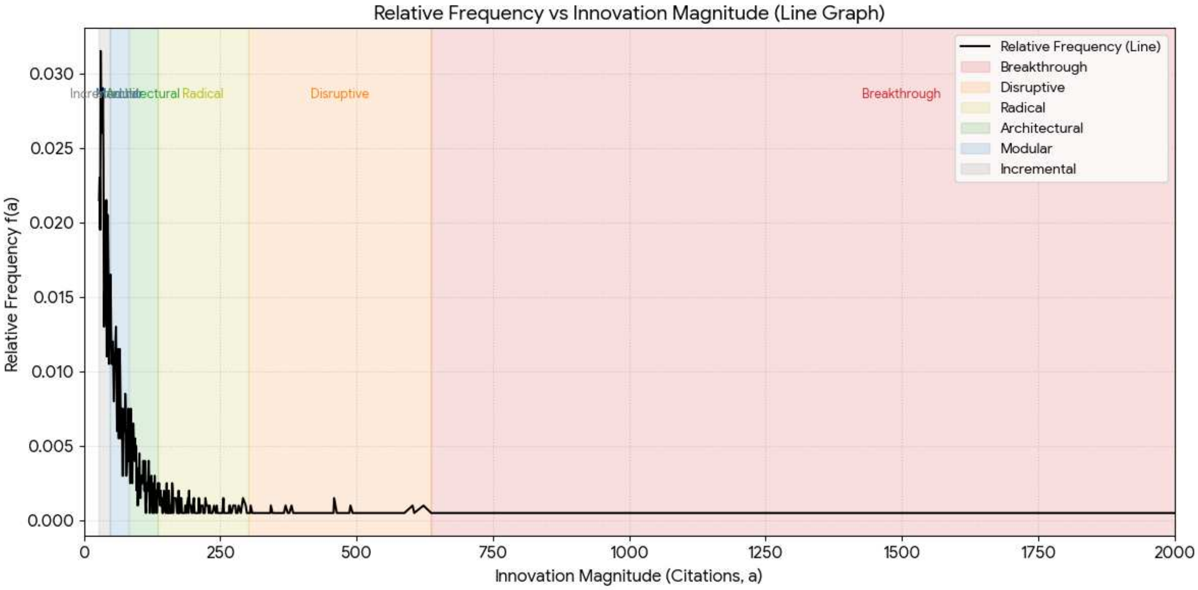
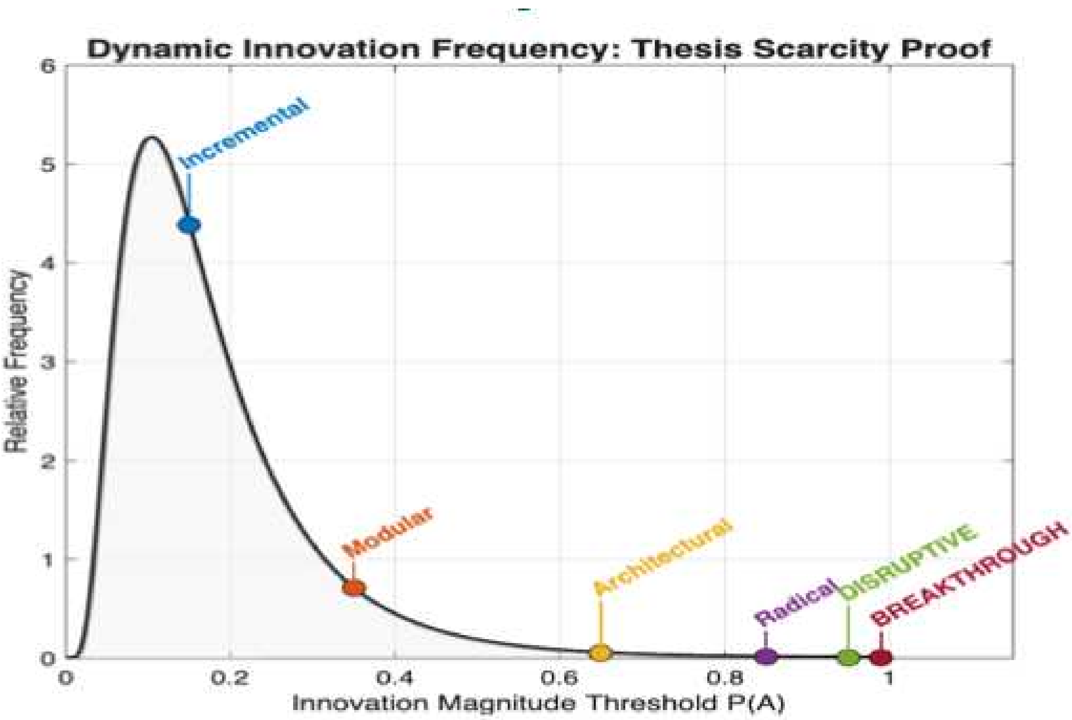


Figure (20). Observational data showing the Power Law behavior of EVT. Citations are from Web of Science data base.

Figure (20) provides the foundation for the categorical framework, visualizing the Innovation Magnitude Distribution. You can see a classic "long-tail" distribution that mathematically defines our six categories of innovation by plotting citation frequencies on the Y axis.



80% of Citations come from 20% of research

Figure (21). This is a Pareto distribution where calculated innovation categories are plotted on the simulated Power Law curve.

Figure (21) shows how the distribution allows for the modeling of dynamic innovation category reproduction while accounting for the heavy-tailed nature of scientific breakthroughs. Systems thinking requires looking beyond the median contributor and finding patterns.

Modeling the life cycle of innovation depends on understanding how these few extreme values drive the entire enterprise. By applying EVT and Bayesian methods to a Pareto framework, we can better predict the scaling of impactful science within complex research environments.

A rigorous, mathematical framework for categorizing Six-Level Taxonomy of Innovation Evolution was established. Defining the spectrum of change from incremental improvements to total paradigm shifts was performed. Figure (22) illustrates the process of system identification by mapping empirical observational data (the "Entangled Photons Dataset") onto a formal mathematical structure. By fitting the cumulative growth of citations or publications to the Bass Diffusion Model, shown in Figure (23) the analysis extracts latent parameters specifically the Coefficient of Innovation ($p \approx 0.00024$), and the Coefficient of Imitation ($q \approx 0.1663$), which serve as the governing logic for the system's behavior. This approach transforms raw time-series data into a predictive framework, where the "small p" and "large q" values quantify the transition from stochastic discovery to deterministic social contagion. The annotation of distinct innovation levels (Incremental through Breakthrough) demonstrates how the multi-model framework was used to discretize continuous observational curves to provide a method for validating whether a model's internal state transitions align with the actual historical maturation of a technology or scientific field.

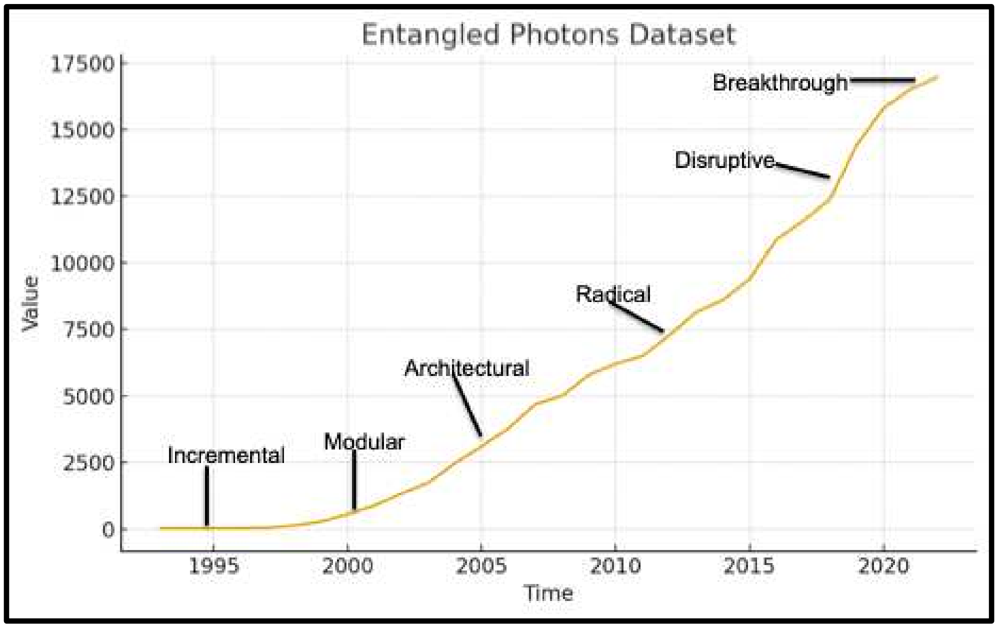


Figure (22). Bass Innovation Diffusion of Nobel Prize Winner in Physics Anton Zeilinger "Experimental Quantum Teleportation"

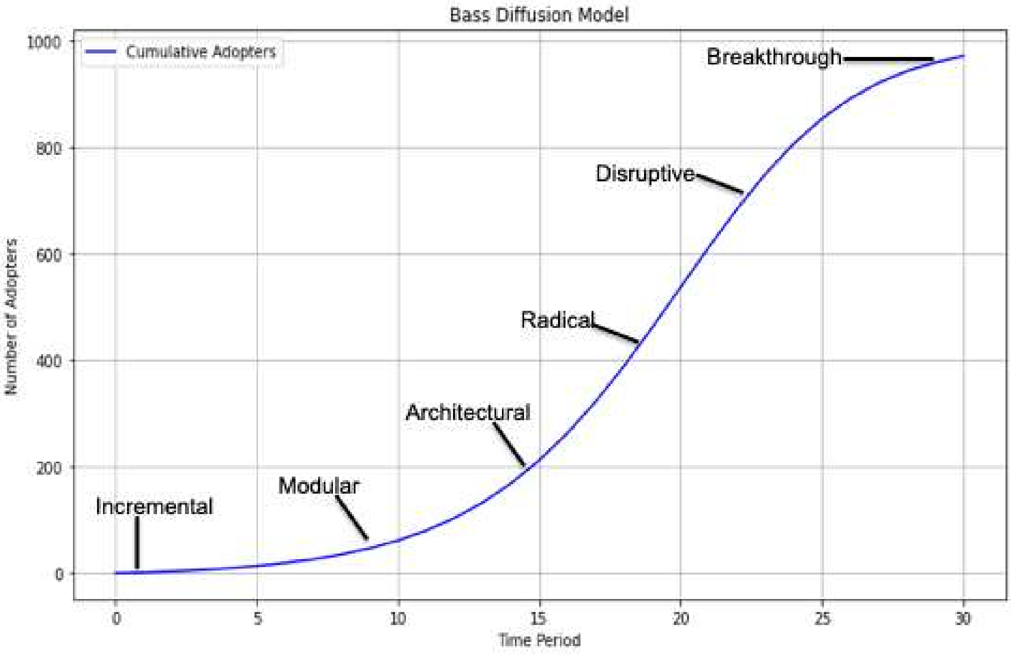


Figure (23). Simulated Levels of Innovation using Bass Diffusion

Figure (22) and (23) show how an idea progresses through the six categories, from Incremental to Breakthrough. The early phase is dominated by p-driven growth, where adoption is slow and experimental. As the q-driven growth of imitation takes over, you can see the steep acceleration through Radical and Disruptive stages. This computational success confirms that our model's logic is sound and capable of serving as a predictive tool for evaluating the life cycle of emerging research.

A Vensim model was created to simulate this pattern of behavior for research adoption over time. The model and the observational data match with high fidelity regarding the long-term trend and the final magnitude. The Vensim model is smoother than the real-world data, which contains historical noise and fluctuations and is shown in Figure (24). The close alignment of the two non-linear curves suggests that a 60% adoption probability is a highly accurate parameter for simulating the diffusion of citations in this scientific field.

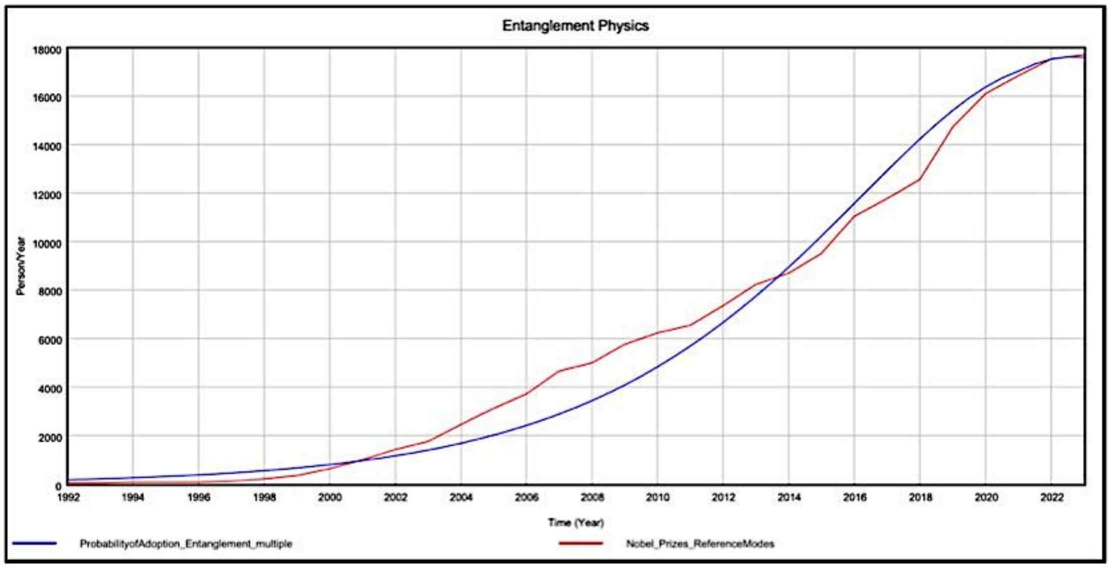


Figure (24). Shows the Dynamic Model reference simulation of Citations in Entanglement

Most researchers would conclude that this "gains confidence in the model" because the simulated behavior mirrors the historical reality, the reference mode, almost perfectly by the end of the time horizon.

A sensitivity analysis was performed to demonstrate the model’s prediction was sensitive to changes of research ideas, “Purpose”, “Structure”, and “Behavior” that effect citation adoption over time. The sensitivity analysis shows the citation rate is not just a random walk; it is heavily dictated by these changes. This is shown in Figure (25) and Figure (26) respectfully. The fact that the observed data (red) resides within the 50-75% sensitivity bounds provides high confidence that the underlying mechanics of the change in “Purpose”, “Structure”, and “Behavior” variables are driving the citation patterns correctly.

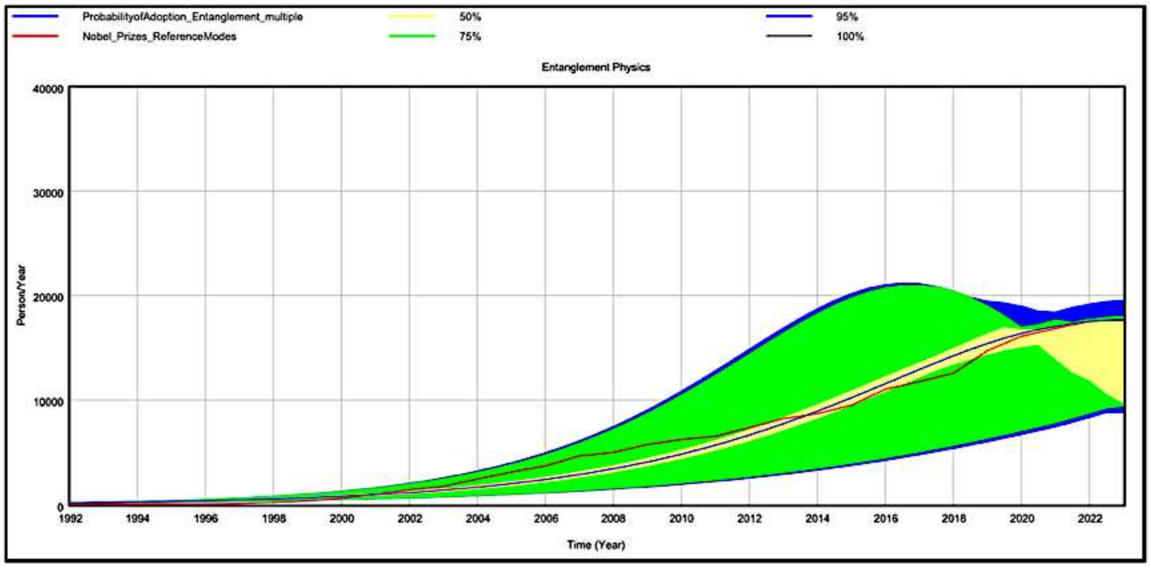


Figure (25). Shows the Sensitivity analysis of the Dynamic Model with reference in red, Hypothesis probability 60% of being cited with changes in Structure, Purpose, and Behavior varying from +40% to -40%.

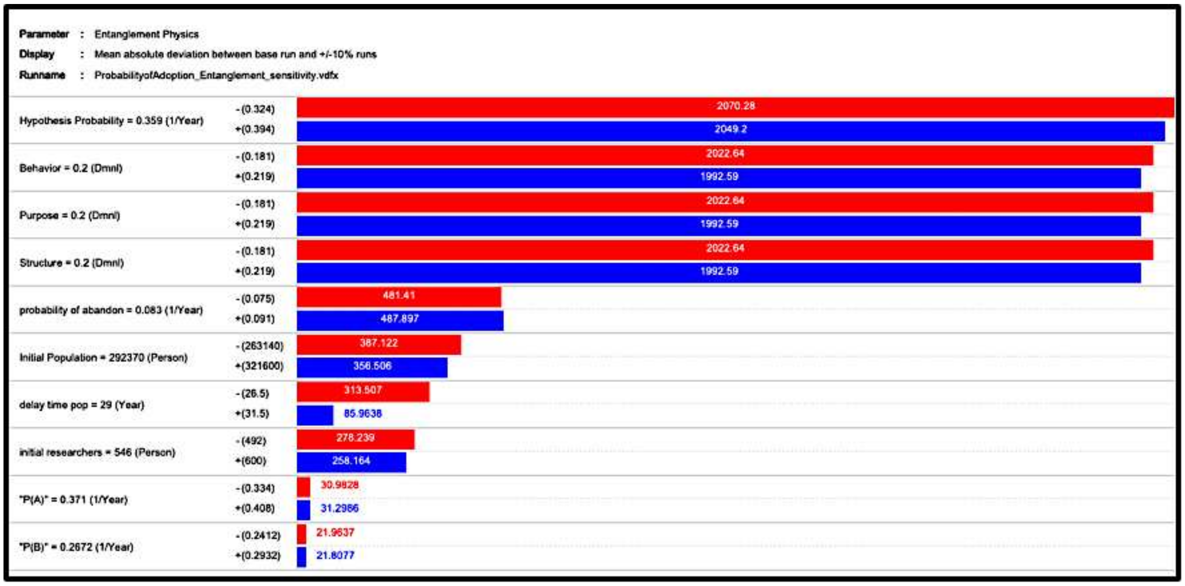


Figure (26). Shows sensitivity analysis of the variables in the Dynamic Model in which the top four variables generate the most change in the model.

Figures (25) and (26) are statistical calculations performed by the Vensim software.

4.2 Simulating Innovation Ecosystems with Agent-Based Models

To operationalize this unified framework and test its core hypotheses, computational and statistical methods was employed. These simulations provide the empirical evidence that validates the framework's structure and reveals the hidden dynamics of innovation evolution. This section presents the key findings from this interactive model.

An Agent-Based Model (ABM) was developed to simulate a research community composed of individual agents, or "researchers." These agents generate, share, and adopt ideas based on a set of defined rules and attributes, such as Clarity, Rigor, Impact, and Innovativeness. The simulation models how ideas diffuse across the six categories of innovation, from Incremental to Breakthrough, based on agent interactions shown in Figure (27).

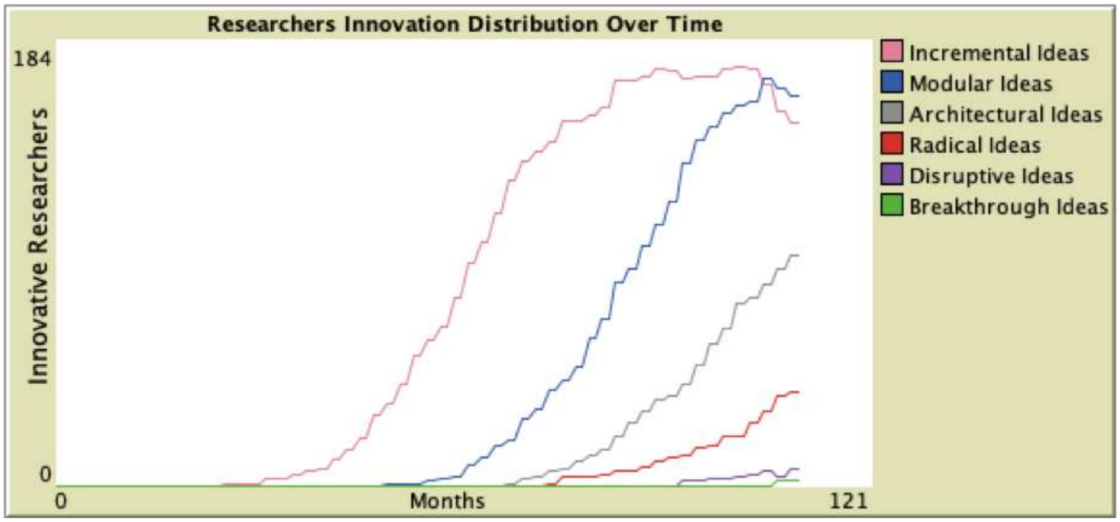


Figure (27). Agent based model with parameters: Number of Researchers (1000), Change in Purpose (61%) Structure (61%) Behavior (61%) 10 Year Run Time.

Figure (27) visualizes the Staggered Diffusion of Innovation across the research enterprise over a 121-month simulation.

Genetic Algorithms (GA) were used to simulate the evolution of research attributes over multiple generations to validate the ABM model. This represents the competitive landscape of ideas, where fitter concepts with more impactful attributes are selected, survive, and propagate, while weaker ones fade. This computational approach allows us to observe the emergent, system-level patterns that arise from individual-level behaviors.

4.3 Analyzing the Innovation Cascade: Key Statistical Findings

Statistical analysis of the simulation data provides robust, quantitative evidence for the framework's evolutionary structure. The key findings confirm that innovation is not a random process but a structured, sequential cascade. Implications of correlation analysis:

- A strong positive correlation exists between Incremental & Modular ideas (r = 0.775), suggesting that foundational improvements co-evolve with component-level changes.
- A moderate correlation is found between Modular & Architectural ideas (r ≈ 0.6), indicating that architectural shifts often rely on modular foundations.
- In contrast, there is a very weak correlation between Incremental & Breakthrough ideas (r = 0.134).

Granger Causality Analysis:

- The very weak direct correlation between Incremental and Breakthrough ideas (r = 0.134) is a critical insight that is explained by the Granger Causality analysis. Breakthroughs do not emerge directly from incremental work; rather, they are the final output of a multi-stage causal cascade, where each preceding level of innovation is a necessary but not immediately correlated step.

- The Granger Causality Test confirms a statistically significant ($p < 0.01$) predictive cascade across all adjacent transitions: Incremental → Modular → Architectural → Radical → Disruptive → Breakthrough. This is a cornerstone finding, confirming that innovation progresses sequentially, with the successful establishment of each stage acting as a necessary precursor for the next (Lam et al., 2023).

Implications of volatility analysis:

- Breakthrough and Disruptive ideas are the most volatile, appearing in sporadic, high-impact bursts rather than as a steady stream.
- Conversely, Incremental ideas remain the most stable, forming a consistent and predictable base of activity that underpins the entire ecosystem.

These findings carry significant strategic implications for how organizations should approach R&D portfolio management and investment. The correlation is shown in Figure (28).

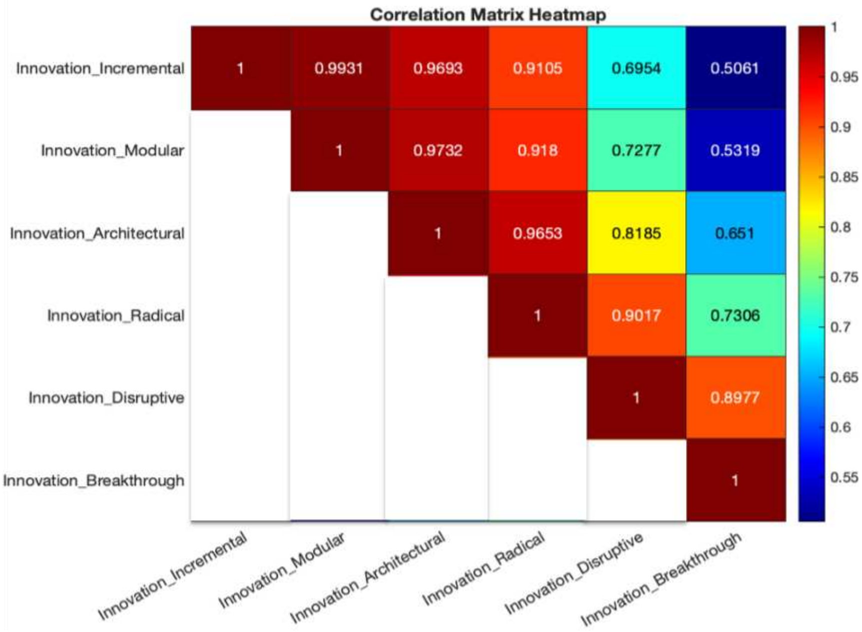


Figure (28). This figure shows the correlation between each innovation category illustrating the feed forward connection of the process of evolution from Incremental to Breakthrough.

Figure (28) visualizes the Pearson Correlation Coefficient among six different types of innovation ideas generated by the agent model: Breakthrough, Radical, Disruptive, Incremental, Modular, and Architectural (Benesty et al., 2009). The heatmap uses a color gradient to represent the correlation strength, where deep red indicates strong positive correlation, and white indicates negligible correlation.

Another statistical technique used in this dissertation is the Kullback-Leibler (KL) Divergence, also known as Relative Entropy, measure technique (Kurian & Allali, 2024). This was used as a non-symmetric measure of the difference between two probability distributions, P and Q where P is observational probabilities gained from bibliometric analysis of citation patterns over time in research communities of interest, and Q is the generated citation patterns over time from dynamic models created for this dissertation. Figure (29) shows the KL divergence of citation in the field of Quantum Teleportation Physics with the research of Nobel Prize winner Anton Zeilinger (green dash line) and the dynamic modeled citation pattern (blue curve). Even though there is not perfect matching of both distributions, the KL divergence of .0649 shows that the generated citation pattern is a strong statistical approximation of the observational data (Scutari, 2024).

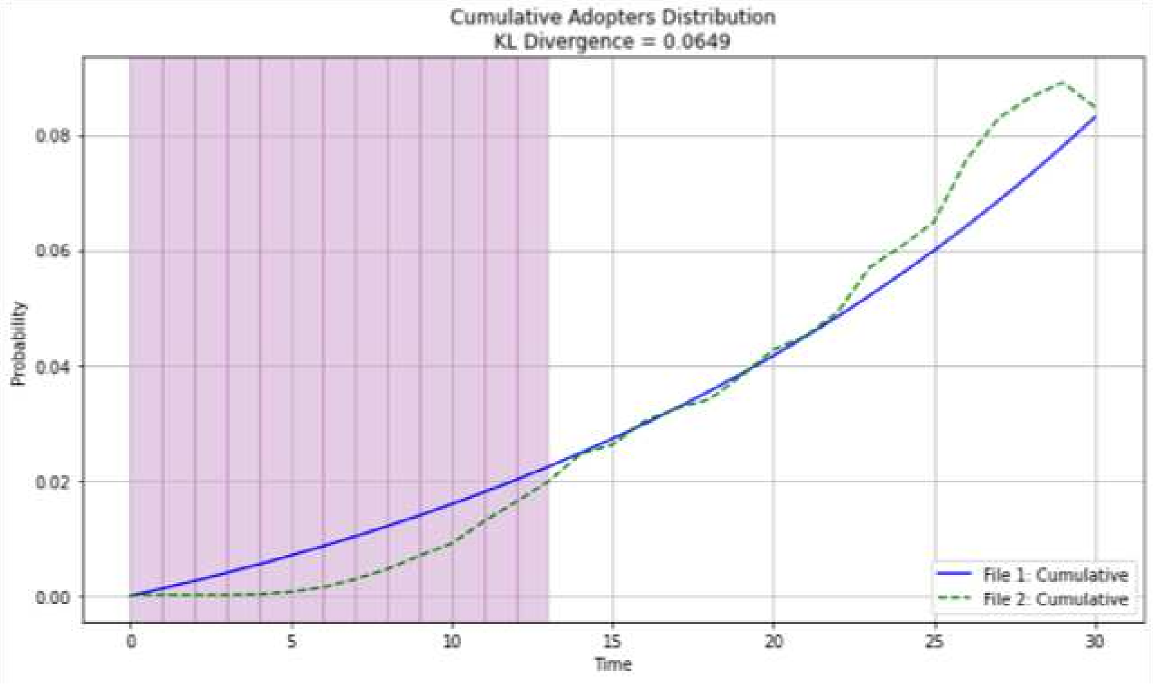


Figure (29). This is the KL Divergence between Observational and Dynamic Model using MATLAB simulation. The green dashed line is based on real world data from innovations in Quantum Teleportation Physics.

Figure (29) shows there is minimal "information loss" when using the model to represent real-world citation growth. The blue line, the simulated, and the dashed green line, the observation, track closely together across the 30-year timeline, with the purple shaded region highlighting the early incubation phase. This result provides the mathematical "stamp of approval" for the multi-model approach, proving that the simulation engine is accurately grounded in reality.

CHAPETR 5: STRATEGIC IMPLICATIONS FOR A RESEARCH ENTERPRISE

5.1 Strategic Implications for R&D Portfolio Management

The true value of this unified framework lies in its ability to translate complex theory and empirical data into actionable guidance for leaders. By providing a new lens through which to view the innovation lifecycle, the model offers a clear roadmap for allocating resources, designing effective policy, and navigating the inherent uncertainties of R&D in the 21st century (Adler et al., 2016).

Using a probabilistic approach offers advantages over raw data analysis by correcting for the "Popularity Bias". Citation data is often skewed for name recognition. Bayes allows you to account for the fact that a high citation count does not automatically guarantee innovation if the base rate of innovation in that specific field is very low (Rouder & Morey, 2019). The probabilistic approach also handles uncertainty.

It acknowledges that citation data is a "proxy" or "signal" rather than a direct measurement of innovation. A Bayesian probabilistic approach uses iterative updating (Smith & Gelfand, 1992). When you gain more data, you can use this as the *new* base line for the next calculation. True innovation is not a guaranteed outcome but a probabilistic one. It emerges at the intersection of what is possible, what is profitable, and what is valuable. This can be conceptualized using a triadic Venn diagram model, shown in Figure (30), which defines the probability of innovation based on three overlapping domains.

- Technological Feasibility (Possible): The domain governed by the laws of science and the capabilities of engineering.

- Economic Profitability (Profitable): The domain governed by market viability, resource availability, and investment potential.
- Stakeholder Value (Valuable): The domain governed by user needs, societal impact, and alignment with organizational goals.
- Innovation: The central intersection where an idea is simultaneously feasible, profitable, and valuable.
- Risk and Utility: The resulting strategies modeled through simulation are evaluated using financial metrics, quantifying uncertainty via Shannon Entropy and measuring potential gain through Expected Utility (EU) and corresponding ROI. This framework identifies high-performing strategies that balance low uncertainty (entropy) with high returns (utility/ROI).

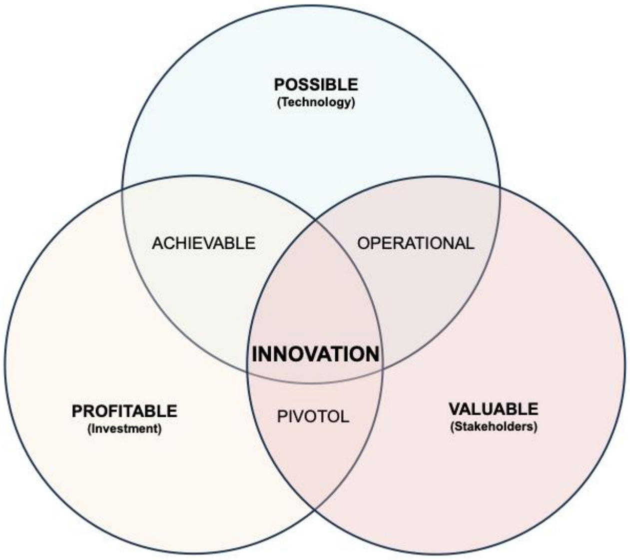


Figure (30). Venn Diagram of Innovation Probabilities and Intersections to help with innovation creation and R&D investment decisions.

Using Bayesian probability theory with information updating, we can dynamically modify the likelihood of achieving true innovation as new evidence becomes available. For example, based on sample data, if we know an initiative is both technologically feasible (Event A) and economically profitable (Event B), the probability of innovation becomes P (Innovation |A ∩ B) = 0.6. If we know it is profitable (Event B) and valuable to stakeholders (Event C), the probability rises to P (Innovation |B ∩ C) = 0.667. This demonstrates how observing joint evidence significantly increases confidence in an innovation's ultimate success.

5.2 Overcoming the Innovator's Dilemma with a Balanced Portfolio

The six level innovation framework, discussed in previous chapters, offers a direct solution to the Innovator's Dilemma. By understanding the causal cascade from Incremental to Breakthrough, organizations can move beyond the false choice between optimizing for today and investing for tomorrow. The management flight simulators in this chapter demonstrate that successful R&D strategies require a consciously balanced portfolio that supports both exploitation and exploration. By sustaining activities like Incremental and Modular innovation and disruptive and breakthrough exploration, true paradigm game changing innovation can occur. Figure (31) showcases a Management Flight Simulator that can help achieve this outcome. It is one of the interactive tools developed for this dissertation. It shows the strongest argument for Systems Thinking. It proves that an R&D enterprise cannot simply buy a breakthrough by throwing money at a problem. Instead, leadership must engineer the organization to reduce Resistance and build Capacitance.

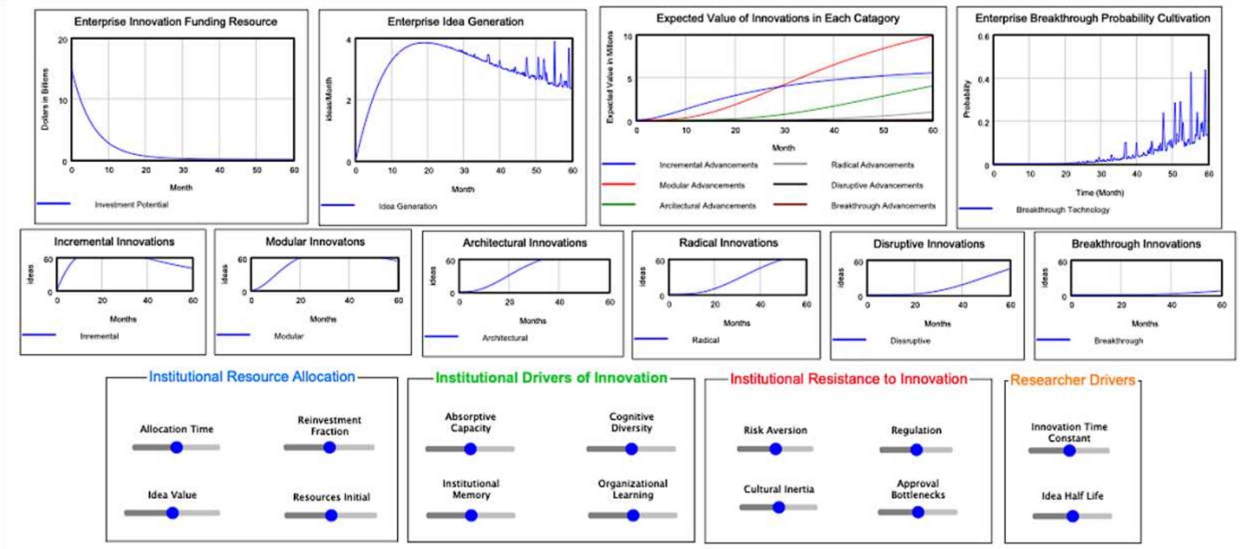


Figure (31). This is a Management Flight Simulator of Innovation Motive Force (IMF) for a R&D Enterprise. User adjusts the sliders to better understand the current state and find the best point of leverage on the innovative output of the organization under study.

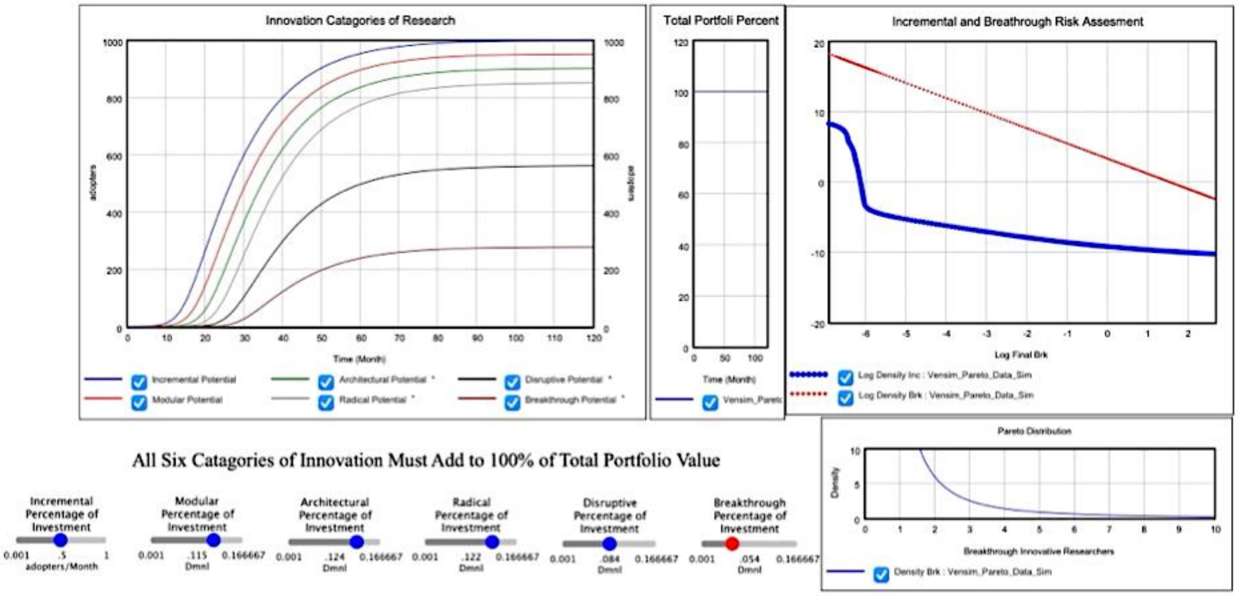
This interactive tool, shown in Figure (31), was developed for this dissertation to serve as a "digital twin" of a research enterprise, allowing leadership to test policy decisions in a risk-free, virtual environment before implementing them in the real world. The information from this simulator reveals a crucial policy insight: organizations cannot focus solely on incremental or breakthrough innovation. The empirical evidence proves that Incremental ideas are the indispensable base layer of the innovation pyramid and Breakthrough innovations are the game changing transformation that increase an advantage well above an advisory's capability. Incremental innovations are the enablers for higher-impact innovations, and starving them of resources will, over time, eliminate the very foundation from which breakthroughs emerge. Modular, Architectural, Radical, and Disruptive need enough funding to transform research into breakthrough capabilities.

To simulate the risk verses the probability of innovation in a R&D organization, another management flight simulator was built in Vensim (Witt, 2016). The model simulates the percentage of investment an organization or an individual (Program Officer) could make in the six different categories of innovation proposed in this dissertation. The outputs of the simulator are a graph of the adoption rate of each of the categories, from Incremental to Breakthrough, a Pareto graph that shows the probability of an extreme event that has been categorized as a breakthrough innovation, and a log-log plot of a Pareto distribution to show risk of investments from the slope of the line. This dissertation uses the slope of the log-log plot to turn an abstract concept like "innovation risk" into a precise, mathematical metric. This dynamic model, developed from all the dissertation research could be used in Naval S&T portfolio investment strategies.

In a risk adverse portfolio, the log-log plot exhibits a very steep downward slope (high α), the risk profile for a portfolio would be low. This signifies a "Sustaining" strategy. The enterprise is extremely good at making small improvements to existing Naval platforms. In the Pareto distribution, the "tail" is thin or non-existing. This means there is a very low statistical probability of discovering the next "transformational technology" before an adversary does.

In a "Disruptive" Portfolio, the log-log plot exhibits a gentle, flatter downward slope (low α, near 1.1 to 1.3). The risk profile is high risk with high impact. This is an "Exploratory" strategy. The "Risk of Failure" is higher. Many projects might end as bad ideas, but the system is structurally designed to increase the probability of breakthroughs for transformational capabilities. The Naval Advantage is that this portfolio creates the "Heavy Tail" where breakthroughs are frequent enough to be part of the long-term Naval strategy, rather than just lucky accidents.

Figure (32) shows the Optimal Strategic Equilibrium for a Naval R&D portfolio. By shifting the investment strategy from 100% incremental to a more diversified distribution, specifically increasing the Breakthrough Percentage of Investment to approximately 5%, we observe a fundamental shift in the system's long-term viability. Tiered growth is seen in this diversified simulation where cascading effects are seen with Modular, Architectural, and Radical categories achieving S-curve growth, with each successive tier plateaus at a slightly lower adopter counts of approximately 950, 900, and 820 respectively. The log-log plot shows the blue dots, representing incremental research, dropping sharply around the -6.5 mark which indicates high-density, low-variance outcomes that essentially guarantee small-scale results. The “Breakthrough” innovation slope (red dotted line) represents the frontier of breakthrough science. In this diversified portfolio simulation, this line extends downward and to the right. This illustrates that as the final “Breakthrough" value increases, the probability density of achieving it decreases which is a representation of high-risk, high-reward research. Only after shifting investment to 8.4% for Disruptive and 5.4% for Breakthrough do “long-shot" categories begin to show visible growth on the 10-year horizon.



All Six Catagories of Innovation Must Add to 100% of Total Portfolio Value

Incremental Percentage of Investment: 0.001 .5 1 adopters/Month
Modular Percentage of Investment: 0.001 .115 0.166667 Dmnl
Architectural Percentage of Investment: 0.001 .124 0.166667 Dmnl
Radical Percentage of Investment: 0.001 .122 0.166667 Dmnl
Disruptive Percentage of Investment: 0.001 .084 0.166667 Dmnl
Breakthrough Percentage of Investment: 0.001 .054 0.166667 Dmnl

Figure (32). This is a R&D Enterprise diversified portfolio simulation with a power law tail for Breakthrough innovation. This slide represents the “Optimal Strategic Equilibrium” for a R&D portfolio, as indicated in the bottom right graph by the power law heavy tail. By balancing the investment strategy into a diversified distribution, specifically increasing the Breakthrough percentage of investment to just 5%, we observe a R&D enterprise’s long-term viability. Users adjust the sliders to find a balanced portfolio of investment among the six categories of innovation.

The Pareto Distribution (Fat-Tail Plot) of Figure (32) in the lower right-hand corner, specifically models the "Extreme Value Theory" component of the research portfolio. In the two previous figures, there was a zero investment in Disruptive and Breakthrough research categories. When breakthrough investment was at the minimum (0.1%), this graph was completely empty, indicating no "impactful transformational science" was being generated. Once investments in disruptive research reaches 8.4% and investment in breakthrough research reaches 5.4%, a blue Pareto curve appears. This curve represents a power-law distribution, where a few "super-star" researchers or projects generate much of the impact, while most projects yield smaller results.

Figure (33) shows a modified state of the Innovation Category Investment Simulation, where the investment strategy has shifted from the previous 100% incremental baseline to a more diversified research portfolio. Unlike the previous single-line graph, the 120-month projection now displays multiple active growth curves for different innovation types. The “Incremental and Breakthrough Risk Assessment”, the log-scale plot, shows a significant change in which the blue dots Incremental innovation density curve has flattened and elongated compared to the baseline, suggesting more variability in the incremental category due to the diversified investment.

The red line, “Breakthrough”, now show a prominent downward-sloping red line. This represents a broader spectrum of potential risk and reward for breakthrough innovations being modeled within the system.

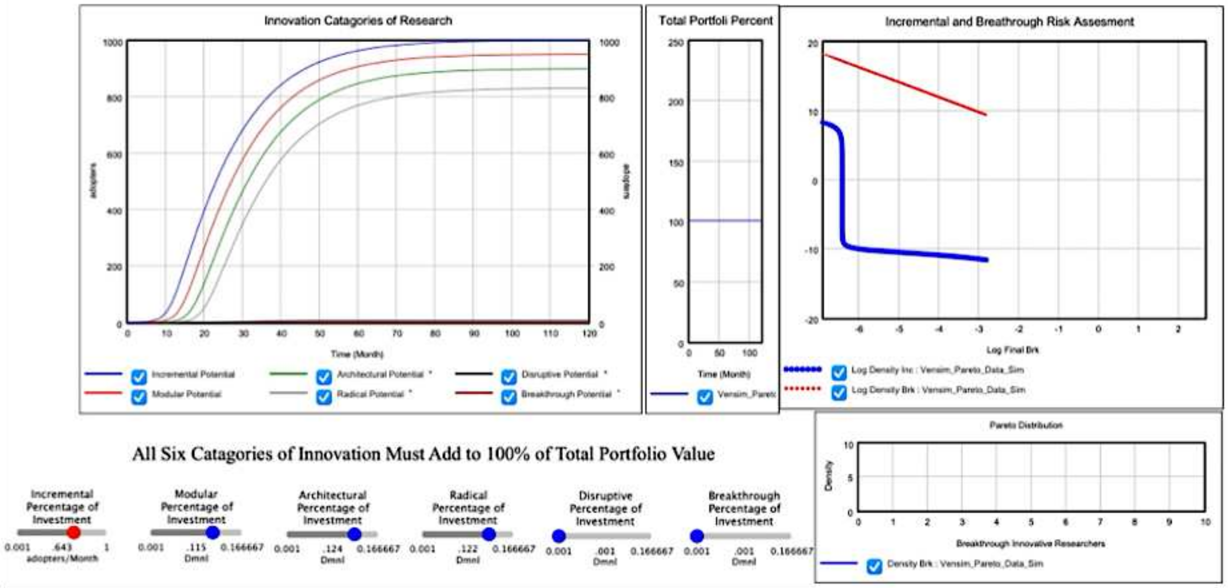


Figure (33). This figure is a modified state of the innovation category for investment management flight simulator for a R&D Enterprise. The figure illustrates an investment strategy simulation of the first four categories of innovation. We observe the systemic impact of a risk adverse portfolio with a reduced probability of Breakthrough research. The bottom right graph does not show the power law distribution that is indicative of game changing investments.

Figure (33) illustrates the Modified State of our investment simulation, providing a direct contrast to the previous balanced baseline. Here, we observe the systemic impact of a diversified research portfolio, where resources have been strategically reallocated across four innovation categories.

Figure (34) shows a dashboard interface for Increment investment only. It displays the Vensim simulation variables (sliders) used to analyze how different types of research investments impact a portfolio over time. The specific scenario shown, with innovation category 100% Incremental innovation investments, indicates an R&D enterprise where all resources are funneled into the least risky category. The “Incremental and Breakthrough Risk Assessment” graph that is on the top right shows a log-scale scatter plot with “Log Final Brk vs. Log Density” showing two distinct data clusters. The blue dots, Log Density of Incremental innovations, form a vertical drop, representing the high-density, low-variability nature of incremental research. The red dots, Log

Density of Breakthrough innovations show a small, high-positioned cluster representing the breakthrough potential, which is minimal and almost not visible in this simulation.

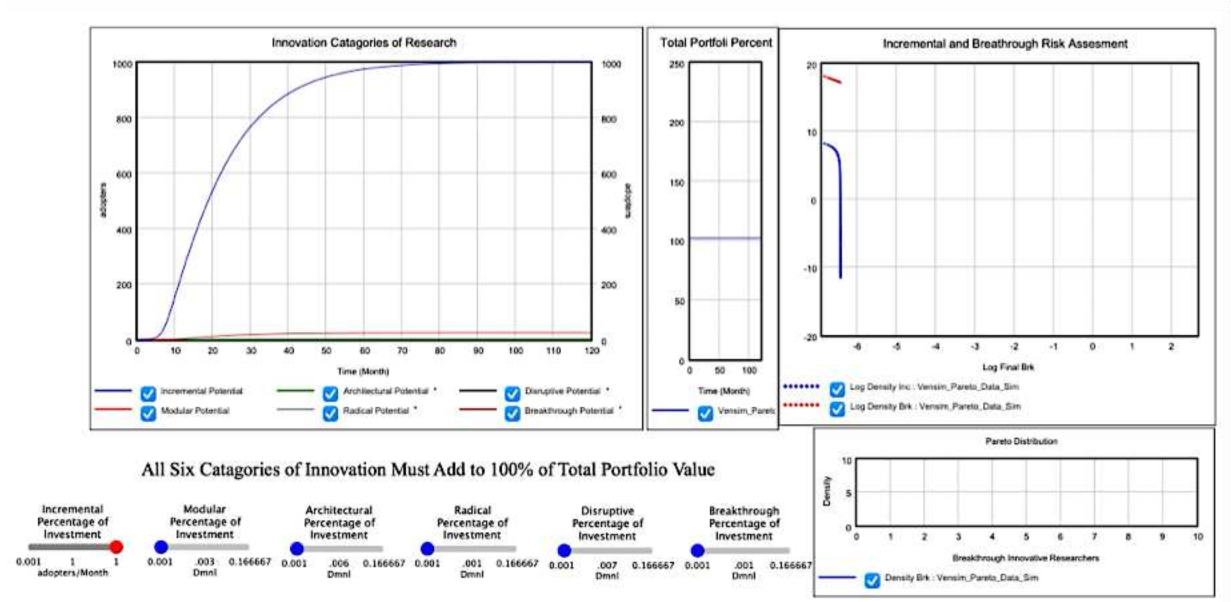


Figure (34). This figure demonstrates a baseline stress test of the management flight simulation, modeling a scenario where the research portfolio is restricted to 100% Incremental innovation investments. This serves as a "control case" to illustrate the systemic stagnation that occurs when all other innovation categories and risk is entirely avoided.

Figure (34) demonstrates a baseline stress test of our investment simulation, modeling a scenario where the research portfolio is restricted to 100% Incremental innovation investments. This serves as a "control case" to illustrate the systemic stagnation that occurs when breakthrough risk is entirely avoided.

Figure (35) illustrates the systemic collapse of adoption when the research enterprise pivots almost entirely away from incremental stability. This plot shows a dramatic departure from the previous "S-curve" success seen in the more balanced portfolios. The simulation shows an adoption failure due to cutting of Incremental investment to 10% and increasing Breakthrough investments to 90%, in which none of the six categories achieve a successful logistic growth curve that is indicative of balance probabilities of innovation. The blue line in the innovation category plot shows a negligible linear crawl, failing to reach even 100 adopters by month 120. This indicates stagnation of incremental advancements. The other five categories, including Breakthrough, remain effectively at zero. The model demonstrates that without a base of incremental investments to provide infrastructure or readiness, a massive investment in breakthroughs will fail to translate into realized adopters within a 10-year window. This is what is described in the "Innovation Paradox" (Zeng et al., 2017).

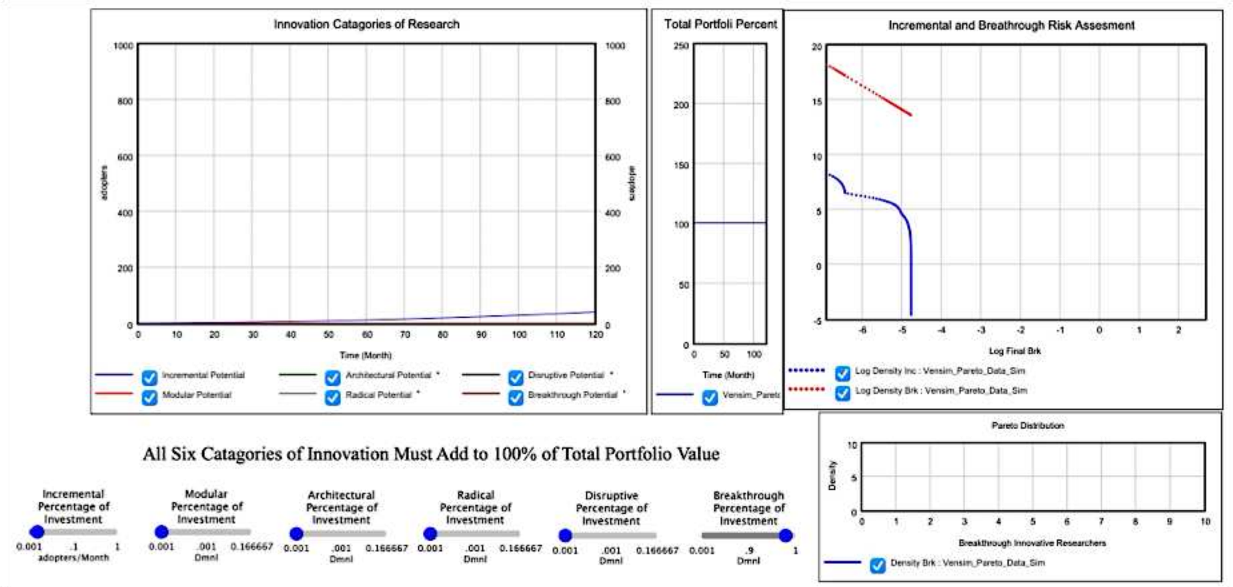


Figure (35). This figure illustrates the systemic collapse of innovation adoption when a R&D research enterprise pivots away from stability and only funds risky Breakthroughs. The result is a total collapse of the innovation ecosystem. Without the "steady state" funding of incremental and modular projects to provide the foundational infrastructure and adopter base, the breakthrough potential fails to launch.

Figure (35) clearly demonstrates the Innovation paradox in which to achieve radical, disruptive, or breakthrough innovations, an enterprise must maintain a stable core. This simulation serves as a critical warning to leadership that disruption at all costs is just as dangerous as stagnation, reinforcing the need for the balanced Optimal Equilibrium we discussed in the previous slide.

Figure (36) show the Extreme Value Theory (EVT) justification for an investment framework, contrasting a "Safe Portfolio" with a "Moonshot Portfolio." It visualizes the fundamental trade-off between predictable steady-state returns and the "fat-tailed" potential of breakthrough innovations.

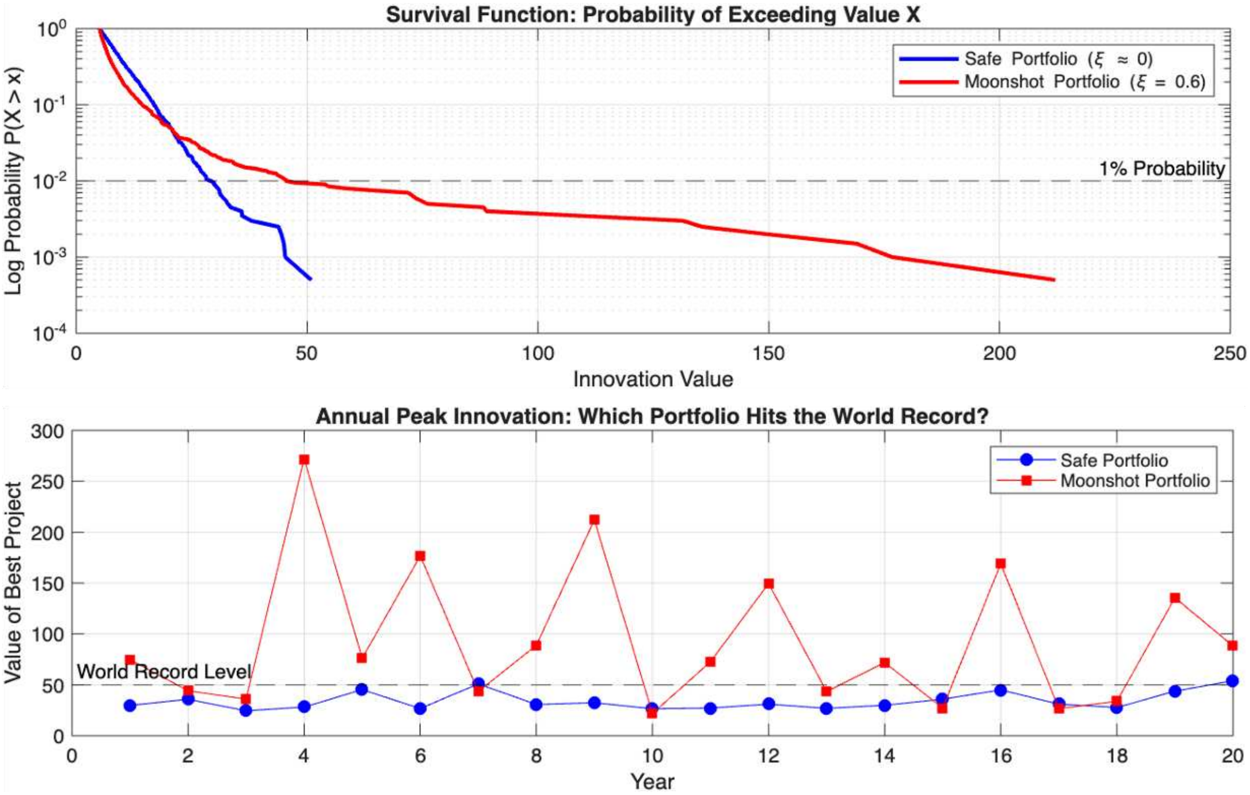


Figure (36). This is a R&D Enterprise Management Flight Simulation of innovation investment comparing risk adverse (Safe) and Moonshot (risky) portfolios. This helps with understanding minimum allowable risk aversion threshold.

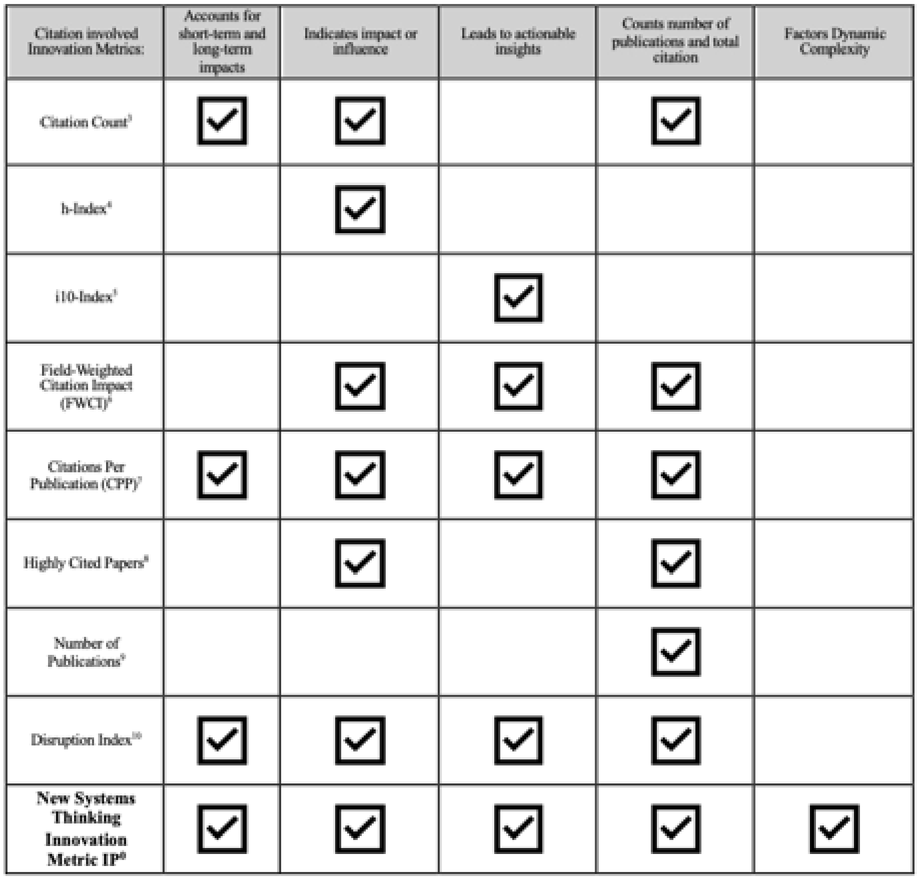
In the top graph of Figure (36), the Survival Function shows the “Safe Portfolio”, in blue, provides high probability for low-value outcomes. This indicates that the “Safe Portfolio” hits a "wall" at an innovation value of 50. The Moonshot Portfolio, in red, has a significantly thicker tail, maintaining a 1% probability of achieving impacts four to five times greater than the safe limit. The bottom graph, Annual Peak Innovation, illustrates this in practice which shows that the safe portfolio never reaches the "World Record" level, while the “Breakthrough Generation Portfolio”, despite higher volatility, produces frequent massive spikes that could lead to disruptive capabilities.

5.3 A New Metric for a New Model: Innovation Procreation (IP^0)

To manage the balancing of risk with the probability on innovation, a new metric was created for this dissertation research. The proposed six level framework introduced the Innovation Procreation (IP^0) metric, which measures the likelihood of an idea being adopted and spreading throughout a community, the infectiousness.

IP^0 was calculated from the agent-based model and dynamic systems models used for this dissertation. This new metric is for identifying innovative science and technology research using data to replace TRLs as a metric for measuring innovation maturity. Because the rate of knowledge generation is critical to both economic growth and military power, it is essential to use methods that account for the time-dependent nature of innovation. Traditional TRLs measure feasibility, but they fail to measure potency. A technology can be at TRL 8 but remain a dead end if it lacks the modular or architectural flexibility to spawn further innovation. The Innovation Procreation (IP^0) metric shifts the focus from, how ready is it to deploy to how ready is it to deploy and, how fast can it be improved. This is something current approaches fail to capture. In the framework of this dissertation an innovation reaches maturity when its IP^0 stabilizes at a high plateau, not when it is physically built and ready to deploy. If innovation’s citations are self-replicating, new research doing the citing are being highly cited, IP^0 rises signaling high maturity and low adoption risk. This is shown in the agent model Figure (35).

Table (3) showing different metrics used for qualitative analysis of impact and productivity of innovative research. An IP0 value greater than 1 indicates that researcher will pass to more than one other person suggesting that the innovation will likely spread through the relevant research population.



Citation involved Innovation Metrics:	Accounts for short-term and long-term impacts	Indicates impact or influence	Leads to actionable insights	Counts number of publications and total citation	Factors Dynamic Complexity
Citation Count[3]	☑	☑		☑	
h-Index[4]		☑			
i10-Index[5]			☑		
Field-Weighted Citation Impact (FWCI)[6]		☑	☑	☑	
Citations Per Publication (CPP)[7]	☑	☑	☑	☑	
Highly Cited Papers[8]		☑		☑	
Number of Publications[9]				☑	
Disruption Index[10]	☑	☑	☑	☑	
New Systems Thinking Innovation Metric IP^0	☑	☑	☑	☑	☑

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[3] Tahamtan, I., Bornmann, L. What do citation counts measure? An updated review of studies on citations in scientific documents published between 2006 and 2018. *Scientometrics* **121**, 1635–1684 (2019). https://doi.org/10.1007/s11192-019-03243-4

[4] Understanding the H-index: A Comprehensive Guide (typeset.io)

[5] https://www.kressup.com/i10-index-calculate-i10-index.html

[6] The pros and cons of key metrics (bradford.ac.uk)

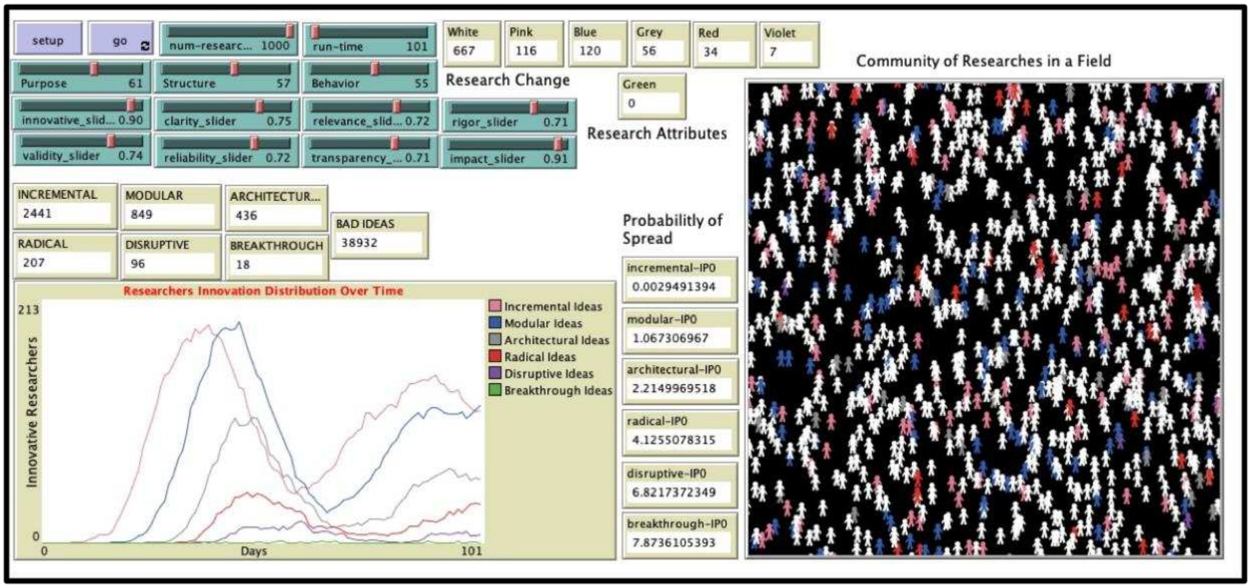
[7] Vernon, M.M., Danley, C.M. & Yang, F.M. Developing a measure of innovation from research in higher education data. *Scientometrics* **126**, 3919–3928 (2021). https://doi.org/10.1007/s11192-021-03916-z

[8] Huang, H., Zhu, D. & Wang, X. Evaluating scientific impact of publications: combining citation polarity and purpose. *Scientometrics* **127**, 5257–5281 (2022). https://doi.org/10.1007/s11192-021-04183-8

[9] Vernon, M.M., Danley, C.M. & Yang, F.M. Developing a measure of innovation from research in higher education data. *Scientometrics* **126**, 3919–3928 (2021). https://doi.org/10.1007/s11192-021-03916-z

[10] Leibel, C., Bornmann, L. What do we know about the disruption index in scientometrics? An overview of the literature. *Scientometrics* **129**, 601–639 (2024). https://doi.org/10.1007/s11192-023-04873-5

The right panel in Figure (37) of the agent model shows a dynamic field of researchers represented by colored icons. White 667 is the most common. Pink 116, Blue 120, Grey 56, Red 34, Violet7, represent researchers with different idea types. Green 2 is cyclic and get that high values before returning to 0. The graph at the bottom shows how each innovation type fluctuates across 101-time units with Incremental and Modular ideas peaking early and in high numbers. Architectural and Radical ideas emerged mid-run. Disruptive and Breakthrough ideas are rare and appear late. This suggests a diffusion of research where simple ideas spread early; complex ones arise more slowly. The key insights for this run of the agent model are, bad ideas dominate suggesting most innovations fail. Breakthroughs are rare but have the highest spread potential. Incremental innovation is the most common. The simulation rewards clarity, relevance, and impact in generating quality ideas.



num-researc... 1000
run-time 101
Purpose 61
Structure 57
Behavior 55
innovative_slid... 0.90
clarity_slider 0.75
relevance_slid... 0.72
rigor_slider 0.71
validity_slider 0.74
reliability_slider 0.72
transparency_... 0.71
impact_slider 0.91

White 667
Pink 116
Blue 120
Grey 56
Red 34
Violet 7
Green 0

INCREMENTAL 2441
MODULAR 849
ARCHITECTUR... 436
RADICAL 207
DISRUPTIVE 96
BREAKTHROUGH 18
BAD IDEAS 38932

incremental-IP0 0.0029491394
modular-IP0 1.067306967
architectural-IP0 2.2149969518
radical-IP0 4.1255078315
disruptive-IP0 6.8217372349
breakthrough-IP0 7.8736105393

Figure (37). Key Result – Agent-Based Simulation. The double humps or cyclic nature of the curves in the graph are indicative of the saturation of old ideas and the emergence of new ideas created by the feedback of breakthrough to start the cycle over.

The simulation shown in Figure (37) confirmed the "Innovation Pyramid" theory. Incremental ideas dominate the landscape, while Breakthroughs remain exceptionally rare. On the right, you can see the "Community of Researchers," where colors represent the current level of innovation they are pursuing. Crucially, the Probability of Spread (IP^0) values show that as an idea gains complexity, moving from Incremental to Breakthrough, its potential for systemic "infection" or spread increases significantly. This highlights that while breakthroughs are hard to achieve, once they emerge, they have a much higher "viral" impact on the organization than incremental innovations.

The likelihood ratio of an idea being adopted as modeled by the Agent model, is calculated by the IP^0 and is displayed in Table (4).

Table (4) shows Innovation categories with the metric that indicates infectiousness of the idea. The higher the IP^0 the more contagious the innovation.

Idea Type	IPO
Incremental	0.0029
Modular	1.067
Architectural	2.215
Radical	4.126
Disruptive	6.822
Breakthrough	7.874

A limitation of employing IP^0 with real world data is it can suffer for reporting lag of data. This would make it difficult to see the infectiousness of a breakthrough research project in real time.

Table (4) shows Breakthrough and Disruptive ideas spread more easily, but they occur far less frequently. Once introduced, they spread exponentially with IP0 values as high as 7.87.

5.4 Application to National and Organizational Strategy

The framework for innovations as investigated in the dissertation functions as a diagnostic and predictive engine for addressing pressing strategic challenges. For organizations like the Department of War, which have historically lacked a common metric for measuring the impact of basic research programs, this model offers a way to define, measure, and predict the outcomes of foundational science investments.

The Innovation Motive Force (IMF) analogy also serves as a powerful diagnostic tool. If an organization has a high IMF (strong vision, ample funding) but low output, the model prompts leaders to investigate sources of high resistance (bureaucracy, cultural inertia). If there are significant lags between investment and results, the concepts of feedback loops and organizational capacitance can help explain and manage those delays.

The research on the Unified Innovation Models and Systems Thinking serves as the theoretical and computational "operating system" required to execute the strategic overhaul outlined in the DOW agenda.

The research explicitly addresses the exact failures cited by the Secretary of War, specifically the reliance on linear models and offers the rigorous metrics and frameworks necessary to operationalize the DOW’s new "Integrated Ecosystem."(Transforming the Defense Innovation Ecosystem to Accelerate Warfighting Advantage, n.d.)

Both the DOW memorandum and the research papers identify the same root cause of failure in the current defense ecosystem:

- The DOW Agenda: The Secretary of War states that dysfunction stems from a "linear model that gates progress through sequential stages" (like a conveyor belt), declaring this model "dangerous to mission accomplishment" because it fails to reflect reality.
- The Research: The dissertation and papers argue that traditional frameworks are "static, linear, and isolated," failing to capture the "complex, nonlinear, and evolutionary nature" of innovation.
- The Tie-In: The research validates the Secretary's directive by scientifically proving *why* the linear model fails (it ignores feedback loops and emergence) and provides the Complex Adaptive System framework to replace it.

The DOW memorandum establishes a single, empowered Chief Technology Officer (CTO) to set technical direction and "align innovation organizations around outcomes". The research provides the physics-based analogy to model this alignment:

- The DOW Agenda: The CTO must apply pressure to "clear bureaucratic blockers" and align the ecosystem.
- The Research: Defines Innovation Motive Force (IMF) as the systemic driver (funding, policy, vision) analogous to Voltage (EMF) in a circuit. It models Bureaucratic Friction as "Resistance" (R) and Institutional Memory as "Capacitance" (C).
- The Tie-In: The CTO's mandate effectively creates the IMF. The research provides the Kirchhoff's Innovation Law (KIL) framework to calculate if the CTO's "voltage" is sufficient to overcome the "resistance" of the DOW bureaucracy to ensure the "current" (knowledge flow) reaches the warfighter.

The DOW memo mandates that by FY2028, every Portfolio Acquisition Executive must include an "Innovation Insertion Increment (III)" for rapid capability insertion. The research provides the missing metrics to justify and measure these increments:

- The DOW Agenda: Needs to measure "warfighting advantage" and stop treating innovation as an unmeasurable abstraction.
- The Research: Introduces Innovation Procreation (IP^0), a metric similar to viral reproduction rates (R_0), to quantify the "infectiousness" and adoption potential of a specific technology.
- The Tie-In: The IP^0 metric gives DOW leaders a quantitative tool to decide which technologies warrant an "Insertion Increment." It moves decision-making from qualitative guessing to quantitative probability, supporting the DOW's goal of "data-informed risk-taking".

The DOW organizes innovation into three specific outcomes shown in Table (5). The research's Six-Level Evolutionary Framework provides the granular roadmap for achieving them.

Table (5) shows the DOW Research levels with same definitions of Modular, Architectural, Radical and Disruptive but fails to include Incremental and Breakthrough.

DOW Agenda Goal	Corresponding Research Innovation Level	Strategic Implication
Technology Innovation (Defense-unique, classified)	Radical Breakthrough	The research shows these require a "prolonged buildup" and high-risk tolerance. The DOW must protect/classify these as they reset the paradigm.
Product Innovation (Commercial adoption/scaling)	Modular Architectural	The research defines this as reconfiguring components (Modular) or systems (Architectural). This matches the DOW goal of "harnessing commercial technology" rather than building from scratch.
Operational Capability (New ways of fighting)	Disruptive	The research defines Disruptive innovation as creating new value networks or displacing established systems. This aligns with the DOW's goal to find "disruptive applications of new and existing capabilities".

The DOW memo explicitly mentions the need to "pivot from only asking companies to build to specification" and warns against "gizmo culture".

- The Research: Explicitly cites Clayton Christensen’s Innovator’s Dilemma as a core failure mode where organizations optimize for the present (incremental) at the expense of the future (disruptive).
- The Tie-In: The research demonstrates via Agent-Based Modeling (ABM) that Incremental Innovations form the necessary "base layer" for breakthroughs. It advises the DOW that they cannot simply "buy" breakthroughs; they must fund a balanced portfolio where incremental advances in the Mission Engineering and Integration Activity (MEIA) feed into the disruptive prototypes of the Strategic Capabilities Office (SCO).

The dissertation explicitly states its goal is to bridge the gap in literature for "predicting innovative basic research programs in the Department of Defense".

While the DOW memo provides the political and organizational mandate (Purpose and Structure), the research provides the scientific and mathematical methodology (Behavior and Metrics) required to execute that mandate effectively. It transforms the Secretary's vision from a bureaucratic reorganization into a quantifiable, engineered system.

5.5 R&D Organization Implementation

To implement this in a new organization, we must move beyond linear framework flow charts and static spreadsheets. A R&D organization should start by gathering Historical Data, specifically citation time-series patterns and program officer assessments of their portfolios to build prior beliefs for analysis by management flight simulator tools. The management tools should then be tuned in an Enterprise System Engineering dynamic mental model, calibrating the 'Resistance' of the organization's bureaucracy and its 'Capacitance' for new ideas. The framework for implementing Phase 1 and Phase 2 can be seen in Figure (38).

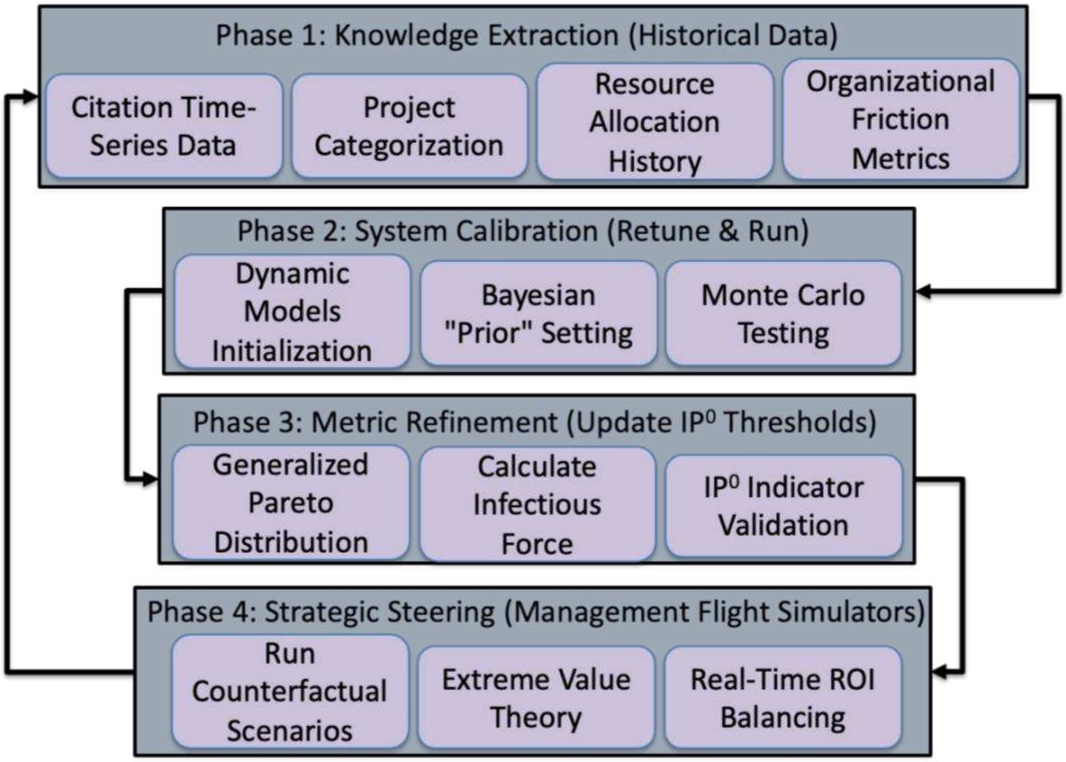


Figure (38). R&D Organization implementation of Innovation Life Cycle and Evolution framework. These steps are necessary to ensure that IP^0 and Management Flight Simulator more accurately represent the innovation behavior of the specific organization under investigation.

Figure (38) is a four-stage process that matures from baseline data to a dynamic "Flight Simulator" for management. Once calibrated, R&D organizational managers should proceed to Phases 3 and 4 as shown in Figure (38). A manager should update the IP^{o} thresholds to ensure that the definition of a 'Breakthrough' is mathematically anchored to the organization's specific research field. The final step is to present the Management Flight Simulator to leadership for analysis and counterfactual experiment from their perspective. This allows them to test Investment Policies in a risk-free environment, identifying the exact allocation needed to ensure that incremental progress eventually evolves into the high-magnitude breakthroughs required for a strategic edge.

The details of the sub models in each of the four phases are as follows: In Phase 1, citation Time-Series Data is for collecting at least 5 to10 years of internal and external citation data for R&D projects. This is the raw material for calculating IP^{0}. Project Categorization, the Subjective Prior probability, is for a Program Officer Self-Assessment to capture the perceived innovativeness and risk of past FY projects. Resource Allocation History is to document the historical split between Incremental, Modular, Architectural, Radical, Disruptive, and Breakthrough investments. Organizational Friction Metrics are for identifying "Resistance" variables such as average time for approval, risk-aversion culture surveys, and legacy system constraints. Model Initialization, in Phase 2, is for inputting the historical resource efficiency and organizational capacitance into a Vensim or MATLAB management flight simulator. Bayesian "Prior" Setting is used for the historical data to set the initial probability distributions for project success. Monte Carlo analysis is performed by running thousands of simulations to determine the "Natural Selection" rate, of a R&D organization’s ideas. This identifies where the bad research ideas are highest. In Phase 3, Threshold Mapping is performed by using the Generalized Pareto Distribution (GPD) to analyze the "Tail" of citation data to set specific magnitude boundaries for the six innovation categories.

Calculating Infectious Force is used for calibrating the transmissibility, Contact Rate, and Duration of research adoption coefficients. The Indicator Validation is to ensure the current IP^0 results are catching the “High-Magnitude events” that traditional TRLs are missing. The final phase, Phase 4, starts by running counterfactual scenarios by using simulators to test different investment distributions. The Extreme Value Theory (EVT) results are used to find the 5% to 15% breakthrough allocation funding percentage that avoids both stagnation and systemic collapse. The Real-Time ROI Balancing is used to monitor the expected utility verses uncertainty daily. If a project's IP^0 spikes, a manager could use the Bayesian flight simulator to justify an immediate "pivot" of resources to capitalize on the momentum.

Future work and expansion of this research, for a graduate student could involve the obvious next evolution steps that require transitioning from a "Digital Twin" of a R&D enterprise to a “R&D Enterprise Active Autonomous Controller) (RDEAAC). The proposed research would focus on integrating Artificial Intelligence (AI) with the existing Management Flight Simulators to automate R&D resource rebalancing in real-time. This dissertation successfully replaced linear innovation "pipelines" with a Complex Adaptive System (CAS) model, an Innovation Procreation metric, and the Innovation Motive Force (IMF) framework. However, the managerial flight simulators currently rely on manual human inputs. It is conceivable that a future graduate student could develop a Large Language Model (LLM) engine to automate signal detection to identify high-magnitude IP^0 spikes across global patent and citation databases without human intervention, quantify cognitive diversity by moving beyond subjective capacitance measures to objective, data-driven metrics, and adjust R&D trajectories dynamically as external influences fluctuate.

CHAPTER 6: CONCLUSIONS AND FUTURE WORK

6.1 Forword Toward a Dynamic and Predictive Science of Innovation

The central paradox of any Innovation Research Enterprise is that the most impactful breakthroughs are, the least predictable. Traditional management via Technology Readiness Levels attempts to manage this uncertainty by forcing non-linear scientific discovery into a linear engineering pipeline. This research demonstrates that such a framework or mentality often leads to the Innovator's Dilemma which is over-funding mature, low-risk incremental innovations while starving the Black Swans, Breakthrough innovation, technologies that possess the highest generative potential.

By framing the ability to manage innovation as the ability to manage uncertainty and complexity, this dissertation provides a shift in previous perspectives. Uncertainty should no longer be eliminated through rigid milestones; uncertainty should be a measure to be quantified and leveraged.

The introduction of the Innovation Procreation (IP^0) metric allows organizations like the Department of War (DOW) or Naval S&T to move beyond standard TRLs to the point where a technology is technically ready and has the ability to diffuse and create systemic impact in a research community of interest.

For too long, the management of innovation has been treated more as an art than a science, guided by intuition and flawed metrics. This paper has argued that this approach is no longer tenable. Innovation is not a linear, isolated, or purely random process; it is a dynamic, evolutionary Complex Adaptive System with discernible structures, causal relationships, and feedback loops. The Unified Innovation Model presented here offers a new paradigm. It integrates

Systems Thinking, a six-level evolutionary lifecycle, and a multi-model analytical suite comprising probabilistic, causal, and systemic analogies. Validated through computational modeling, this framework provides an evidence-based and predictive methodology for understanding how small, incremental ideas evolve into world-changing breakthroughs.

Ultimately, this work provides a powerful toolkit for leaders, policymakers, and R&D managers. It equips them to move beyond reactive decision-making and toward a more predictive science of innovation—one that allows them to allocate resources more effectively, manage technology portfolios with greater foresight, and ultimately, engineer more impactful science.

Innovating is not random nor is it fully planned. Innovations can be modeled as an evolving system that grows through connections, behaviors, and feedback. Innovation responds to stimulus and spreads through interactions. To understand it, more than one model was used to simulate the interconnections. The life cycle and evolution innovation model draws from biology, systems theory, causality, and individual behavior was deemed the best tools for this endeavor. This approach can be used for measuring present research innovativeness and for shaping future innovations. The Innovator's Dilemma describes the paradox where successful organizations fail to adopt disruptive innovations that initially underperforms existing technologies or procedures.

This failure often leads to the organizations decline as others overtake them with disruptive alternatives. Examples of the Innovator’s Delima include Kodak, which failed to capitalize on digital photography. Nokia, which ignored the smartphone paradigm shift and Blockbuster, which underestimated Netflix’s digital model.

Historically, innovation was often viewed as a linear progression from research to development, leading to application. This perspective shifted as the multifaceted nature of innovation became apparent, which led to more non-linear models that consider multiple factors such as technology maturity, societal forces, and enterprise structures. Dynamic models for innovation have been created for business operations, personnel management, and product improvement (Ghaffarzadegan et al., 2023). The new life cycle and evolution innovation model was created to be used for science and technology research. At the top level, this new model incorporates the stage descriptions shown in Table (6) to be used for indicating the different levels of innovations.

Table (6). St Stages of Innovation Categories

Innovation Type	Stage Description
Incremental	Process refinements, continuous improvement
Modular	Component-level recombination
Architectural	System-wide restructuring
Radical	New paradigms replacing old frameworks
Disruptive	Destructive-to-dominant technology transitions
Breakthrough	Historic innovation leaps redefining fields

This table outlines the six major types of innovation. Incremental innovation refers to gradual improvements, refining processes, or pursuing small improvement. Modular innovation occurs where existing elements are recombined in new ways without altering the larger system.

Architectural innovation involves a restructuring of entire systems. Radical innovation brings entirely new paradigms that replace old frameworks with fundamentally different approaches. Disruptive innovation shifts science and technologies that often starts niche areas before spreading broadly. Breakthrough innovation represents historic leaps that redefine entire fields of science and technologies, opening new industries or scientific domains. Together, these categories illustrate the spectrum of innovation from minor refinements to transformative shifts.

A structured, multi-model approach to innovation that blends innovation pathways, decision models, and organizational strategies provides a powerful means to both exploit current advantages and explore emerging disruptions (Kuhlmann et al., 2023). This research demonstrates that navigating the Innovator’s Dilemma requires an integrated framework that can capture the evolutionary dynamics of innovation. This paper combined Bass diffusion modeling, causal inference, genetic algorithms, agent-based simulations, and Monte Carlo analysis as a framework to be used to infer innovation as a living, adaptive system rather than as a static or linear process.

The analysis of publication time series and citation patterns illustrates how small changes in attributes such as clarity, rigor, and impact cascade into significant differences in innovation outcomes. The introduction of the Innovation Procreation (IP^0) metric provides a quantitative means of distinguishing between ideas likely to fail and those with the potential to become disruptive or breakthrough innovations. Simulation results confirm that while most ideas remain incremental or are abandoned, rare breakthrough innovations spread widely once they emerge, underscoring the importance of sensitivity to early signals of transformative potential.

The new six-stage life cycle and evolution model offers both a conceptual and computational structure for organizations and policymakers. It enables them to classify innovations more precisely, quantify uncertainty, and evaluate the return on research investments under complex and uncertain conditions. This multi-model approach to the innovation life cycle and evolution bridges the lack of robust, science-driven metrics for assessing the impact of basic research. This framework could be used by stakeholders as a decision-support tool that explains how innovation evolves to assist in guiding strategies for fostering and sustaining the breakthroughs that drive scientific and technological progress.

The United States Navy faces a paradox in its science and technology (S&T) sector, characterized by both remarkable advancements and concerning trends from adversaries that threaten to outpace US innovation. The governance of RDT&E investment is crucial for sustaining long-term economic growth and military power, necessitating a shift from profit-maximizing strategies. Rapid advances in technology are often mistaken for continuous breakthroughs, overshadowing the lengthy early phases of innovation that will impact military power in the future.

A unique constraint in modeling Naval innovation is the impact of security classification on bibliometric data. As a technology matures from a scientific concept to a naval application, it often transitions from open-access journals to Controlled Unclassified Information (CUI) or classified status.

The power of the dynamic models described for this paper are the ability to deduce the cause, a change in structure, purpose, and behavior, from the effect, increased citations, to give the probability of innovation for Naval application. In scientific discovery and engineering, the alteration of an element's structure, the redefinition of its purpose, and the modification of its behavior are fundamental processes that drive innovation. Although the laws of physics explain much of the world around us, we still do not have a realistic description of causality in a truly complex hierarchical structure (Ellis, 2005). This paper attempts to do so using Systems Dynamics, Systems Principles, and Systems Thinking. Naval engineering has evolved through cycles of bold experimentation and slow refinement. The transition from sail to steam, the development of nuclear propulsion, the rise of naval aviation, and the integration of networked systems followed unique innovation paths. Lessons from this history show that innovation depends on structure, feedback, and timing. The dynamic models created for this paper may allow these factors to be tested virtually.

This study presented a System Dynamics framework to model the diffusion of foundational knowledge within the Naval innovation ecosystem. By utilizing Nobel Prize-winning research as a validated proxy for high-impact discovery, we have demonstrated how technical "shocks" permeate scientific populations.

The findings in this study suggest that the innovation pipeline begins with the creation of knowledge that is tracked through the maturation of citations. It was noted that the ultimate success of an innovation for Naval applications is dependent on its transition across organizational and security boundaries.

Citations serve as a critical validation signal that reduces perceived risk for investment decisions. They must be understood as a lagging indicator of scientific maturity rather than a leading indicator of fleet integration. By quantifying knowledge diffusion, this model could provide Naval leadership with a baseline for understanding how foundational breakthroughs eventually populate the beginning of the pipeline and provide the technical certainty required to bridge the "Valley of Death" and deliver decisive capabilities to the warfighter.

6.2 Systems Thinking is the way to manage Science, Engineering, and Technology Development:

Systems Thinking will dominate how all Science, Engineering and Technology research will be framed in the future. The future of Science, Engineering, and Technology (SET) research necessitates a departure from reductionist management toward the dominance of Systems Thinking as the primary framing for innovation. As traditional linear models collapse under the weight of modern complexity, Systems Thinking provides the essential cognitive and computational infrastructure to view the research enterprise not as a series of isolated milestones, but as a Complex Adaptive System (CAS) governed by non-linear feedback and emergent behaviors. In the context of the Department of War (DOW), this shift is critical; it moves the focus from managing individual "inputs" to understanding the dynamic "procreation" of ideas where incremental gains cumulatively trigger modular, architectural, and ultimately radical paradigm shifts. By adopting a systems-aware methodology, a R&D enterprise can finally transcend the Innovator's Dilemma, utilizing tools like System Dynamics and Agent-Based Modeling to forecast the temporal evolution of breakthroughs and align strategic R&D investment with the chaotic, yet structured, reality of scientific discovery. The interest in this capability for innovation is evident by the acceptance for publication of the paper, "Advancing the Navy's Technological Innovation Pipeline through System Thinking and Dynamic Modeling" written by me for the Naval Engineering Journal. This paper can be seen in Appendix E.

Traditional R&D management is often trapped in a balancing feedback loop: as an organization becomes successful at a specific technology, it creates rigid processes to protect that success, which inadvertently stifles the "evolutionary mutation" required for the next breakthrough. The multi-model approach breaks this cycle by framing innovation as a Complex Adaptive System (CAS) where exploration is not a luxury, but a survival mechanism.

By utilizing Agent-Based Modeling (ABM) to simulate the "procreation" of ideas at the researcher level, this dissertation framework allows leaders to see the emergent properties of the system before they manifest as failures. It shifts the focus from managing static outcomes to managing the dynamic potential (IP^0) of the research ecosystem. This ensures that the enterprise does not just "do science" efficiently, but "evolves science" effectively, maintaining a continuous trajectory from incremental refinements to radical, disruptive, and breakthrough paradigm shifts.

6.3 The Future of Innovation in the context of the Artificial Intelligence Revolution:

The dynamic systems models, ABMs, and management flight simulations created for this dissertation, all illustrate how different categories of innovation build on each other and propagate through a community at varying rates and time scales. The innovation time-lag highlights the delay between Incremental, Modular, Architectural, Radical, Disruptive, and Breakthrough research. All of the models and simulation shown in this dissertation provide justification for patience in the six-innovation categorical funding. A "Breakthrough" may take 100+ months to manifest even a, but its emergence is predicated from the preceding growth of the other categories.

The rise of Artificial Intelligence (AI), as an example of the true nature of innovation, is examined using the lens of the framework created in this dissertation. AI is discussed as a singular event, when it is a breakthrough born from the convergence of the six distinct structural innovation categories. Even though advanced algorithms today provide the logic, use, new capabilities never seen, the innovation itself is anchored in the physical and systemic evolution of computing software and hardware. With all the new capabilities envisioned for AI, it is conceivable that it could become the “Operating System” of a research enterprise. A true Artificial General Intelligence (AGI), the next step in AI research, won’t just help make decisions; it could reconfigure the architecture of innovation itself, moving an entire organization from a linear growth model to a power-law-driven "Breakthrough" framework.

6.3.1 Redefining how Impactful Science is engineered using AI:

AI could be used to assist in the engineering of impactful science by first recalling every failed R&D project from the last 50 years, preventing the reinventing of the wheel. This would provide Incremental Value. AI could then be used to automate the administrative paperwork of grants, allowing humans to focus on the high-level Systems Thinking. This would provide Modular Value in the context of this dissertation. Instead of best guessing forecasting, AI could run millions of simulations of market or war fighting outcomes for an R&D investment optimization based on data instead of a few decision makers. This would be a Radical shift in the way enterprises operate. AI could then be used to find the hidden links between unrelated areas of science and apply the value to unforeseen capabilities. This would be a Disruptive value in the application of innovations. A truly advanced AGI could then control the investment process so that decisions are no longer made in a meeting of the few at the top; decisions would be a continuous living and evolving process by an "Operating System" of the enterprise. This would be a Breakthrough in R&D enterprise management.

A possible limitation to the AI driven future of innovation is as AI automates the all the known scientific and technology research, it may make it harder to predict disruptive and breakthrough ideas. This is due to the fact that all AI algorithms are trained on historical data. AI can reinforce existing paradigms including the "Innovator's Dilemma" which is not a desired outcome.

The most immediate impact of applying AI to innovation systems management is the temporal compression of the life cycle and evolution. Traditionally, life cycle is slowed by human bottlenecks. The pattern shift would be created by AI moving the ideation and validation of innovative research phases from months to hours. The IP^0 connection would be used by AI to reduce the time it takes for one idea to procreate another, and the infectiousness of the innovation would spike. You no longer see a slow upward curve; you see a vertical "Flash Innovation" event. Faster vs. Slower: While the discovery is faster, the institutional absorption often becomes a bottleneck (Specialized CPU/OS category), potentially creating a "Slower" tail-end as organizations struggle to govern the output.

The future of Engineering Impactful Science in the age of AI will require moving beyond managing parts, silos, and favorite linear paradigms to managing systemic architectures. By leveraging the six categories of innovation framework, IP^0, extreme value theory, and Pareto power law distributions, a research enterprise can shift portfolio management in real time to respond to the fast-changing influence of today’s world. We can modify our traditional hit-or-miss approach to a logical, data driven, mathematically sound precise framework of continuous breakthrough generation.

6.4 Limitations of the New Innovation Framework:

There are a few methodological and operational limitations of the Dynamic Innovation Models conceived, designed, and built to address the failures of static metrics. The Unified Innovation Model and Dynamic Based Innovation Model rely on complex system dynamics, Bayesian analytics, and causal inference. This research acknowledges several limitations inherent to this advanced approach. First, as shown in the dissertation, it is impossible to have a single metric for innovation. No single metric can be used to quantify or predict innovation. Accurately forecasting innovation requires the heavy computational burden of the multi-model approach. This dissertation combed Agent-Based Modeling, Vensim Dynamic Models, Genetic Algorithms, Bayesian Inference models, and Bass Diffusion, which are complex to build and interpret. The complexity of learning and being fluent with the tools used to create the models may be a limitation for those who want to quickly begin innovation forecasting for a R&D organization.

Another possible limitation, especially for the Department of War, is security classification constraints. When modeling innovation in military contexts, a unique constraint is the impact of security classifications. As a technology matures from a basic scientific concept to an applied military capability, it often transitions from open-access academic journals to Controlled Unclassified Information (CUI) or fully classified status, cutting off the bibliometric data necessary to track its continued diffusion. This could limit the accuracy of predicting innovations if citation patterns and patent patterns are used for input data to all the models discussed in this dissertation.

Another possible limitation of this new innovation framework is the simplifying assumptions in modeling. To make predictions, dynamic models must sometimes rely on simplifying assumptions. For example, some differential equations used to estimate the future spread of knowledge assume a homogeneous population of researchers where individuals move between categories at proportional rates, which may oversimplify highly fragmented or siloed scientific communities.

Labor-Intensive Data Engineering could create some limitations to this new innovation framework. Creating causal models to isolate variables that genuinely drive innovation, like Purpose, Structure, and Behavior, requires extensive, labor-intensive data mining. Literature reviews and dataset compilations are always subject to search engine limitations and researcher bias.

The foundational premise of "Engineering Impactful Science" is that traditional frameworks and metrics for managing research and development (R&D) are fundamentally flawed because they treat innovation as a static, linear process rather than a Complex Adaptive System. This new innovation framework, as discussed, researched, and validated in this dissertation, has a few limitations. These limitations can be overcome for improving innovation cultivation in a R&D enterprise. Even though complex, the “Strategic Simulators” sets policies, the Bayesian/Monte Carlo simulations manage projects, and the ROI IP^{0} modules provide the real-time feedback loops.

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APPENDIX A: MATLAB SCRIPT DOCUMENTATION

Extreme Value Theory Modeling Using the Generalized Pareto Distribution (GPD)

Documentation and Script

This document describes a MATLAB script that implements Extreme Value Theory (EVT) using the Generalized Pareto Distribution (GPD). The script computes return levels, evaluates lifetime risk, and visualizes extreme-event behavior using both a return level curve and a risk heatmap.

1. Purpose of the Script

The script demonstrates how to model rare but high-impact events using EVT. Rather than modeling the full distribution of events, EVT focuses on values that exceed a specified high threshold. These exceedances are modeled using the Generalized Pareto Distribution (GPD), which is particularly suited for heavy-tailed phenomena such as financial crashes, floods, infrastructure failure, or breakthrough innovations.

2. Model Configuration

The model is configured using four primary parameters:

- Shape parameter (xi): Controls tail heaviness. A value greater than zero indicates heavy-tailed, power-law behavior.
- Scale parameter (sigma): Controls spread of extreme exceedances.
- Threshold (u): Defines the minimum level beyond which events are considered extreme.
- Exceedance rate (N_u_per_year): Average number of threshold exceedances per year.

In the script, xi = 0.5 indicates heavy-tailed behavior, sigma = 1.6 controls the dispersion of extremes, u = 5.0 defines the extreme-event threshold, and N_u_per_year = 1 defines the average exceedance frequency.

3. Return Level Calculation

The return level represents the magnitude of an event expected to occur once every T years. The formula used is:

$$\text{Return Level} = u + (sigma/xi) * ((N\_u\_per\_year * T)^{xi} - 1)$$

This relationship shows how extreme-event magnitude grows as return period increases. When $xi > 0$, the growth is super-linear, reflecting heavy-tailed amplification.

4. Lifetime Risk Calculation

The script also computes the probability of observing a T-year event at least once over a specified lifespan n using:

$$\text{Risk} = 1 - (1 - 1/T)^n$$

This converts rare annual probabilities into practical planning metrics. For example, a 100-year event has a significantly higher probability of occurring over a 30-year infrastructure lifespan than its single-year probability suggests.

5. Visualization Outputs

The script produces two visual outputs:

A. Return Level Plot (semi-log scale): Shows event magnitude as a function of return period. Heavy-tailed growth becomes visually apparent.

B. Risk Heatmap: Displays cumulative lifetime risk across combinations of event return periods and project lifespans. High-risk regions are highlighted to support decision-making.

6. Practical Utility

This modeling framework is useful for:

- Infrastructure design and flood modeling
- Financial risk and stress testing

- Insurance loss estimation
- Climate risk planning
- Modeling breakthrough or disruptive events in innovation systems

Because the GPD captures heavy-tailed behavior, it avoids the systematic underestimation of extreme events that occurs with normal distributions.

7. Strategic Insight

The key insight from the script is that rare events compound over time. Even low-probability events become highly likely over long exposure periods. When the shape parameter indicates heavy-tailed behavior, extreme outcomes are structurally expected rather than anomalous. This has direct implications for long-term planning, resilience engineering, and strategic risk management.

The script therefore serves as both a technical demonstration of EVT and a practical decision-support tool for understanding nonlinear risk escalation.

Extreme Value Theory Modeling Using the Generalized Pareto Distribution (GPD) Script

```
%% Extreme Value Theory: GPD, Return Levels, and Lifetime Risk
clear; clc; close all;
% --- 1. Model Configuration ---
xi = 0.5;          % Shape parameter (xi > 0 means heavy-tailed/Power Law)
sigma = 1.6;       % Scale parameter (spread of the extremes)
u = 5.0;           % Threshold (e.g., a 5% market drop or 5m flood)
N_u_per_year = 1;  % Average number of events exceeding 'u' per year
% --- 2. Return Level Calculation ---
% We calculate the magnitude of the event for different time horizons
T = logspace(0, 1, 10); % Return Periods from 1 to 1000 years
% GPD Return Level Formula
return_levels = u + (sigma/xi) * ((N_u_per_year * T).^xi - 1);
% --- 3. Lifetime Risk Calculation ---
% Probability of seeing a "T-year event" at least once over 'n' years
n_years_life = [1, 2, 3, 4, 5]; % Common infrastructure/loan lifespans
T_event = [1, 2, 3, 4, 5];   % Specific return periods to check
[TT, NN] = meshgrid(T_event, n_years_life);
% Risk Formula: Risk = 1 - (1 - P)^n  where P = 1/T
risk_matrix = 1 - (1 - (1./TT)).^NN;
% --- 4. Visualization ---
figure('Color', 'w', 'Position', [100, 100, 1200, 500]);
% Plot A: Return Level (Magnitude vs. Time)
```

```
subplot(1, 2, 1);

semilogx(T, return_levels, 'LineWidth', 2.5, 'Color', [0.85 0.33 0.1]);

hold on;

% Highlight the 100-year Return Level

rl_100 = u + (sigma/xi) * ((N_u_per_year * 10)^xi - 1);

plot(100, rl_100, 'ko', 'MarkerFaceColor', 'k', 'MarkerSize', 8);

%%text(120, rl_100, sprintf('100-Yr Level: %.1f', rl_100), 'FontWeight', 'bold');

grid on;

title('Return Level: How Big is the Big One?');

xlabel('Return Period (Years - Log Scale)');

ylabel('Event Magnitude');

legend('GPD Model Projection', 'Location', 'NorthWest');

% Plot B: Risk Heatmap (Probability of Failure)

subplot(1, 2, 2);

imagesc(risk_matrix * 10); % Convert to percentage

colormap(flipud(hot)); % Red = High Risk, White/Yellow = Low Risk

colorbar;

caxis([0 100]);

% Formatting the Heatmap

set(gca, 'XTick', 1:length(T_event), 'XTickLabel', string(T_event) + "yr");

set(gca, 'YTick', 1:length(n_years_life), 'YTickLabel', string(n_years_life) + "yr life");

title('Total Risk (%) Over Lifetime');

xlabel('Target Event (Return Period)');
```

```
ylabel('Project Lifespan');
% Add text values to the heatmap
for i = 1:numel(risk_matrix)
    [r, c] = ind2sub(size(risk_matrix), i);
    text(c, r, sprintf('%.1f%%', risk_matrix(i)*10), ...
        'HorizontalAlignment', 'center', 'Color', 'blue', 'FontWeight', 'bold');
end
```

Bayesian Innovation Inference & Risk Simulator Documentation and Script

1. Executive Summary

This MATLAB script provides a dynamic simulation of the Bayesian Multi-Model Framework proposed in this dissertation. It integrates System Dynamics (SD) stock-and-flow logic with Extreme Value Theory (EVT) principles to classify innovations based on cumulative citation data (Data 3). The model specifically validates the core research hypothesis: while the confidence in an innovation's status grows sigmoid ally over time, the natural frequency of such events remains heavily skewed toward incrementalism.

2. Theoretical Framework and Data Definitions

The model operates on four primary data streams, mapping Bayesian variables to the System Dynamics framework:

- Data 1: Prior Probability P(H) – Represents the initial "Base Rate" of innovation. Set at 0.20 for this simulation, it reflects the inherent skepticism required to avoid "Innovation Bubbles".
- Data 2: Likelihood Ratio (LR+) – The "Signal Strength" of the citation metric, defined as the ratio of Sensitivity (True Positive Rate) to the False Positive Rate (Citation Noise).
- Data 3: Evidence Signal (E) – The cumulative flow of citations over a 100-month period, modeled as a sigmoid growth curve to represent the "recognition lag" often seen in breakthrough research.
- Data 4: Posterior Probability P(H|E) – The final output representing the updated belief in the innovation's magnitude.

3. Mathematical Methodology

3.1. Bayesian Update in Odds Form

To align with the continuous nature of system dynamics, the script utilizes the Odds-Likelihood form of Bayes’ Theorem:

Posterior Odds = Prior Odds} x $(LR+)^{DATA3}$

This calculation produces the non-linear "S-curve" recognition pattern, identifying the Inflection Point where Data 3 (Evidence) mathematically overcomes Data 1 (Prior).

3.2. Risk-Based Classification (Farmer/F-N Curves)

The model incorporates the Farmer (F-N) Curve to define tolerability thresholds.

- ALARP Zone (95%): The "As Low As Reasonably Practicable" threshold for Disruptive Innovations.
- Acceptance Zone (99%): The threshold where evidence is sufficient to classify an idea as a Breakthrough.

4. Visualization and Interpretation

4.1. Figure 1: The Probability Trajectory

This figure tracks the growth of Data 4 (Posterior) across six distinct innovation levels: Incremental, Modular, Architectural, Radical, Disruptive, and Breakthrough. It highlights the "Transition to Certainty" as the reinforcing loops of the system take over.

4.2. Figure 2: Signal-to-Noise Analysis

This diagnostic plot demonstrates the vulnerability of the system to Citation Inflation. It shows the collapse of Data 2 (Likelihood Ratio) as the community's ability to reject non-innovative ideas (Specificity) decreases.

4.3. Figure 3: Dynamic Frequency Distribution

A visual proof of the dissertation scarcity argument. By using a log-normal distribution anchored to Data 1 and Data 2, this plot confirms that high-magnitude innovations (Breakthroughs) exist only in the "Long Tail" of the frequency curve.

5. Implementation Notes for Defense

- Parameter Sensitivity: Increasing the false_positive_rate shifts the Inflection Point to the right, modeling the delay in recognizing "Sleeping Beauty" innovations.
- Color Palette: The script uses a journal-quality, high-contrast palette to ensure distinctness for architectural and radical classifications in print format.

MATLAB Script for Bayesian Innovation Inference & Risk Simulator

```
% Comprehensive Bayesian Innovation Inference & Risk Simulator
% Optimized for Journal Publication: Distinct Color Palette & Adjusted Offsets
clear; clc; close all;

%% 1. Parameters & Initial Conditions (DATA 1 & 2)
t = 0:1:100;
prior_prob = 0.20;             % DATA 1: Base rate
sensitivity = 0.95;            % DATA 2: True Positive Rate
false_positive_rate = 0.01;     % DATA 2: Citation Noise

% Calculate Likelihood Ratio (LR+)
LR_plus = sensitivity / false_positive_rate;

%% 2. Dynamic Bayesian Update (DATA 3 & 4)
prior_odds = prior_prob / (1 - prior_prob); %
% DATA 3: Evidence Signal (Sigmoid Growth)
evidence_signal = 1 ./ (1 + exp(-0.12 * (t - 50)));

% DATA 4: Posterior Probability P(H|E)
posterior_odds = prior_odds .* (LR_plus .^ evidence_signal);
posterior_prob = posterior_odds ./ (1 + posterior_odds);

%% 3. Identify Critical Transition Points
idx_inf = find(posterior_prob >= 0.5, 1);
if ~isempty(idx_inf)
   t_inf = double(t(idx_inf)); p_inf = double(posterior_prob(idx_inf));
else
   t_inf = NaN;
end

%% 4. Define Journal-Quality Distinct Colors
% Colors: Incremental, Modular, Architectural, Radical, Disruptive, Breakthrough
cat_colors = [
   0.00, 0.45, 0.74; % Deep Blue
   0.85, 0.33, 0.10; % Burnt Orange
   0.93, 0.69, 0.13; % Golden Yellow
   0.49, 0.18, 0.56; % Royal Purple
   0.47, 0.67, 0.19; % Forest Green
   0.64, 0.08, 0.18  % Dark Red
];

levels = [0.15, 0.35, 0.65, 0.85, 0.95, 0.99];
labels = {'Incremental','Modular','Architectural','Radical','DISRUPTIVE','BREAKTHROUGH'};
```

```
%% 5. Figure 1: Bayesian Probability & Thresholds
figure('Name', 'Bayesian Probability Update', 'Color', 'w', 'Position', [50, 250, 800, 600]);
plot(t, posterior_prob, 'k', 'LineWidth', 2.5, 'DisplayName', 'Data 4: Posterior P(H|E)'); hold on;
yline(prior_prob, 'k--', 'Data 1: Prior P(H)', 'LineWidth', 1.2);

for i = 1:6
    yline(levels(i), ':', 'Color', cat_colors(i,:), 'LineWidth', 2);
    text(2, levels(i)+0.02, labels{i}, 'Color', cat_colors(i,:), 'FontSize', 10, 'FontWeight', 'bold');
end

if ~isnan(t_inf)
    plot(t_inf, p_inf, 'ko', 'MarkerFaceColor', [0.3 0.3 0.3], 'MarkerSize', 8);
    text(t_inf + 3, 0.45, sprintf('Evidence Overcomes Prior\n(Month %d)', t_inf), 'FontWeight',
'bold');
    text(t_inf - 5, 0.55, 'Transition to Certainty \rightarrow', 'HorizontalAlignment', 'right', 'Color',
[0.2 0.2 0.2]);
end
grid on; title('Data 4 Growth: Bayesian Classification across 6 Levels', 'FontSize', 14);
xlabel('Time (Months)', 'FontSize', 12); ylabel('P(A)', 'FontSize', 12); ylim([0 1.05]);

%% 6. Figure 2: Likelihood Ratio (Data 2) Analysis
figure('Name', 'Signal-to-Noise Analysis', 'Color', 'w', 'Position', [870, 500, 500, 400]);
spec_range = 0.8:0.005:0.99; fpr_r = 1 - spec_range;
plot(spec_range, sensitivity./fpr_r, 'Color', [0.2 0.6 0.2], 'LineWidth', 2); grid on;
title('Data 2: LR+ Sensitivity Analysis', 'FontSize', 12); xlabel('Specificity'); ylabel('LR+');

%% 7. Figure 3: Dynamic Frequency Distribution (Legible Publication Quality)
figure('Name', 'Dynamic Frequency Distribution', 'Color', 'w', 'Position', [870, 50, 600, 500]);
x_dist = linspace(0.001, 0.999, 1000);
mu_dyn = log(prior_prob);
sigma_dyn = 1.2 / log10(LR_plus);
y_dist = lognpdf(x_dist, mu_dyn, sigma_dyn);

plot(x_dist, y_dist, 'k', 'LineWidth', 2); hold on;
fill(x_dist, y_dist, [0.95 0.95 0.95], 'FaceAlpha', 0.5, 'EdgeColor', 'none');

for i = 1:6
    freq_val = lognpdf(levels(i), mu_dyn, sigma_dyn);
    scatter(levels(i), freq_val, 70, 'MarkerFaceColor', cat_colors(i,:), 'MarkerEdgeColor', 'k');

    % USER MODIFICATION: New y_offset logic for precise placement
    y_offset = (mod(i,2)*0.05 + 0.05) * max(y_dist);

    % Draw leader lines and labels
    line([levels(i) levels(i)], [freq_val, freq_val + y_offset], ...
        'Color', cat_colors(i,:), 'LineStyle', '-', 'LineWidth', 1);
```

```
    text(levels(i), freq_val + y_offset, labels{i}, ...
        'Color', cat_colors(i,:), 'FontSize', 10, 'FontWeight', 'bold', ...
        'Rotation', 35, 'VerticalAlignment', 'bottom');
end

grid on; title('Dynamic Innovation Frequency: Thesis Scarcity Proof', 'FontSize', 13);
xlabel('Innovation Magnitude Threshold P(A)', 'FontSize', 11);
ylabel('Relative Frequency', 'FontSize', 11); xlim([0 1.15]);
```

S&T Innovation Portfolio Simulator (EVT-Based) Documentation and Script

This document describes a MATLAB simulation model designed to compare two science and technology (S&T) research portfolio strategies using Extreme Value Theory (EVT). The simulator evaluates how different statistical tail behaviors influence long-term breakthrough performance in research investment portfolios.

1. Purpose of the Simulator

The simulator compares two research funding strategies over a 20-year horizon. Each portfolio funds 100 projects per year. The objective is to understand which strategy is more likely to generate rare, category-defining breakthroughs.

Rather than comparing average performance, the model focuses on extreme outcomes.

Breakthrough innovation is modeled using the Generalized Pareto Distribution (GPD), a standard tool in Extreme Value Theory for modeling rare, high-impact events.

2. Portfolio Definitions

Portfolio A – 'Incremental/Safe'

- Shape parameter (xi ≈ 0.05): Nearly light-tailed, close to Gaussian behavior
- Scale parameter (sigma = 5): High consistency
- Threshold (theta = 5): Minimum innovation level considered significant

This portfolio represents steady, reliable, incremental innovation.

Portfolio B – 'Moonshot/Radical'

- Shape parameter (xi = 0.6): Heavy-tailed, power-law behavior
- Scale parameter (sigma = 2): Less consistency, higher volatility
- Threshold (theta = 5): Same baseline for fair comparison

This portfolio represents high-risk, high-reward research investments.

3. Simulation Structure

The MATLAB function gprnd(xi, sigma, theta) generates innovation outcomes from the Generalized Pareto Distribution. Over 20 years, 2,000 simulated projects are generated per portfolio.

Annual maximum values are extracted to simulate the 'best project of the year.' This reflects how institutions are often evaluated — not by average output, but by record-setting achievements.

4. Visualization Components

The simulator produces two key visualizations:

A. Survival Function (Log Scale):

Displays P(X > x) for each portfolio. The heavy-tailed moonshot portfolio shows slower probability decay, meaning extreme outcomes remain plausible even at very high innovation values.

B. Annual Peak Performance Plot:

Shows the best project each year. A defined 'World Record' cutoff represents a category-defining breakthrough. This illustrates which portfolio more frequently exceeds transformative thresholds.

5. Performance Metrics

The simulator reports:

- Maximum innovation value achieved
- Number of 'world record' breakthroughs exceeding the defined cutoff

These metrics quantify both peak magnitude and breakthrough frequency.

6. Strategic Utility

This simulator provides insight into strategic R&D portfolio design. Light-tailed portfolios optimize for reliability and predictable returns. Heavy-tailed portfolios optimize for rare transformative outcomes.

The key insight is that heavy-tailed systems fundamentally change expected long-term performance. While average output may appear similar, the probability of category-defining breakthroughs diverges dramatically.

For organizations seeking technological leadership, this model demonstrates why tail behavior — not average performance — determines strategic dominance.

7. Broader Applications

The EVT-based portfolio framework can be applied to:

- Defense and national security R&D planning
- Venture capital allocation strategy
- University research funding models
- Breakthrough technology forecasting
- Innovation ecosystem simulation and policy design

By modeling innovation as an extreme value process rather than a normal process, decision-makers gain a more realistic understanding of transformative risk and reward.

S&T Innovation Portfolio Simulator Script

```
% S&T Innovation Portfolio Simulator (EVT-Based)
clear; clc;
%% 1. Configuration
years = 20;
grants_per_year = 100;
total_grants = years * grants_per_year;
world_record_cutoff = 50; % The value of a "Category-Defining" breakthrough
% Portfolio A: "Incremental/Safe" (Light Tail)
xi_A = 0.05;    % Close to 0 (Gaussian-like)
sigma_A = 5;    % High consistency
theta_A = 5;    % Threshold u
% Portfolio B: "Moonshot/Radical" (Heavy Tail)
xi_B = 0.6;     % High xi (Power Law / Extreme Value)
sigma_B = 2;    % Low consistency, high peak potential
theta_B = 5;    % Same threshold u for fair comparison
%% 2. Generate Data
% gprnd(xi, sigma, theta, [rows, cols])
outcomes_A = gprnd(xi_A, sigma_A, theta_A, [total_grants, 1]);
outcomes_B = gprnd(xi_B, sigma_B, theta_B, [total_grants, 1]);
% Reshape to track annual bests
yearly_max_A = max(reshape(outcomes_A, [grants_per_year, years]));
yearly_max_B = max(reshape(outcomes_B, [grants_per_year, years]));
```

```
%% 3. Visualization
figure('Color', 'w', 'Position', [100, 100, 1000, 600]);
% Subplot 1: Probability Tails
subplot(2,1,1);
[fA, xA] = ecdf(outcomes_A);
[fB, xB] = ecdf(outcomes_B);
semilogy(xA, 1-fA, 'b', 'LineWidth', 2); hold on;
semilogy(xB, 1-fB, 'r', 'LineWidth', 2);
yline(0.01, '--k', '1% Probability');
grid on;
title('Survival Function: Probability of Exceeding Value X');
xlabel('Innovation Value'); ylabel('Log Probability P(X > x)');
legend('Safe Portfolio (\xi \approx 0)', 'Moonshot Portfolio (\xi = 0.6)');
% Subplot 2: The "World Record" Race
subplot(2,1,2);
plot(1:years, yearly_max_A, 'b-o', 'MarkerFaceColor', 'b'); hold on;
plot(1:years, yearly_max_B, 'r-s', 'MarkerFaceColor', 'r');
yline(world_record_cutoff, 'k--', 'World Record Level', 'LabelHorizontalAlignment', 'left');
title('Annual Peak Innovation: Which Portfolio Hits the World Record?');
xlabel('Year'); ylabel('Value of Best Project');
legend('Safe Portfolio', 'Moonshot Portfolio');
grid on;
```

```
%% 4. Results Output
fprintf('--- Portfolio Performance Report ---\n');
fprintf('Safe Portfolio - Max Value Achieved: %.2f | Records: %d\n', max(outcomes_A), sum(outcomes_A > world_record_cutoff));
fprintf('Moonshot Portfolio - Max Value Achieved: %.2f | Records: %d\n', max(outcomes_B), sum(outcomes_B > world_record_cutoff));
```

APPENDIX B: VENSIM MODEL EQUATIONS AND STRUCTURES

Pareto Innovation Ladder with Feedback (XMILE) — Model Documentation

This document was generated by parsing the provided Vensim XMILE file. It summarizes model structure, equations, units, and dependencies, and provides a Vensim-style equation list.

Simulation Settings

Method: RK4

Time units: Month

START: 0 STOP: 120 DT: 0.125

Stocks (State Variables)

Adopted_Arch

Units: adopters

Initial value: 0.1

Inflows: Adoption_Arch

Outflows: None

Adopted_Brk

Units: adopters

Initial value: 0.1

Inflows: Adoption_Brk

Outflows: None

Adopted_Dis

Units: adopters

Initial value: 0.1

Inflows: Adoption_Dis

Outflows: None

Adopted_Inc

Units: adopters

Initial value: 0.1

Inflows: Adoption_Inc

Outflows: None

Adopted_Mod

Units: adopters

Initial value: 0.1

Inflows: Adoption_Mod

Outflows: None

Adopted_Rad

Units: adopters

Initial value: 0.1

Inflows: Adoption_Rad

Outflows: None

Potential_Arch

Units: adopters

Initial value: 0.001

Inflows: seeds_Arch

Outflows: abandon_Arch, Adoption_Arch

Potential_Brk

Units: adopters

Initial value: 0

Inflows: seeds_Brk

Outflows: abandon_Brk, Adoption_Brk

Potential_Dis

Units: adopters

Initial value: 0

Inflows: seeds_Dis

Outflows: abandon_Dis, Adoption_Dis

Potential_Inc

Units: adopters

Initial value: 1

Inflows: seeds_Inc

Outflows: abandon_Inc, Adoption_Inc

Potential_Mod

Units: adopters

Initial value: 0

Inflows: seeds_Mod

Outflows: abandon_Mod, Adoption_Mod

Potential_Rad

Units: adopters

Initial value: 0

Inflows: seeds_Rad

Outflows: abandon_Rad, Adoption_Rad

Flows (Rates)

Adoption_Arch

Units: adopters/Month

Equation: (p_Arch + q_Arch * ZIDZ(Adopted_Arch , Potential_Arch + Adopted_Arch))
* Potential_Arch * Ub

Adoption_Brk

Units: adopters/Month

Equation: (p_Brk + q_Brk * ZIDZ(Adopted_Brk , Potential_Brk + Adopted_Brk))
* Potential_Brk * Ue

Adoption_Dis

Units: adopters/Month

Equation: (p_Dis + q_Dis * ZIDZ(Adopted_Dis , Potential_Dis + Adopted_Dis))
* Potential_Dis * Ud

Adoption_Inc

Units: adopters/Month

Equation: bass_level_gain * ((p_Inc + q_Inc * ZIDZ(Adopted_Inc , Potential_Inc + Adopted_Inc))
* Potential_Inc * U)*(1 - Adopted_Inc / relevant_population)

Adoption_Mod

Units: adopters/Month

Equation: (p_Mod + q_Mod * ZIDZ(Adopted_Mod , Potential_Mod + Adopted_Mod))
* Potential_Mod * Ua

Adoption_Rad

Units: adopters/Month

Equation: (p_Rad + q_Rad * ZIDZ(Adopted_Rad , Potential_Rad + Adopted_Rad))

* Potential_Rad * Uc

abandon_Arch

Units: adopters/Month

Equation: bad_ideas_Arc *Potential_Arch

abandon_Brk

Units: adopters/Month

Equation: bad_ideas_Brk *Potential_Brk

abandon_Dis

Units: adopters/Month

Equation: bad_ideas_Dis *Potential_Dis

abandon_Inc

Units: adopters/Month

Equation: Potential_Inc *bad_ideas_Inc

abandon_Mod

Units: adopters/Month

Equation: bad_ideas_Mod *Potential_Mod

abandon_Rad

Units: adopters/Month

Equation: bad_ideas_Rad * Potential_Rad

seeds_Arch

Units: adopters/Month

Equation: seeds_Arch_rate

seeds_Brk

Units: adopters/Month

Equation: seeds_Brk_rate

seeds_Dis

Units: adopters/Month

Equation: seeds_Dis_rate

seeds_Inc

Units: adopters/Month

Equation: (seeds_Inc_rate * bass_level_gain * Potential_Inc) * (1 - Potential_Inc / relevant_population)

seeds_Mod

Units: adopters/Month

Equation: seeds_Mod_rate

seeds_Rad

Units: adopters/Month

Equation: seeds_Rad_rate

Key Modeling Assumptions (Inferred from Structure)

1) The model represents a six-stage innovation ladder: Incremental → Modular → Architectural → Radical → Disruptive → Breakthrough. Each stage has a Potential stock (not yet adopted) and an Adopted stock (adopted population).

2) Adoption within each stage uses a Bass-type term (p + q * adopters/(potential+adopters)) multiplied by the remaining Potential.

3) Forward transitions between stages are driven by delayed adoption signals (alpha_* variables) scaled by change_in_PSBU_* coefficients. Backflows are represented by beta_* delayed signals scaled by small fractions (0.05), plus an outer-loop from Breakthrough back to new ideas.

4) Potential stocks are replenished by seeds_* flows and reduced by both adoption and abandonment. Abandonment rates depend on 'bad_ideas_*' parameters multiplied by Potential.

Full Variable Dictionary

A complete variable dictionary (Name, Type, Units, Equation, Dependencies) can be provided in a accompanying CSV file.

Vensim Equation List

A Vensim-formatted equation list can be provided in a accompanying TXT file.

IMF Management Simulator ROI (XMILE) — Model Documentation

This document was generated by parsing Vensim XMILE file. It summarizes the model structure, equations, units, initial values, and dependencies.

Simulation Settings

Method: RK4

Time units: Month

START: STOP: DT:

Stocks (18)

Architectural_Innovations

Units: ideas

Initial value:

Equation: INTEG((Modular to Architectural) - (Arch Decay + Architectural to Radical) , 0)

Arcitectural_ROI

Units:

Initial value:

Equation: INTEG(A ROI Rate , 0)

Available_Resources

Units: capacity

Initial value:

Equation: INTEG((Reinvestment) - (Spending) , 0)

Depends on: Reinvestment, Resources_Initial, Spending

Breakthrough_Innovations

Units: ideas

Initial value:

Equation: INTEG((Disruptive to Breakthrough) - (Break Decay + Breakthrough Flow) , 0)

Breakthrough_ROI

Units:

Initial value:

Equation: INTEG(B ROI Rate , 0)

Cumulative_ROI

Units: capacity

Initial value:

Equation: INTEG(ROI Rate , 0)

Disruptive_Innovations

Units: ideas

Initial value:

Equation: INTEG((Radical to Disruptive) - (Disrup Decay + Disruptive to Breakthrough) , 0)

Disruptive_ROI

Units:

Initial value:

Equation: INTEG(D ROI Rate , 0)

Incremental_Innovations

Units: ideas

Initial value:

Equation: INTEG((Incremental Generation) - (Incremental Decay + Incremental Flow + Incremental to Modular) , 0)

Incremental_ROI

Units:

Initial value:

Equation: INTEG(I ROI Rate , 0)

Innovation_Motive_Force

Units: capacity

Initial value:

Equation: INTEG((Resource Input) - (Capacity Leakage) , 0)

Depends on: Initial_IMF

Modular_Innovations

Units: ideas

Initial value:

Equation: INTEG((Incremental to Modular) - (Modular Decay + Modular to Architectural) , 0)

Modular_ROI

Units:

Initial value:

Equation: INTEG(M ROI RATE , 0)

Probability_of_Innovation

Units: Probability

Initial value:

Equation: INTEG(update probability , 0)

Radical_Innovations

Units: ideas

Initial value:

Equation: INTEG((Architectural to Radical) - (Radical Decay + Radical to Disruptive) , 0)

Radical_ROI

Units:

Initial value:

Equation: INTEG(R ROI Rate , 0)

Stored_Ideas

Units: ideas

Initial value:

Equation: INTEG(Breakthrough Flow + Incremental Flow , 0)

Depends on: Ideas_Initial

Surprise_State

Units: Dmnl

Initial value:

Equation: INTEG(Surprise State adj , 0)

Flows (0)

Auxiliaries (126)

A_ROI_Rate Units:

Equation: p_Architectural * Utility_Architectural

Depends on: Utility_Architectural, p_Architectural

Arch_Decay Units: ideas/Month

Equation: Architectural_Innovations * (LN(2) / Idea_Half_Life)

Depends on: Architectural_Innovations, Idea_Half_Life

Architectural_to_Radical Units: ideas/Month

Equation: Architectural_Innovations * Architectural_Transition_Rate

Depends on: Architectural_Innovations, Architectural_Transition_Rate

Attract_Architectural Units: Dmnl

Equation: EU_Architectural - Sensitivity * H_Architectural

Depends on: EU_Architectural, H_Architectural, Sensitivity

Attract_Breakthrough Units: Dmnl

Equation: EU_Breakthrough - Sensitivity * H_Breakthrough

Depends on: EU_Breakthrough, H_Breakthrough, Sensitivity

Attract_Disruptive Units: Dmnl

Equation: EU_Disruptive - Sensitivity * H_Disruptive

Depends on: EU_Disruptive, H_Disruptive, Sensitivity

Attract_Incremental Units: Dmnl

Equation: EU_Incremental - Sensitivity * H_Incremental

Depends on: EU_Incremental, H_Incremental, Sensitivity

Attract_Modular Units: Dmnl

Equation: EU_Modular - Sensitivity * H_Modular

Depends on: EU_Modular, H_Modular, Sensitivity

Attract_Radical Units: Dmnl

Equation: EU_Radical - Sensitivity * H_Radical

Depends on: EU_Radical, H_Radical, Sensitivity

B_ROI_Rate Units:

Equation: Utility_Breakthrough * p_Breakthrough

Depends on: Utility_Breakthrough, p_Breakthrough

Break_Decay Units: ideas/Month

Equation: Breakthrough_Innovations * (LN(2) / Idea_Half_Life)

Depends on: Breakthrough_Innovations, Idea_Half_Life

Breakthrough_Flow Units: ideas/Month

Equation: Breakthrough_Innovations * Breakthrough_Utilization_Rate * xm * (u_surprise ^ (-1 / alpha))

Depends on: Breakthrough_Innovations, Breakthrough_Utilization_Rate, alpha, u_surprise, xm

Doc: Disruptive Innovations * Disruptive Transition Rate *

xm * (u safe ^ (-1 / alpha))

Breakthrough_Share Units: Probability

Equation: ZIDZ(Breakthrough_Flow, Total_Idea_Generation)

Depends on: Breakthrough_Flow, Total_Idea_Generation

Capacitance Units: Dmnl

Equation: MAX(0.1, (Institutional_Memory + Absorptive_Capacity + Organizational_Learning + Cognitive_Diversity) / 4)

Depends on: Absorptive_Capacity, Cognitive_Diversity, Institutional_Memory, Organizational_Learning

Capacity_Leakage Units: capacity/Month

Equation: Leakage_Fraction * Innovation_Motive_Force

Depends on: Innovation_Motive_Force, Leakage_Fraction

D_ROI_Rate Units:

Equation: p_Disruptive * Utility_Disruptive

Depends on: Utility_Disruptive, p_Disruptive

Disrup_Decay Units: ideas/Month

Equation: Disruptive_Innovations * (LN(2) / Idea_Half_Life)

Depends on: Disruptive_Innovations, Idea_Half_Life

Disruptive_to_Breakthrough Units: ideas/Month

Equation: Disruptive_Innovations * Disruptive_Transition_Rate

Depends on: Disruptive_Innovations, Disruptive_Transition_Rate

Doc: Disruptive Innovations * Disruptive Transition Rate *

xm * (u safe ^ (-1 / alpha))

EU_Architectural Units: Dmnl

Equation: 100 * Utility_Architectural / (Total_Utility + small)

Depends on: Total_Utility, Utility_Architectural, small

EU_Breakthrough Units: Dmnl

Equation: 100 * Utility_Breakthrough / (Total_Utility + small)

Depends on: Total_Utility, Utility_Breakthrough, small

EU_Disruptive Units: Dmnl

Equation: 100 * Utility_Disruptive / (Total_Utility + small)

Depends on: Total_Utility, Utility_Disruptive, small

EU_Incremental Units: Dmnl

Equation: 100 * Utility_Incremental / (Total_Utility + small)

Depends on: Total_Utility, Utility_Incremental, small

EU_Modular Units: Dmnl

Equation: 100 * Utility_Modular / (Total_Utility + small)

Depends on: Total_Utility, Utility_Modular, small

EU_Radical Units: Dmnl

Equation: 100 * Utility_Radical / (Total_Utility + small)

Depends on: Total_Utility, Utility_Radical, small

H_Architectural Units: bit

Equation: - p_Architectural * LN(p_Architectural + small) / LN(2)

Depends on: p_Architectural, small

H_Breakthrough Units: bit

Equation: - p_Breakthrough * LN(p_Breakthrough + small) / LN(2)

Depends on: p_Breakthrough, small

H_Disruptive Units: bit

Equation: - p_Disruptive * LN(p_Disruptive + small) / LN(2)

Depends on: p_Disruptive, small

H_Incremental Units: bit

Equation: - p_Incremental * LN(p_Incremental + small) / LN(2)

Depends on: p_Incremental, small

H_Modular Units: bit

Equation: - p_Modular * LN(p_Modular + small) / LN(2)

Depends on: p_Modular, small

H_Radical Units: bit

Equation: - p_Radical * LN(p_Radical + small) / LN(2)

Depends on: p_Radical, small

I_ROI_Rate Units:

Equation: Utility_Incremental * p_Incremental

Depends on: Utility_Incremental, p_Incremental

Incremental_Decay Units: ideas/Month

Equation: Incremental_Innovations * (LN(2) / Idea_Half_Life)

Depends on: Idea_Half_Life, Incremental_Innovations

Incremental_Flow Units: ideas/Month

Equation: Incremental_Innovations * Incremental_Utilization_Rate

Depends on: Incremental_Innovations, Incremental_Utilization_Rate

Incremental_Generation Units: ideas/Month

Equation: eta * Innovation_Activity

Depends on: Innovation_Activity, eta

Incremental_to_Modular Units: ideas/Month

Equation: Incremental_Innovations * Incremental_Transition_Rate

Depends on: Incremental_Innovations, Incremental_Transition_Rate

Init_P_(A) Units: Probability

Equation: base_rate_data_of_probability_of_innovations

Depends on: base_rate_data_of_probability_of_innovations

Innovation_Activity Units: capacity/Month

Equation: Innovation_Potential / (Resistance * Innovation_Time_Constant)

Depends on: Innovation_Potential, Innovation_Time_Constant, Resistance

Innovation_Potential Units: capacity

Equation: Innovation_Motive_Force / Capacitance

Depends on: Capacitance, Innovation_Motive_Force

KL_Architectural Units: bit

Equation: p_Architectural_lag * (LN((p_Architectural_lag + small)/(q_Architectural + small)) / LN(2))

Depends on: p_Architectural_lag, q_Architectural, small

KL_Breakthrough Units: bit

Equation: p_Breakthrough_lag * (LN((p_Breakthrough_lag + small)/(q_Breakthrough + small)) / LN(2))

Depends on: p_Breakthrough_lag, q_Breakthrough, small

KL_Disruptive Units: bit

Equation: p_Disruptive_lag * (LN((p_Disruptive_lag + small)/(q_Disruptive + small)) / LN(2))

Depends on: p_Disruptive_lag, q_Disruptive, small

KL_Incremental Units: bit

Equation: p_Incremental_lag * (LN((p_Incremental_lag + small)/(q_Incremental + small)) / LN(2))

Depends on: p_Incremental_lag, q_Incremental, small

Doc: p Incremental * (LN((p Incremental + small)/(q Incremental + small)) / LN(2))

KL_Modular Units: bit

Equation: p_Modular_lag * (LN((p_Modular_lag + small)/(q_Modular + small)) / LN(2))

Depends on: p_Modular_lag, q_Modular, small

KL_Radical Units: bit

Equation: p_Radical_lag* (LN((p_Radical_lag + small)/(q_Radical + small)) / LN(2))

Depends on: p_Radical_lag, q_Radical, small

KL_Surprise Units:

Equation: KL_Incremental + KL_Modular + KL_Architectural + KL_Radical + KL_Disruptive + KL_Breakthrough

Depends on: KL_Architectural, KL_Breakthrough, KL_Disruptive, KL_Incremental, KL_Modular, KL_Radical

Log_Likelihood_Ratio Units:

Equation: KL_slope * (KL_Surprise - KL_mid)

Depends on: KL_Surprise, KL_mid, KL_slope

M_ROI_RATE Units:

Equation: p_Modular * Utility_Modular

Depends on: Utility_Modular, p_Modular

Modular_Decay Units: ideas/Month

Equation: Modular_Innovations * (LN(2) / Idea_Half_Life)

Depends on: Idea_Half_Life, Modular_Innovations

Modular_to_Architectural Units: ideas/Month

Equation: Modular_Innovations * Modular_Transition_Rate

Depends on: Modular_Innovations, Modular_Transition_Rate

P_(_not_A) Units: Probability

Equation: 1-Probability_of_Innovation

Depends on: Probability_of_Innovation

P_Regime_posterior Units:

Equation: SMOOTH(P_Regime_posterior_raw, Belief_Update_Time)

Depends on: Belief_Update_Time, P_Regime_posterior_raw

P_Regime_posterior_raw Units:

Equation: Posterior_Odds / (1 + Posterior_Odds)

Depends on: Posterior_Odds

Posterior_Odds Units:

Equation: Prior_Odds * EXP(Log_Likelihood_Ratio)

Depends on: Log_Likelihood_Ratio, Prior_Odds

Prior_Odds Units:

Equation: P_Regime_prior / (1 - P_Regime_prior + small)

Depends on: P_Regime_prior, small

Probability_of_Innovative_Idea Units: Dmnl

Equation: subject_matter_judgment_of_innovation

Depends on: subject_matter_judgment_of_innovation

ROI_Rate Units: capacity/Month

Equation: Total_Utility

Depends on: Total_Utility

R_ROI_Rate Units:

Equation: p_Radical * Utility_Radical

Depends on: Utility_Radical, p_Radical

Radical_Decay Units: ideas/Month

Equation: Radical_Innovations * (LN(2) / Idea_Half_Life)

Depends on: Idea_Half_Life, Radical_Innovations

Radical_to_Disruptive Units: ideas/Month

Equation: Radical_Innovations * Radical_Transition_Rate

Depends on: Radical_Innovations, Radical_Transition_Rate

Reinvestment Units: capacity/Month

Equation: Reinvestment_Fraction * Total_Idea_Generation * Idea_Value

Depends on: Idea_Value, Reinvestment_Fraction, Total_Idea_Generation

Resistance Units: Dmnl

Equation: MAX(0.1, (Risk_Aversion + Cultural_Inertia + Regulation + Approval_Bottlenecks) / 4)

Depends on: Approval_Bottlenecks, Cultural_Inertia, Regulation, Risk_Aversion

Resource_Input Units: capacity/Month

Equation: Spending

Depends on: Spending

Score_Architectural Units: Dmnl

Equation: EXP(Attract_Architectural)

Depends on: Attract_Architectural

Score_Breakthrough Units: Dmnl

Equation: EXP(Attract_Breakthrough)

Depends on: Attract_Breakthrough

Score_Disruptive Units: Dmnl

Equation: EXP(Attract_Disruptive)

Depends on: Attract_Disruptive

Score_Incremental Units: Dmnl

Equation: EXP(Attract_Incremental)

Depends on: Attract_Incremental

Score_Modular Units: Dmnl

Equation: EXP(Attract_Modular)

Depends on: Attract_Modular

Score_Radical Units: Dmnl

Equation: EXP(Attract_Radical)

Depends on: Attract_Radical

Score_Sum Units: Dmnl

Equation: Score_Incremental + Score_Modular + Score_Architectural + Score_Radical + Score_Disruptive + Score_Breakthrough

Depends on: Score_Architectural, Score_Breakthrough, Score_Disruptive, Score_Incremental, Score_Modular, Score_Radical

Spending Units: capacity/Month

Equation: Available_Resources / Allocation_Time

Depends on: Allocation_Time, Available_Resources

Spending_Architectural Units: capacity/Month

Equation: w_Architectural_smooth * Spending

Depends on: Spending, w_Architectural_smooth

Spending_Breakthrough Units: capacity/Month

Equation: w_Breakthrough_smooth * Spending

Depends on: Spending, w_Breakthrough_smooth

Spending_Disruptive Units: capacity/Month

Equation: w_Disruptive_smooth * Spending

Depends on: Spending, w_Disruptive_smooth

Spending_Incremental Units: capacity/Month

Equation: w_Incremental_smooth * Spending

Depends on: Spending, w_Incremental_smooth

Spending_Modular Units: capacity/Month

Equation: w_Modular_smooth * Spending

Depends on: Spending, w_Modular_smooth

Spending_Radical Units: capacity/Month

Equation: w_Radical_smooth * Spending

Depends on: Spending, w_Radical_smooth

Surprise_State_adj Units: 1/Month

Equation: (Surprise_Trigger - Surprise_State) / Trigger_Response_Time

Depends on: Surprise_State, Surprise_Trigger, Trigger_Response_Time

Surprise_Trigger Units: Dmnl

Equation: SMOOTH(Surprise_Trigger_raw)

Depends on: Surprise_Trigger_raw

Doc: 1 / (1 + EXP(-KL Gain * (KL Surprise - KL Threshold)))

Surprise_Trigger_raw Units:

Equation: 1 / (1 + EXP(-KL_Gain * (KL_Surprise - KL_Threshold)))

Depends on: KL_Gain, KL_Surprise, KL_Threshold

TOutput Units: ideas/Month

Equation: Incremental_Flow + Modular_to_Architectural + Architectural_to_Radical + Radical_to_Disruptive + Disruptive_to_Breakthrough + Breakthrough_Flow

Depends on: Architectural_to_Radical, Breakthrough_Flow, Disruptive_to_Breakthrough, Incremental_Flow, Modular_to_Architectural, Radical_to_Disruptive

Total_Idea_Generation Units: ideas/Month

Equation: Incremental_Flow + Breakthrough_Flow

Depends on: Breakthrough_Flow, Incremental_Flow

Total_Utility Units: capacity/Month

Equation: Utility_Architectural + Utility_Breakthrough + Utility_Disruptive + Utility_Incremental + Utility_Modular + Utility_Radical

Depends on: Utility_Architectural, Utility_Breakthrough, Utility_Disruptive, Utility_Incremental, Utility_Modular, Utility_Radical

Utility_Architectural Units: capacity/Month

Equation: Architectural_to_Radical * Idea_Value

Depends on: Architectural_to_Radical, Idea_Value

Utility_Breakthrough Units: capacity/Month

Equation: Breakthrough_Flow * Idea_Value

Depends on: Breakthrough_Flow, Idea_Value

Utility_Disruptive Units: capacity/Month

Equation: Disruptive_to_Breakthrough * Idea_Value

Depends on: Disruptive_to_Breakthrough, Idea_Value

Utility_Incremental Units: capacity/Month

Equation: Idea_Value * Incremental_Flow

Depends on: Idea_Value, Incremental_Flow

Utility_Modular Units: capacity/Month

Equation: Idea_Value * Modular_to_Architectural

Depends on: Idea_Value, Modular_to_Architectural

Utility_Radical Units: capacity/Month

Equation: Idea_Value * Radical_to_Disruptive

Depends on: Idea_Value, Radical_to_Disruptive

alpha Units: Dmnl

Equation: MAX(0.5, Base_Alpha * (Resistance / Reference_Resistance))

Depends on: Base_Alpha, Reference_Resistance, Resistance

false_positve_rate Units: Dmnl

Equation: research_commuity_judgment_of_not_innovation

Depends on: research_commuity_judgment_of_not_innovation

marginal_likelihood_P_(B) Units: Probability

Equation: (Probability_of_Innovative_Idea * Probability_of_Innovation) + (false_positve_rate * "P_(_not_A)")

Depends on: Probability_of_Innovation, Probability_of_Innovative_Idea, false_positve_rate

p_Architectural Units: Dmnl

Equation: Architectural_to_Radical / (TOutput + small)

Depends on: Architectural_to_Radical, TOutput, small

p_Architectural_lag Units: Dmnl

Equation: SMOOTH(p_Architectural, KL_Lag_Time)

Depends on: KL_Lag_Time, p_Architectural

p_Breakthrough Units: Dmnl

Equation: Breakthrough_Flow / (TOutput + small)

Depends on: Breakthrough_Flow, TOutput, small

p_Breakthrough_lag Units: Dmnl

Equation: SMOOTH(p_Breakthrough, KL_Lag_Time)

Depends on: KL_Lag_Time, p_Breakthrough

p_Disruptive Units: Dmnl

Equation: Disruptive_to_Breakthrough / (TOutput + small)

Depends on: Disruptive_to_Breakthrough, TOutput, small

p_Disruptive_lag Units: Dmnl

Equation: SMOOTH(p_Disruptive, KL_Lag_Time)

Depends on: KL_Lag_Time, p_Disruptive

p_Incremental Units: Dmnl

Equation: Incremental_Flow / (TOutput + small)

Depends on: Incremental_Flow, TOutput, small

p_Incremental_lag Units: Dmnl

Equation: SMOOTH(p_Incremental, KL_Lag_Time)

Depends on: KL_Lag_Time, p_Incremental

p_Modular Units: Dmnl

Equation: Modular_to_Architectural / (TOutput + small)

Depends on: Modular_to_Architectural, TOutput, small

p_Modular_lag Units: Dmnl

Equation: SMOOTH(p_Modular, KL_Lag_Time)

Depends on: KL_Lag_Time, p_Modular

p_Radical Units: Dmnl

Equation: Radical_to_Disruptive / (TOutput + small)

Depends on: Radical_to_Disruptive, TOutput, small

p_Radical_lag Units: Dmnl

Equation: SMOOTH(p_Radical, KL_Lag_Time)

Depends on: KL_Lag_Time, p_Radical

posterior_probability_of_innovation_given_citations Units: Probability

Equation: (Probability_of_Innovative_Idea * Probability_of_Innovation) / "marginal_likelihood_P_(B)"

Depends on: Probability_of_Innovation, Probability_of_Innovative_Idea

q_Architectural Units: Dmnl

Equation: SMOOTH(p_Architectural_lag, KL_Memory_Time)

Depends on: KL_Memory_Time, p_Architectural_lag

q_Breakthrough Units: Dmnl

Equation: SMOOTH(p_Breakthrough_lag, KL_Memory_Time)

Depends on: KL_Memory_Time, p_Breakthrough_lag

q_Disruptive Units: Dmnl

Equation: SMOOTH(p_Disruptive_lag, KL_Memory_Time)

Depends on: KL_Memory_Time, p_Disruptive_lag

q_Incremental Units: Dmnl

Equation: SMOOTH(p_Incremental_lag, KL_Memory_Time)

Depends on: KL_Memory_Time, p_Incremental_lag

q_Modular Units: Dmnl

Equation: SMOOTH(p_Modular_lag, KL_Memory_Time)

Depends on: KL_Memory_Time, p_Modular_lag

q_Radical Units: Dmnl

Equation: SMOOTH(p_Radical_lag, KL_Memory_Time)

Depends on: KL_Memory_Time, p_Radical_lag

u Units: Dmnl

Equation: RANDOM_UNIFORM(0,1,21)

Doc: RANDOM UNIFORM(0,1,21)

u_safe Units: Dmnl

Equation: MAX(1e-06, u)

Depends on: u

u_surprise Units:

Equation: u_safe * (1 + Max_Surprise_Boost * Surprise_State)

Depends on: Max_Surprise_Boost, Surprise_State, u_safe

Doc: u safe * Surprise Multiplier

update_probability Units: Probability

Equation: posterior_probability_of_innovation_given_citations-Probability_of_Innovation

Depends on: Probability_of_Innovation, posterior_probability_of_innovation_given_citations

w_Architectural Units: Dmnl

Equation: Score_Architectural / (Score_Sum + small)

Depends on: Score_Architectural, Score_Sum, small

w_Architectural_smooth Units: Dmnl

Equation: SMOOTH(w_Architectural, Allocation_Time)

Depends on: Allocation_Time, w_Architectural

w_Breakthrough Units: Dmnl

Equation: Score_Breakthrough / (Score_Sum + small)

Depends on: Score_Breakthrough, Score_Sum, small

w_Breakthrough_smooth Units: Dmnl

Equation: SMOOTH(w_Breakthrough, Allocation_Time)

Depends on: Allocation_Time, w_Breakthrough

w_Disruptive Units: Dmnl

Equation: Score_Disruptive / (Score_Sum + small)

Depends on: Score_Disruptive, Score_Sum, small

w_Disruptive_smooth Units: Dmnl

Equation: SMOOTH(w_Disruptive, Allocation_Time)

Depends on: Allocation_Time, w_Disruptive

w_Incremental Units: Dmnl

Equation: Score_Incremental / (Score_Sum + small)

Depends on: Score_Incremental, Score_Sum, small

w_Incremental_smooth Units: Dmnl

Equation: SMOOTH(w_Incremental, Allocation_Time)

Depends on: Allocation_Time, w_Incremental

w_Modular Units: Dmnl

Equation: Score_Modular / (Score_Sum + small)

Depends on: Score_Modular, Score_Sum, small

w_Modular_smooth Units: Dmnl

Equation: SMOOTH(w_Modular, Allocation_Time)

Depends on: Allocation_Time, w_Modular

w_Radical Units: Dmnl

Equation: Score_Radical / (Score_Sum + small)

Depends on: Score_Radical, Score_Sum, small

w_Radical_smooth Units: Dmnl

Equation: SMOOTH(w_Radical, Allocation_Time)

Depends on: Allocation_Time, w_Radical

Constants (43)

Absorptive_Capacity

Units: Dmnl

Value: 1

Allocation_Time

Units: Month

Value: 6

Approval_Bottlenecks

Units: Dmnl

Value: 1

Architectural_Transition_Rate

Units: 1/Month

Value: 0.06

Base_Alpha

Units: Dmnl

Value: 2.5

Belief_Update_Time

Units: Month

Value: 1

Breakthrough_Utilization_Rate

Units: 1/Month

Value: 0.05

Cognitive_Diversity

Units: Dmnl

Value: 1

Cultural_Inertia

Units: Dmnl

Value: 1

Disruptive_Transition_Rate

Units: 1/Month

Value: 0.02

Idea_Half_Life

Units: Month

Value: 60

Idea_Value

Units: capacity/ideas

Value: 0.1

Ideas_Initial

Units: ideas

Value: 0

Incremental_Transition_Rate

Units: 1/Month

Value: 0.1

Incremental_Utilization_Rate

Units: 1/Month

Value: 0.05

Initial_IMF

Units: capacity

Value: 20

Innovation_Time_Constant

Units: Month

Value: 1

Institutional_Memory

Units: Dmnl

Value: 1

KL_Gain

Units: 1/bit

Value: 8

KL_Lag_Time

Units:

Value: 1

KL_Memory_Time

Units: Month

Value: 6

KL_Threshold

Units: bit

Value: 0.08

KL_mid

Units: bit

Value: 0.08

KL_slope

Units: 1/bit

Value: 15

Leakage_Fraction

Units: 1/Month

Value: 0.02

Max_Surprise_Boost

Units: Dmnl

Value: 2

Modular_Transition_Rate

Units: 1/Month

Value: 0.08

Organizational_Learning

Units: Dmnl

Value: 1

P_Regime_prior

Units: Dmnl

Value: 0.05

Radical_Transition_Rate

Units: 1/Month

Value: 0.04

Reference_Resistance

Units: Dmnl

Value: 1

Regulation

Units: Dmnl

Value: 1

Reinvestment_Fraction

Units: Dmnl

Value: 0.05

Resources_Initial

Units: capacity

Value: 15

Risk_Aversion

Units: Dmnl

Value: 1

Sensitivity

Units: Dmnl

Value: 0.1

Trigger_Response_Time

Units: Month

Value: 0.5

base_rate_data_of_probability_of_innovations

Units:

Value: 0.01

eta

Units: ideas/capacity

Value: 0.5

research_commuity_judgment_of_not_innovation

Units: Dmnl

Value: 0.067

small

Units: Dmnl

Value: 1e-06

subject_matter_judgment_of_innovation

Units: Dmnl

Value: 0.08

xm

Units: Dmnl

Value: 5

Key Modeling

1) Stocks represent accumulations of innovation-related quantities (e.g., ideas, knowledge, capability, or value) that change through inflow/outflow rate variables (flows).

2) ROI is treated as an output of the system derived from resource allocation, innovation output, and/or payoff functions embedded in the auxiliary equations.

3) Time-step integration uses the method and DT defined in sim_specs; all rate variables should be dimensionally consistent with the chosen time unit.

Provided Exports

- Variable dictionary (CSV): IMF_Management_Simulator_ROI_variable_dictionary.csv
- Vensim equation list (TXT): IMF_Management_Simulator_ROI_vensim_equations.txt
- Dependency graph (Graphviz DOT):

IMF_Management_Simulator_ROI_dependency_graph.dot

APPENDIX C: STATISTICAL PROOFS FOR EVT APPLICATION AND DYNAMIC SCIENTIFIC METHOD

Extreme Value Theory: GPD, Return Levels, and Lifetime Risk

GPD = Generalized Pareto Distribution

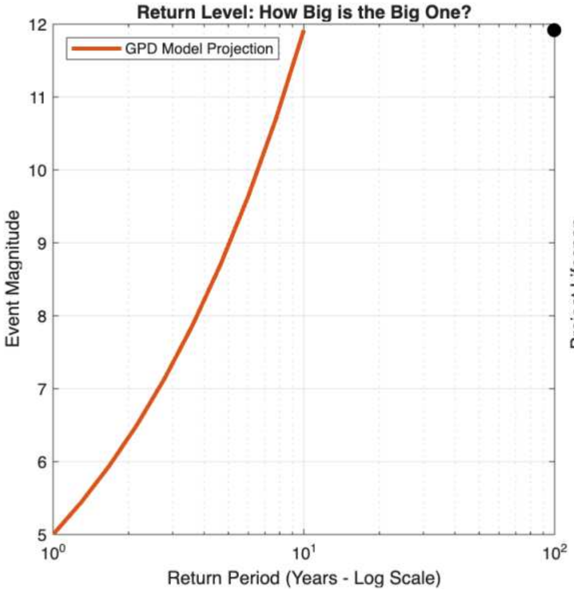
Model Configuration

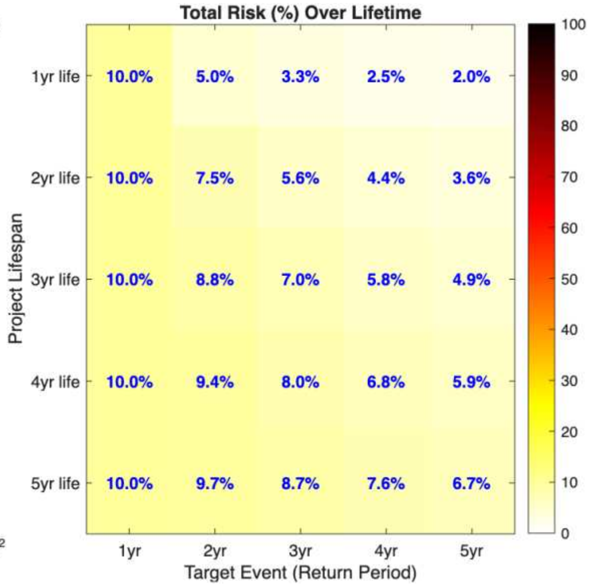
xi = 0.5; Shape parameter (xi > 0 means heavy-tailed/Power Law)

sigma = 1.6; Scale parameter (spread of the extremes)

u = 5.0; Threshold (e.g., a 5% market drop or 5m flood)

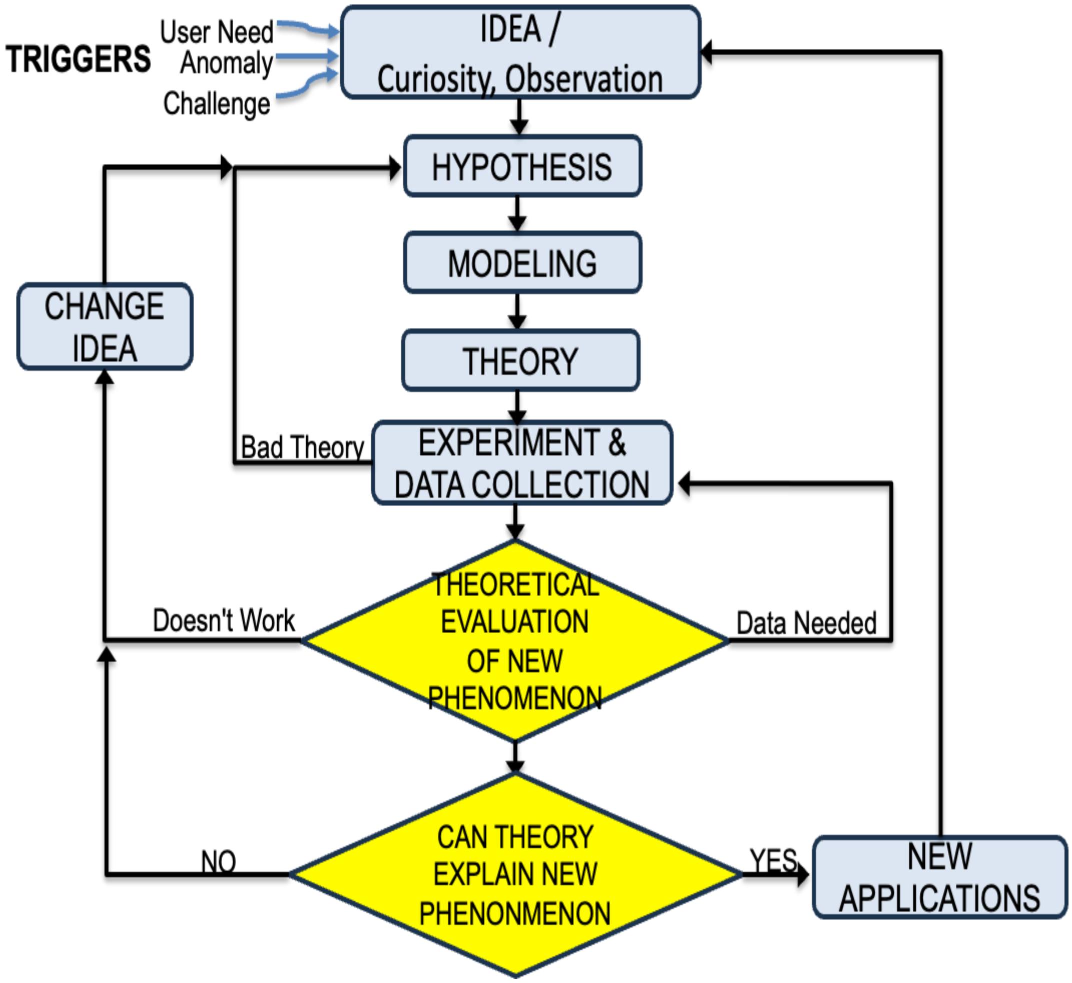
N_u_per_year = 1; Average number of events exceeding 'u' per year

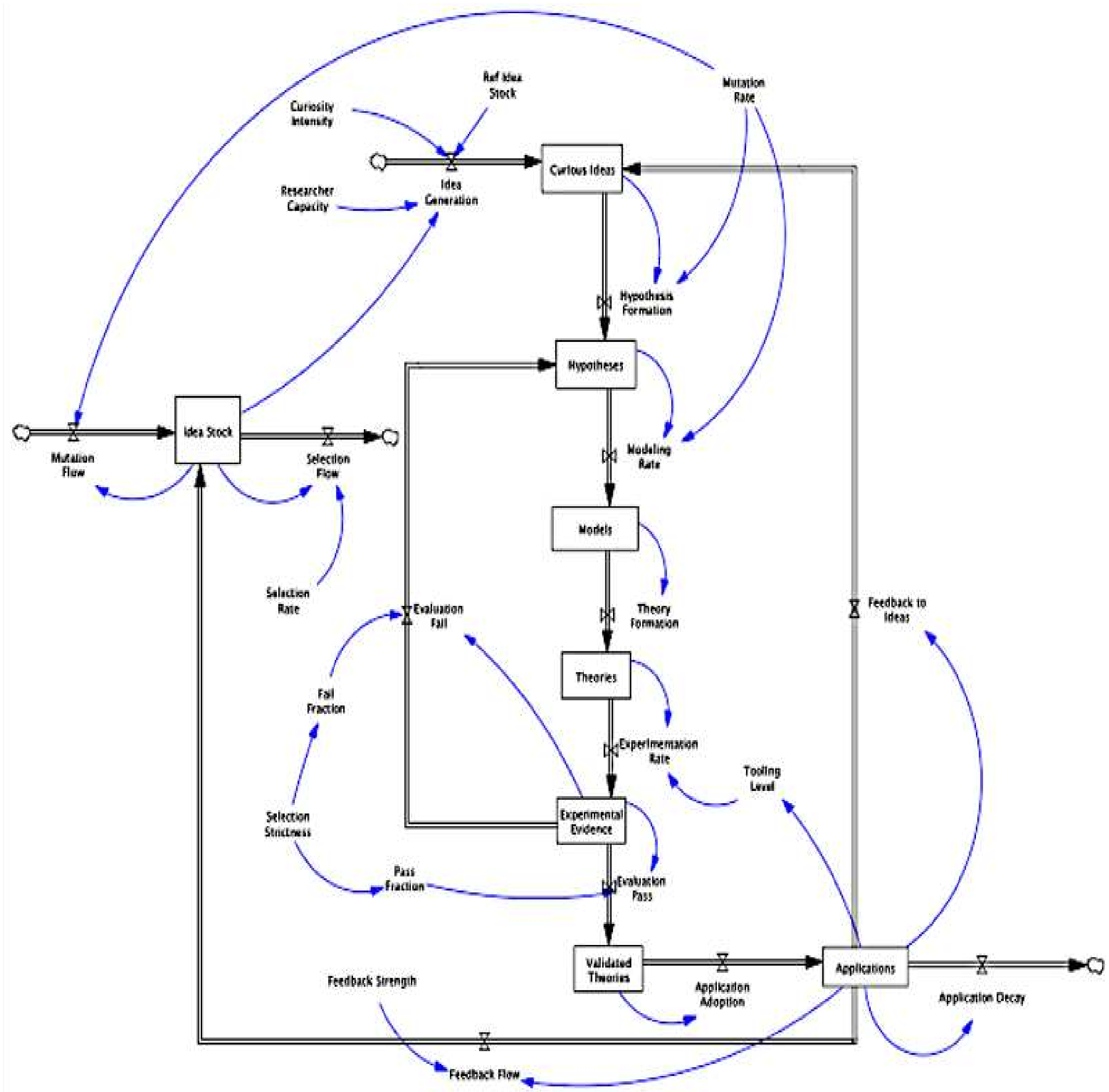




	1yr	2yr	3yr	4yr	5yr
1yr life	10.0%	5.0%	3.3%	2.5%	2.0%
2yr life	10.0%	7.5%	5.6%	4.4%	3.6%
3yr life	10.0%	8.8%	7.0%	5.8%	4.9%
4yr life	10.0%	9.4%	8.0%	6.8%	5.9%
5yr life	10.0%	9.7%	8.7%	7.6%	6.7%

DYNAMIC IDEA CREATION in RESEARCH: The SCIENTIFIC METHOD as INNOVATION CREATION ENGINE





The idea creation method functions as the operational algorithm that mutates and selects ideas through recursive feedback, converting uncertainty into structured learning and enabling the progression from incremental to breakthrough innovation. The model enables simulation-based exploration of how individual ideas grow and change with feedback from using experimentation to "kill" weak ideas.

APPENDIX D: PROGRAM OFFICER CLOSEOUT SURVEY

Program Officer Annual Closeout Survey - With submitter name.

* Required

* This form will record your name, please fill your name.

Program Officer Self-Assessment of own Portfolio Hardness/Difficulty

Concerning S&T problem difficulty, what percentage of the number of S&T Problems that you worked on in FY25 fall into each of the categories (1-5) below? Characterize the technical difficulty of the S&T problem, not support, administration, equipment, fees, etc. (The sum of answers in this section must equal 100%.)

1. Percentage of your S&T projects in FY25 that represent minor refinements to existing technologies or straightforward application of well-understood scientific principles. Likely to succeed with minimal risk.

Number must be between 0 ~ 100

2. Percentage of your S&T projects in FY25 that extend existing scientific knowledge or technologies into new, but closely related, areas. Requires solid science and engineering practice but doesn't demand significant scientific or technological breakthroughs.

Number must be between 0 ~ 100

3. Percentage of your S&T projects in FY25 requiring substantial scientific research or technology development effort and overcoming moderate research or technical hurdles. May involve integrating multiple technologies or adapting new science concepts from different fields.

Number must be between 0 ~ 100

4. Percentage of your S&T projects in FY25 aimed at achieving significant breakthroughs in a field. Involves exploring unproven concepts, overcoming major technical or research barriers, and potentially creating entirely new technologies or solving key scientific problems.

Number must be between 0 ~ 100

5. Percentage of your S&T projects in FY25 tackling fundamental scientific or extensive technological problems with the potential to revolutionize a field or achieve a breakthrough to move a technology forward. Characterized by one or more of the following: extremely high technical risk, long timelines, foundational problems, high technology or integration complexity, and a high probability of failure.

Number must be between 0 ~ 100

Program Officer Self-Assessment of own S&T Execution Quality

Concerning S&T execution quality, what percentage of the number of S&T Projects that you ran in FY25 falls into each of the categories (6-10) below? (The sum of answers in this section must equal 100%.)

6. In FY25, the percentage of my S&T projects where a lack of technical or programmatic understanding or experience resulted in insufficient technical guidance, management, or poor quality.

Number must be between 0 ~ 100

7. In FY25, the percentage of my S&T projects where I demonstrated project management and technical skills, but occasionally missed technical or programmatic issues, or addressed them reactively.

Number must be between 0 ~ 100

8. In FY25, percentage of my S&T projects where I effectively managed the project and provided adequate technical oversight, ensuring the scientific validity of the work and the integrity of the results.

Number must be between 0 ~ 100

9. In FY25, percentage of my S&T projects where I demonstrated exceptional scientific or technological leadership, proactively identifying and addressing technical challenges, fostering innovation, and ensuring high standards of scientific or technology development rigor.

Number must be between 0 ~ 100

10. In FY25, percentage of my S&T projects where I demonstrated transformative scientific or technological leadership, inspiring the team to achieve ambitious goals, pushing the boundaries of knowledge, and making significant contributions to the field.

Number must be between 0 ~ 100

11. With regard to the time spent on your FY25 S&T Problems versus the quality and quality S&T products select the response that best fits.

Strongly Disagree Disagree NeutralAgree Strongly agree

On average, the time I spent on S&T problems was directly proportional to the quantity and quality of results or S&T products produced.

On average, the funding I spent on S&T problems was directly proportional to the quantity and quality of results or S&T products produced.

12. Additional comments with regard to execution quality.

Program Officer Self-Assessment of own S&T Projects' Naval Relevance

Concerning the Naval Relevance of the S&T Projects that you ran in FY25, what percentage of the number of S&T projects was in each of the following categories (13 -17)? For projects with low TRL, basic or applied research, estimate the envisioned direct Naval Relevance if the work were to continue and progress to a higher maturity. (The sum of answers in this section must equal 100%.)

13. In FY25, percentage of my S&T projects with little to no discernible relevance to current or projected Navy/Marine Corps operational needs or problems. Transition to operational use is highly unlikely.

Number must be between 0 ~ 100

14. In FY25, percentage of my S&T projects with some tangential relevance to Navy/Marine Corps operations, but the potential impact is limited or unknown. Transition to operational use is challenging.

Number must be between 0 ~ 100

15. In FY25, percentage of my S&T project that address recognized Navy/Marine Corps needs or problems and has the potential to provide a noticeable improvement in operational or tactical capabilities or exact end technology is not known but the project seems to cover a set of Navy/Marine Corps problems. Transition to operational use is feasible with moderate effort.

Number must be between 0 ~ 100

16. In FY25, percentage of my S&T projects that address critical Navy/Marine Corps needs and problems and have the potential to significantly enhance operational or tactical capabilities or solve several Navy/Marine Corps problems. Transition to operational use is highly likely.

Number must be between 0 ~ 100

17. In FY25, percentage of my S&T projects that represent breakthrough technologies with the potential to fundamentally change Navy/Marine Corps operations and provide a decisive advantage in future conflicts. Transition to operational use is a high priority.

Number must be between 0 ~ 100

Program Officer Assessment of Research Performer and Principal Investigator Cadre

Concerning your performers and principal investigators that conducted S&T work for you in FY25, what percentage of the number of their S&T projects fall into each of the categories (18-22) below? With regard to a possible concern, "why would I pick a bad performer," you may have chosen a performer that did not perform to your expectations. i.e., you thought you picked a good per-former, but they did not work out as planned. (The sum of answers in this section must equal 100%.)

18. Lacks fundamental S&T knowledge and produces flawed research resulting in no peer-reviewed publications, failed experiments, un-replicable results, or a lack of impactful contributions to S&T project objectives. Demonstrates no innovation or understanding of current

advancements, unable to collaborate or communicate effectively, and resistant to feedback, hindering their potential to contribute meaningfully to S&T deliverables.

Number must be between 0 ~ 100

19. Possesses basic S&T understanding but struggles with complex problems and rigorous methodologies, resulting in research with inconsistencies and limited impact, evidenced by low-quality datasets, incomplete analysis, few citations, limited contribution to patents or publications, or little contribution to S&T objectives. Shows minimal innovation and needing guidance to apply cutting-edge techniques, participating inconsistently in collaborations and struggling to articulate technical findings clearly, impeding their progress towards impactful S&T deliverables.

Number must be between 0 ~ 100

20. Demonstrates competent S&T knowledge and conducts sound research with reproducible results, contributing consistently to project goals and exhibiting awareness of current advancements, evidenced by successful completion of experiments, well-documented code, contributions to technical reports, patent applications, and publication in reputable, though not necessarily top-tier, journals, or contributions to S&T objectives and solving of S&T problems. Contributes constructively to team collaborations and communicates technical information effectively, demonstrating the foundational skills for generating reliable S&T deliverables.

Number must be between 0 ~ 100

21. Possesses deep S&T expertise and independently conducts high-impact research, developing novel solutions and contributing significantly to the advancement of the field, evidenced by high-impact publications in leading journals, successful patent applications with significant commercial potential, presentations at prestigious conferences, the development of widely adopted methods or tools, or high impact with S&T objectives or problems. Proactively seeking out and mastering new techniques, leading collaborations effectively and communicating complex technical ideas with clarity and influence, demonstrating the potential to generate world-class S&T deliverables.

Number must be between 0 ~ 100

22. Exhibits exceptional S&T mastery, pioneering groundbreaking research that transforms the field and earns international recognition, evidenced by numerous publications in the very top journals, highly cited work, seminal patents that define new technologies, invitations to give keynote addresses at major conferences, or the development of paradigm-shifting theories or technologies. Inspiring and leading others with exceptional vision and communication skills, consistently pushing the boundaries of scientific knowledge and generating transformative S&T deliverables recognized as world-class contributions.

Number must be between 0 ~ 100

Program Officer Assessment of Performer Quantity, Quality, and Availability

Concerning the performers available to address the S&T goals, needs, and aspirations of Program Officers in accomplishing their program objectives, select the most appropriate statement concerning the Performers and Principal Investigator pool that ONR can draw from across government labs, academia, industry, and other partnerships.

23. Quantity. Select the best description on the quantity of performers and PIs in your S&T domain.

There are not enough performers and PIs in my area of interest to meet the needs of my S&T program.

There are an adequate number of performers and PIs in my area of interest, but the community is small, so I select from known performers without much refresh.

There is a large number of performers and PIs from which I can choose, giving me several selection choices.

There is a robust and rich number of performers and PIs in my area of interest allowing me to be very selective in my performer choices, pick specialized subareas, and have access to an abundant range of institutions and individuals.

24. Quality. Select the best description on the quality of performers and PIs in your S&T domain.

The quality of performers and PIs I can access are not of the highest standard within the worldwide talent pool and in their technical fields.

The quality of the performers and PIs I can access are sufficient for most of the work I want to accomplish in my S&T program, but not they do not conduct the most cutting edge or revolutionary work.

The performers and PIs I can access are from very high-quality institutions and are leaders in the S&T fields that I need the most in my S&T program. The pool I can access makes significant contributions to their S&T communities.

The quality of the performers I can access are of premier and world-renowned quality. The institutions and PIs are recognized and preeminent leaders in their fields and are doing revolutionary and groundbreaking research in S&T
areas of direct interest to my program.

25. Availability. Select the best description on the availability of performers and PIs in your S&T domain.

I have difficulty finding performers and PIs because ONR is not a desired sponsor of performers and PIs that I need to build my S&T program. I have challenges finding performers willing to work for ONR, DON, or the DOW.

I have a very competitive market to find performers and PIs that I need to build my S&T program. ONR is not the only sponsor of performers in my S&T field, and industry and other organizations are also competing for the same performers with attractive incentives such that I may not be able obtain premier talent. e.g., I cannot compete with Google in some areas.

I can find performers and PIs in the S&T areas I need for my S&T program and I am as competitive as other organizations in finding high quality talent to work for ONR.

I have a competitive advantage and can consistently pull in premier and world class performers. ONR is a preferred partner for performers and PIs in my needed S&T fields to work with.

Program Officer Assessment of Top 3 PIs

In the next four sections provide information about your top 3 PIs. The first section is information about you, and the following 5 sections are information about your top 3 PIs. If you don't have a top 3, fill in for what you have.

26. What Focus Area do you primarily work in?

27. What NNR do you primarily work in?

Naval Engineering   Ocean Acoustics   Sea-Based Aviation

Tactical Oceanography   Undersea Medicine   Undersea Weapons   None

Top 3 PI Information. #1 Performer

Fill in the information below for your #1 Performer.

28. Last Name of this PI?

29. First Name of this PI?

30. Institution of this PI?

31. What Focus Area does this PI primarily work in?

32. What NNR does this PI primarily work in?

Naval Engineering   Ocean Acoustics   Sea-Based Aviation

Tactical Oceanography   Undersea Medicine   Undersea Weapons   None

33. How is this PI relevant to Navy or Marine Corps needs?

34. Where is this PI in their career?

Early Career   Mid Career   Late Career

35. What attributes put this PI into you top list? (Pick 3)

Insight & Innovation - Executed projects that displayed more revolutionary ideas and novel advancements that most PIs.

Execution & Productivity - Displayed exceptional ability to execute S&T projects in areas such as milestones, reports, deliverables, financials, and volume of work better than most PIs.

Technical Prowess - Displayed scientific and/or technological knowledge, depth, currency, and prowess better than most PIs.

People Mentored - Mentored other researchers who then became ONR-funded PIs and/or mentored other researchers that significantly addressed naval S&T problems better than most PIs.

Impact on NNRs - Executed S&T projects that impacted the advancement of NNRs better than most PIs.

Collaboration - Displayed connections and relationships with other research organizations worldwide better than most PIs.

Leadership - Displayed superior and inspirational leadership in their research institutions and communities better than most PIs.

Technology Transition Track Record - Delivered more technology that was fielded to the Navy and Marine Corps better than most PIs.

Naval Relevance of Projects - Executed projects that had direct impact and progress on Navy and Marine Corps S&T problems better than most PIs.

36. Are there any other attributes why this PI is in your top list, which are not listed in the above selections?

Top 3 PI Information. #2 Performer

Fill in the information below for your #2 Performer.

37. Last Name of this PI?

38. First Name of this PI?

39. Institution of this PI?

40. What Focus Area does this PI primarily work in?

41. What NNR does this PI primarily work in?

42. How is this PI relevant to Navy or Marine Corps needs?

43. Where is this PI in their career?

Early Career Mid Career Late Career

44. What attributes put this PI into you top list? (Pick 3)

Insight & Innovation - Executed projects that displayed more revolutionary ideas and novel advancements that most PIs.

Execution & Productivity - Displayed exceptional ability to execute S&T projects in areas such as milestones, reports, deliverables, financials, and volume of work better than most PIs.

Technical Prowess - Displayed scientific and/or technological knowledge, depth, currency, and prowess better than most PIs.

People Mentored - Mentored other researchers who then became ONR-funded PIs and/or mentored other researchers that significantly addressed naval S&T problems better than most PIs.

Impact on NNRs - Executed S&T projects that impacted the advancement of NNRs better than most PIs.

Collaboration - Displayed connections and relationships with other research organizations worldwide better than most PIs.

Leadership - Displayed superior and inspirational leadership in their research institutions and communities better than most PIs.

Technology Transition Track Record - Delivered more technology that was fielded to the Navy and Marine Corps better than most PIs.

Naval Relevance of Projects - Executed projects that had direct impact and progress on Navy and Marine Corps S&T problems better than most PIs.

45. Are there any other attributes why this PI is in your top list, which are not listed in the above selections?

Top 3 PI Information. #3 Performer

Fill in the information below for your #3 Performer.

46. Last Name of this PI?

47. First Name of this PI?

48. Institution of this PI?

49. What Focus Area does this PI primarily work in?

50. What NNR does this PI primarily work in?

51. How is this PI relevant to Navy or Marine Corps needs?

52. Where is this PI in their career?

Early Career Mid Career Late Career

53. What attributes put this PI into you top list? (Pick 3)

Insight & Innovation - Executed projects that displayed more revolutionary ideas and novel advancements that most PIs.

Execution & Productivity - Displayed exceptional ability to execute S&T projects in areas such as milestones, reports, deliverables, financials, and volume of work better than most PIs.

Technical Prowess - Displayed scientific and/or technological knowledge, depth, currency, and prowess better than most PIs.

People Mentored - Mentored other researchers who then became ONR-funded PIs and/or mentored other researchers that significantly addressed naval S&T problems better than most PIs.

Impact on NNRs - Executed S&T projects that impacted the advancement of NNRs better than most PIs.

Collaboration - Displayed connections and relationships with other research organizations worldwide better than most PIs.

Leadership - Displayed superior and inspirational leadership in their research institutions and communities better than most PIs.

Technology Transition Track Record - Delivered more technology that was fielded to the Navy and Marine Corps better than most PIs.

Naval Relevance of Projects - Executed projects that had direct impact and progress on Navy and Marine Corps S&T problems better than most PIs.

54. Are there any other attributes why this PI is in your top list, which are not listed in the above selections?

Program Officer Assessment of People and Infrastructure

Evaluate the questions below concerning Program Officer, Infrastructure and Resources.

55. Concerning if ONR has sufficient number of Program Officers needed for all Research Areas, select the best responses.

Strongly Disagree Disagree NeutralAgree Strongly Agree

There are defined and required Research Areas that do not have dedicated Program Officers assigned or available.

The current number of Program Officers allows for consistent application of innovation, invention, planning, and review across all Research Areas.

There are not enough Program Officers to allow for proactive engagement within Research Areas and anticipation of potential challenges.

The technical areas Program Officers can cover are sufficiently broad and deep to effectively manage the scope of Research Areas.

There are a sufficient number of Program Officers to adequately cover all currently defined Research Areas within the S&T organization.

56. What Research Areas or Focus Areas need additional POs or POs with different specialties? What are those required and missing specialties.

57. Additional comments concerning the number and technical capabilities of Program Officers:

58. Concerning research equipment and facilities available to do work across required S&T, select the best responses.

Strongly Disagree Disagree NeutralAgree Strongly Agree

Researchers and developers have timely access to the specialized equipment required to conduct S&T experiments, research, and development.

Existing laboratory and research facilities provide adequate space and configuration to support ongoing S&T research and development activities.

Researchers have access to sufficient data storage, computing power, and software licenses to effectively process and analyze research data.

Researchers have access to all of the specialized equipment and instrumentation necessary to conduct the full scope of planned research activities.

59. What required and missing equipment, instrumentation, space, infrastructure, or facility is needed to meet S&T objectives?

60. Are there any equipment, instrumentation, space, infrastructure, or facilities that are not the correct quantity? For instance, are we overinvesting in wind tunnels or underinvesting in research ships? Identify areas where the naval research enterprise has an imbalance in either direction of required assets.

61. What research resources could be repurposed to address other S&T priorities?

62. Additional comments concerning S&T research equipment and facilities:

Program Officer Assessment of Time Available to do Program Officer Work

Concerning the duties and work you need to perform to get you job done, where did you spend available time in FY25 and where would you like to spend time?

63. Arrange the list below (using arrows to the right) in order of the most time, on top, to the least

time, on bottom, that you spent in FY25.

64. Arrange the list below (using arrows to the right) in order of the most time, on top, to the least

time, on bottom, where you would like to spend time to be a more effective PO.

65. What other activities do you spend time on that are not listed above? How much time do you spend on them and how much time would you like to spend on them?

66. Which task (does not need to be listed above) did you spend time in FY25 that you would like to get rid of? Include an idea of who should do it if not a PO or how the task could be eliminated.

67. In order to be the most effective, a PO should spend the majority of their time doing the following:

Program Officer Self-Assessment of S&T Program Conducted in FY25

Concerning your S&T Program in FY25 answer the following questions concerning program composition and benchmarks.

68. How many awards (grants, contracts, etc.) did you have in execution in FY25?

The value must be a number

69. You may have had several projects in an award, with a project being an effort going after specific S&T objectives or research questions. How many S&T projects were you executing in FY25?

The value must be a number

70. What was your total budget, of FY25 dollars, for S&T projects you managed in FY25 in 6.1 ? (Include all appropriated funds including core, adds, and outside funding sources.)

The value must be a number

71. What was your total budget, of FY25 dollars, for S&T projects you managed in FY25 in 6.2 ? (Include all appropriated funds including core, adds, and outside funding sources.)

The value must be a number

72. What was your total budget, of FY25 dollars, for S&T projects you managed in FY25 in 6.3 ? (Include all appropriated funds including core, adds, and outside funding sources.)

The value must be a number

73. What was your total budget, of FY25 dollars, for S&T projects you managed in FY25 in 6.4 ? (Include all appropriated funds including core, adds, and outside funding sources.)

The value must be a number

74. What was your total budget, of FY25 dollars, for S&T projects you managed in FY25 in 6.5 and higher? (Include all appropriated funds including core, adds, and outside funding sources.)

The value must be a number

75. How many new projects did you start in FY25?

The value must be a number

76. How many of your projects ended in FY25?

The value must be a number

77. How many papers were published in FY25? as a result of your work (regardless of when the project was funded or executed)

The value must be a number

78. How many different (distinct) performers did you use in FY25?

The value must be a number

79. How many different (distinct) PIs did you use in FY25?

The value must be a number

80. How many performers used in FY25 were new, i.e., first time you used them?

The value must be a number

81. How many PIs used in FY25 were new, i.e., first time you used them?

The value must be a number

82. How many of your projects transitioned to acquisition in FY25 (regardless of when the S&T work was done)?

The value must be a number

83. How many of your projects transitioned directly to the Fleet or Force, by some way other than an acquisition program of record, in FY25 (regardless of when the S&T work was done)?

The value must be a number

84. How many projects completed in FY25 will continue in FY26 to continue the research or develop the technology to a higher TRL based on positive or promising results from the completed project?

The value must be a number

85. How many projects completed in FY25 are done and will not be investigated or developed further?

The value must be a number

86. How many field demonstrations and technology experiments did you conduct in FY25? What were they?

87. How many white papers did you receive in FY25?

The value must be a number

88. How many full proposals did you receive in FY25?

The value must be a number

89. How many of those proposals, received in FY25, were funded as projects in FY25?

The value must be a number

90. How many of those proposals, received in FY25, will be funded as projects in FY26?

The value must be a number

91. Of white papers and proposals received in FY25, for those not selected, what was the primary reason? For example, quality, cost, naval relevance, limited funding, others were better.

92. What other duties do you have other than direct S&T Program Management? For example, NATO panels, TTCP, COI, ICEPPR, etc.

93. How will your S&T programs affect Naval Kill Chains? *

94. Do you need to provide a classified answer to the question about Naval Kill Chains? *

Yes No

95. What relevant companies are working in the S&T areas that you are working in? *

96. What government labs or warfare centers are working in the S&T areas that you are working in? *

Program Office Tradecraft

Concerning Program Officer Tradecraft what lessons did you learn in FY25 that can help other POs?

97. In FY25 what is a major lesson you learned concerning how to be a better program officer which could be used by other POs?

98. If you would like to explain that lesson learned further upload what happened and what you learned so we can put it into Program Officer best practices.

File number limit: 4 Single file size limit: 10MB Allowed file types: Word, Excel, PPT, PDF, Image, Video, Audio

99. How are you measuring the outcomes of your S&T projects? *

100. If would like to include amplifying information about how you measure the S&T outcomes of your projects upload the information here.

File number limit: 1 Single file size limit: 10MB Allowed file types: Word, Excel, PPT, PDF, Image, Video, Audio

101. Additional comments:

APPENDIX E: PUBLICATION IN THE NAVAL ENGINEERING JOURNAL

Advancing the Navy's Technological Innovation Pipeline through System Thinking and Dynamic Modeling

By Quentin E. Saulter

Abstract

Today's Naval operations rely on past technological innovations. Different platforms, weapons, sensors, command and control systems, have evolved through long complex research, engineering, testing, and acquisition paths. The Navy's technological innovation pipeline starts with research investigations in academic institutions, progresses through applied research in laboratories, then to developed prototypes from industry to validation via engineering trials which culminates in acquisition and full-scale operational deployment. This pipeline connects early discovery of innovations to mission-ready systems. This paper introduces an innovation life cycle and evolution framework designed to maintain future Naval superiority. Current accepted frameworks for understanding and finding leverage of innovation's life cycle and evolution, for the purpose of improving selection and investment strategies for Naval applications, are non-dynamic. They fail to account for temporal dynamics, feedback, and interdependencies of innovations. A dynamic model-based simulation metric for Naval innovation was created for deducing technological advancements from citation time series patterns that showed probabilities of new capabilities for investment. Causal analysis of citating innovative research was used to simulate how changes in purpose, structure, and behavior affect innovation. Systems Thinking, Systems Dynamics, and Bayesian Analytics are also used to enable quantitative modeling and analysis of the complex interplay of random variables, feedback loops, and time delays that influence innovation. This paper has shown that a dynamic multi model approach can deduce the cause of innovation from the effect of increased citations of Naval research projects, to give probabilities of new innovations. This new framework can be used to provide the Naval Research Enterprise insights into potential outcomes and bottlenecks within the ecosystem.

Keywords: Innovation, Complexity, Causal Inference, System Dynamics, Probability, Information Diffusion

The views expressed in this article are those of the authors and do not reflect the official policy or position of the Office of Naval Research, the U.S. Naval Research Laboratory, the Department of Defense, or the U.S. Government. All information and sources for this paper were drawn from unclassified materials.

1. Introduction

The Navy's innovation pipeline begins with basic science and early-stage research. The 'innovation pipeline' metaphor is utilized here to represent the flow of intellectual and technical capital through the Navy's Research, Development, and Acquisition (RD&A) framework. This model assumes that innovation is a structured progression where 'raw' scientific concepts are refined through successive stages of validation. Funding often comes from the Office of Naval Research

(ONR), the Office of the Secretary of Defense (OSD), DARPA, or similar agencies (Montalván-Burbano et al., 2020). Promising ideas are developed into mature technologies through applied research, prototyping, and testing. Transition programs, such as the Navy's Future Naval Capabilities (FNC) program, match these technologies to operational needs. From there, systems enter formal acquisition programs. Requirements are further defined, budgets are set, and timelines are fixed. Programs then go through testing, certification, integration, and deployment. The entire process typically takes 10 to 20 years (Park et al., 2023). This structure is linear, risk-averse, and bureaucratic. It favors mature technologies and discourages high-risk, high-reward concepts. Feedback loops in the present acquisition cycle are slow and are often revealed late. The result can be innovations lagging present and future Naval mission needs and capability advancements.

Naval acquisition programs rely on integrating scientific and technological advancements, yet innovation measurement models remain largely static, emphasizing output metrics over causal mechanisms. While dynamic innovation models exist in areas such as business operations, personnel management, and product improvement, they have not been widely applied to Naval acquisition (Ghaffarzadegan et al., 2023).

While the current model provides a robust framework for analyzing the Science and Technology (S&T) phase of innovation, it is important to acknowledge that S&T is only one component of the broader Navy Research, Development, and Acquisition (RD&A) ecosystem. In the Department of the Navy, innovation is not a linear path but a complex transition from basic research (6.1) and applied research (6.2) through to advanced component development and eventual fleet integration.

A primary challenge in Naval innovation is the 'transition' phase, moving a concept from an S&T environment into a formal Program of Record. This study focuses on the early-stage modeling of innovation; however, future iterations of this model should integrate acquisition variables, such as Technology Readiness Levels (TRLs) and Integration Readiness Levels (IRLs), to better account for the non-S&T hurdles that influence total innovation throughput. By centering on the S&T portion, this paper establishes a baseline for the technical feasibility of innovation, which must then be coupled with policy and budgetary frameworks to achieve full-scale implementation.

This paper attempts to derive dynamic models for the cause of innovation from time series data of publications and citation patterns. These models can be used to assess and guide innovation integration in Naval research and acquisition. To properly evaluate innovation, understanding its significance within a research context must be achieved (Wang et al., 2023). The academic world has put forth various interpretations of innovation. Most innovation researchers have adopted the definition, Innovation = Invention + Exploitation (Dewangan & Godse, 2014). According to literature reviews, invention is the process of developing a practical solution to a problem. When exploitation is added to invention, an innovation is "the successful exploitation of new inventions.” It can be shown that the exploitation of new inventions is critical for adopting innovations. This paper modifies the definition of innovation as “Innovation for Naval application is defined as a systemic endeavor that generates groundbreaking solutions for the warfighter. This process begins with scientific concepts (the discovery of new phenomena) and matures into technology (the practical application of knowledge), ultimately culminating in the delivery of products or services that provide direct operational utility.” that brings about a positive change to address an unmet need, challenge, or solve a significant problem in science, society, or industry (Aspray, 1997). This definition incorporates invention and exploitation and expands innovating to encompass a research enterprise system.

2. Background

2.1 *Department of Defense (DOD) research, development, test, and evaluation (RDT&E):*

The Department of Defense carries out research, development, testing, and evaluation (RDT&E), to meet mission-specific operational and strategic needs. RDT&E supports the full spectrum of defense innovation, from early-stage scientific research to final testing and fielding of advanced systems. This includes basic research (6.1), applied research (6.2), advanced technology development (6.3), system development and demonstration (6.5), and operational testing and evaluation (6.6). These efforts help ensure technological superiority, readiness, and the ability to adapt to emerging threats. The Defense Department's RDT&E investments are managed across the Navy, Army, Airforce, Space Command, and other defense agencies, each responsible for a portfolio of programs aligned with national defense objectives. In fiscal year 2022, DOD received $65.7 billion in federal R&D appropriations, representing 41.1% of the total $159.6 billion distributed across all federal agencies for R&D (Gallo, 2022). This investment reflects the critical role of defense-driven innovation in maintaining U.S. military effectiveness and supporting the broader U.S. science and technology research enterprise.

The Department of the Navy (DON) measures innovation by outputs of number of patents, R&D spending, technology readiness levels (TRLs), and acquisition milestones. These metrics are simple to report but poor at forecasting (Vidyadharan et al., 2017). They do not explain why a technology succeeds or fails. They ignore delays, organizational bottlenecks, and feedback from stakeholders' and military operators. These metrics are artifact-based. They focus on what was built or funded without including what can be learned or improved quickly. These metrics miss the dynamics between actors, decisions, and constraints across time. This is of major concern due to faster changes in simple disruptive technologies, new nontraditional ways of war fighting, and possible adversarial asymmetrical operational concepts and technologies.

Understanding the Life Cycle and Evolution of Innovations is essential for the DON to maintain its technological edge and avoid strategic surprise. Adversaries are accelerating their own research and development efforts targeting asymmetric advantages and disruptive technologies. Without a clear systems thinking approach to find a metric of the innovation, the DON risks falling behind in areas critical to future conflict (Arnold & Wade, 2015). To maintain Naval technological edge, it is imperative to identify and fund research and engineering prototype development that could have the most impact for immediate, near future, and long-term capabilities.

The DON received 18.6 % of DOD's R&D appropriations in fiscal year 2022 with similar investments from previous years. These past investments, current investments, and future investments make effective innovation forecasting a critical enabler for the DON to identify emerging trends, evaluate technological maturity, and align RDT&E investments with short, mid, and long-term capability and operational goals. Quantitative indicators are needed to support early detection of potential breakthroughs. These indicators could also help assess where adversaries may be gaining ground, allowing Naval programs to respond with targeted countermeasures or accelerated development. Innovation life cycle and evolution understanding also supports better resource allocation. By identifying which research offers the highest potential impact relative to cost and development risk, decision-makers can prioritize projects with the greatest strategic value. This reduces waste and enhances agility across the Navy’s RDT&E enterprise. The ability to systematically monitor, model, and anticipate innovation trajectories can be central to maintaining operational superiority. It would ensure that Naval forces are equipped, not just with today’s advanced capabilities, but with the tools needed to counter tomorrow’s threats before they materialize.

2.2 *Present Innovation Metrics*:

As previously mentioned, quantitative indicators such as publication metrics, patent activity, funding flows, and technology readiness levels are commonly used to assess innovation. They typically fall short when applied to science and technology (S&T) research for Naval applications. These measures focus on outputs and static artifacts rather than dynamic processes. For instance, a high volume of publications or patents may signal productivity, but not originality, strategic alignment, or readiness for operational use. As demonstrated by the Naval Research Enterprise, Naval innovation breakthroughs emerge from complex and iterative interactions across multiple disciplines, institutions, and timeframes (Dziallas & Blind, 2019). For example, the development of the Aegis Combat System required coordinated advances in radar engineering, computer processing, missile technology, and systems integration. The research for these technologies came from naval research laboratories, defense contractors, and academic institutions. Each research innovation built on prior advances, with feedback loops between testing at sea and operational needs. Emerging technologies also drove continuous refinement through integration. Metrics like funding levels or technology readiness levels only captured late-stage or easily countable phenomena which did not account for previous innovation integration in the evolutionary systems development of Aegis (Ponta et al., 2021). These metrics did not account for exploratory work, failed attempts, tacit knowledge, or the collaborative nature of early-stage discovery for Aegis.

Innovation in S&T does not follow a linear path. It often involves long periods of conceptual development before tangible results appear. Quantitative indicators miss this hidden phase, leading to under valuing of foundational science or disruptive concepts in progress. They also create incentives for short-term outputs over long-term impact. While quantitative indicators offer convenience, they fail to reflect the real drivers and conditions of innovation in Naval S&T ecosystems (Fire & Guestrin, 2019). To capture how innovation unfolds, a multi model process-based, systems thinking approach is necessary to achieve what traditional metrics cannot.

In most cases, the traditional innovation metrics, like citations, fail to capture possible breakthroughs because they are unable to measure and predict what led to or caused an innovation (Bornmann et al., 2020). An alternative method is needed to give insight into the cause factors that are influential in producing citations from innovations. Systems Thinking is one approach to analyzing the cause of innovation. Applying the principles of System Thinking to ascertaining the cause of innovation leads to examining the purpose, structure, behavior, and use of an idea or research (Henderson, 2021). These three factors are linked in feedback loops that cause changes in research or technology that can lead to the emergence of new ideas and knowledge responsible for changes in innovation. Quantifying the cause of how innovation produces more citations, publications, or patents is necessary to have a dynamic metric to measure and predict if a particular research project, scientific theory, product, service, or technology will significantly bring about positive groundbreaking change to address unmet needs or challenges in the Navy's research ecosystems.

2.3 *Theoretical background:*

Dynamic Models and Bayesian Conditional Probability:

The framework of this paper is based on model-based systems thinking in which model simulations with feedback are used for measuring and predicting innovations based on observational studies of time series data of citation and publication patterns of innovative research. It begins with problem definition, focusing on stakeholder needs and the development of predictive metrics. The framework then supports simulations and scenario analyses, capturing dynamic patterns in citations, Bayesian processes, and logistic growth to be used for decision making.

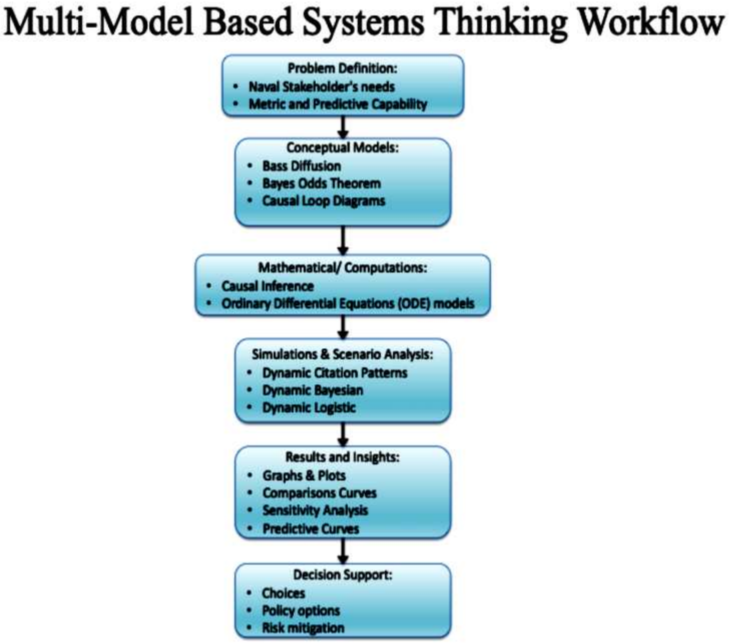


Fig. (1). A structured approach for integrating multiple modeling techniques into systems thinking for naval innovation analysis.

The framework shown in Fig. (1). is used to guide the modeling and simulations of the changes in structure, purpose, behavior, and use, as seen by citation patterns, of previous innovative research or technologies that could cause new innovations. The theoretical methods of information diffusion and Bayesian inference are employed to analyze the citation patterns of Nobel Prize researchers. Information diffusion explains individuals' adoptions of innovation, and collective learning through information sharing. The adoption of innovative research was studied using various models. The one chosen for modeling the diffusion of innovation for this paper was the Bass diffusion model (Massiani & Gohs, 2015). This modeling construct was used to calibrate subsequent models on the innovation diffusion process within a relevant population. This is a highly accepted model of innovation diffusion as seen from literature investigations. The mathematical formula for the Bass diffusion model is shown in Equation (1). This study used a dynamic Bass diffusion model to develop an innovation metric with feedback to simulate how much and how fast an innovative idea disseminates in a relevant population(Horvat et al., 2020). The relevant population are those who work in the same research field in which innovative research generated knowledge that was deemed adoptable. The advent of the internet and social media has revolutionized information diffusion, allowing for rapid and widespread dissemination of information (Meade & Islam, 2006). As information is shared and transmitted, it undergoes modification, amplification, or distortion, leading to positive adoption, or negative abandon, effects. Equation (1) is the differential equation for the rate of information diffusion(Zhang et al., 2023):

$$dN(t)/dt = p * (m - N(t)) + q * N(t) * (m - N(t)) \qquad (1)$$

In this equation:

- N(t) represents the cumulative number of adopters of the innovation at time t,
- m is the potential size of the information area or the maximum number of potential adopters and
- p is the coefficient of innovation, representing the rate at which individuals independently decide to adopt the innovation and
- q is the coefficient of imitation.

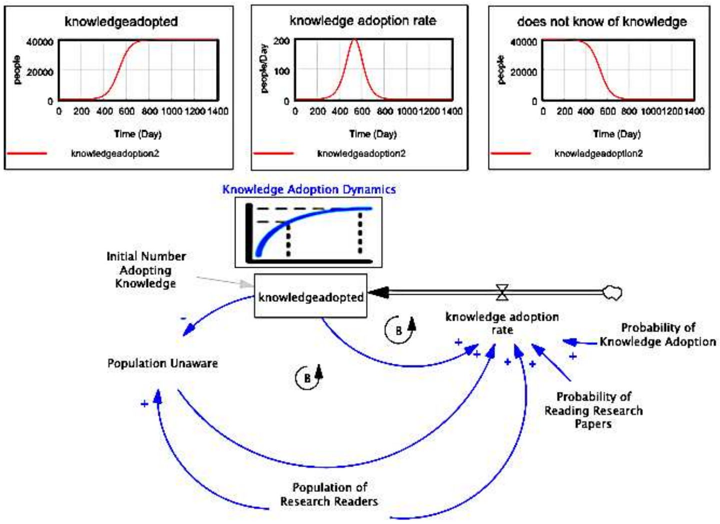


Fig. (2). Dynamic Knowledge Adoption Model: The S-curve is formed when plotting cumulative adopters over time as knowledge is adopted.

In the model for Fig. (2)., the variable (knowledge adoption rate) is equal to (Population Unaware) * (knowledge adopted) * (Probability of Reading Research Papers) *(Probability of Knowledge Adoption) / (Population of Research Readers). The equation shows that the Bass Diffusion model is intrinsically connected to probability (Massiani & Gohs, 2015). This model was used to forecast the adoption of new knowledge or innovation within a specific research population over time. It is based on the premise that the knowledge adoption rate depends on two factors: the innovation effect and the imitation effect. In the model shown in Fig. (2), the innovation effect is equal to the Probability of Knowledge Adoption, and the imitation effect is equal to the Probability of Reading Research Papers. The innovation effect represents the likelihood that an individual will adopt the innovation independently. In contrast, the imitation effect represents the likelihood that an individual will adopt the innovation influenced by those who have already adopted it. The Bass diffusion model uses probabilities to predict the cumulative number of adopters at any given time, providing valuable insights for marketing strategies and product lifecycle management (Orbach, 2016). Therefore, modeling probabilities of adoption of research knowledge and imitation of research knowledge is crucial for effectively applying this model. The results presented here primarily reflect intra-population diffusion. In the context of the Navy, innovation must eventually navigate the boundaries between the S&T community, the acquisition community, and the Fleet. These boundaries are often reinforced by disparate organizational cultures, varying risk tolerances, and information silos. Bayes theorem was used to model and infer the adoption and imitation effect probabilities.

Bayes Theorem, a fundamental principle in probability theory and statistics, provided a way to update the probabilities in this paper based on new evidence (Efron, 2013). The odds ratio form of Bayes Theorem was used to find the inverse probability of innovations from citations. Using odds rather than probabilities, can be useful in various applications such as medical diagnostics and decision theory (Budowle et al., 2011). The odds form of Bayes Theorem is defined as the ratio of the probability of an event occurring to the probability of it not occurring (Smith & Gelfand, 1992). The odds of hypothesis H, given evidence E, denoted as Odds(H|E), are:

$$Odds(H|E) = P(H|E)/P(\neg H|E) \tag{2}$$

Where $\neg H$ is the negation of hypothesis H.

Similarly, the prior odds are:

$$Odds(H) = P(H)/P(\neg H) \tag{3}$$

To express Bayes' Theorem in terms of odds, we need to relate the posterior odds to the prior odds and the likelihood ratio. The likelihood ratio, Λ, is given by:

$$\Lambda = P(E|H)/P(E|\neg H) \tag{4}$$

Bayes Theorem in odds form is:

$$Odds(H|E) = Odds(H) \times \Lambda \tag{5}$$

Or explicitly:

$$\frac{P(H|E)}{P(\neg H|E)} = \frac{P(H)}{P(\neg H)} \times \frac{P(E|H)}{P(E|\neg H)} \tag{6}$$

Where:

- Prior Odds: $Odds(H) = \frac{P(H)}{P(\neg H)}$ represents the initial belief about the hypothesis before considering the new evidence.
- Likelihood Ratio: $\Lambda = \frac{P(E|H)}{P(E|\neg H)}$ quantifies the likelihood of the evidence under hypothesis H compared to its negation.
- Posterior Odds: $Odds(H|E) = \frac{P(H|E)}{P(\neg H|E)}$ represents the updated belief about the hypothesis after considering the new evidence.

2.4 *Systems Thinking Modeling Framework:*

This study applied a systems thinking framework to analyze citation and publication time series, identifying innovation trajectories that mirror those of Nobel laureates as benchmarks for adoption (Rostgaard, 2023). The odds form of Bayes theorem was used for predicting the probability of innovation based on the number of citations over time and patterns of citations of highly cited research. This is depicted in Table (1). Innovative research was defined as Nobel Prize-winning research in in physics. Data on 2026 Nobel laureates was collected and analyzed from Scopus, an abstract and citation database of peer-reviewed literature from scientific journals, books and conference proceedings. In the equation, hypothesis H is Innovation, and evidence E is citations. The odds ratio for the likelihood was developed using bibliometric analysis of Nobel Prize research citations within a specific scientific field of physics. The field of Attosecond Physics was chosen for Bayesian analysis. Citation and publication data was gathered and analyzed for statistical significance in the relationship between citations and innovativeness as indicated by winning a Nobel Prize. The total number of citations of attosecond pulse research articles was 34860 from 2009 to 2024. The total number of citing articles of Nobel Prize research was 4476 as of April 2024. A measure of 10 citations that included a Nobel prize winner, was used to determine highly cited research from non-highly cited research. The odds ratio was calculated using the values in Table (1). The odds ratio tells us that highly cited research is 3.720 times more significant to be as innovative as Nobel Prize research than non-highly cited research(Kruschke, 2021). The log of the odds ratio is $\ln = 1.314$. The log indicates that highly cited research is a good indication of innovative research. Performing a Wald test for statistical significance gives a standard deviation of 0.147 (Gnona & Stewart, 2022).

Table. (1). Odds ratio of Nobel Prize research citations to Highly Cited research in the field of Attosecond Physics.

		Nobel Prize Research In Attosecond Physics	
		Yes	No
Highly Cited Research	Yes	4476	29195
	No	49	1189

$$Odds\ Ratio = \frac{4476 \times 1189}{49 \times 1189} = 3.720 \tag{7}$$

Table. (1) is an effective way to see the cross multiplication represent by equation (6) to obtain an Odds ratio of the probability of the hypothesis that the research is innovative, P(H) over the negation P(¬H) times evidence. The log of the odds ratio is well beyond the mean of a Gaussian distribution of the citations. Thus, the p-value is close to zero, indicating that the null hypothesis is not likely, and the theory that innovation can be deduced from citation patterns is correct. Using Bayes's rule from Equation 6, a calculation of the updated probability of innovation was performed, given the following citations:

$updated\ odds\ of\ innovation = likelihood\ ratio \times prior\ odds\ of\ innovation$. The prior odds of innovation are computed from the number of citations received for the Nobel Prize research over the total number of citations in the field of the Nobel Prize research. This is $prior\ odds = \frac{4476}{34860} = .128$ or 12.8%. The probability of innovation given citation patterns is 47.8%. This is a powerful indication that citation patterns of researcher's citations over time can indicate innovative research.

Using the Bayesian calculations, a multiple-model approach was implemented to discern the innovation probability from data citations and publications statistics. The concept of the model is shown in Fig. (3). This multiple-model approach was used to build a causal inference model on what influences innovations and perform counterfactual investigations of those influences based on the Holism systems principle. Holism Systems Principle was used as a framework to understand the complex interactions of innovation elements with feedback and influences for the underlining causes of innovation(Morin, 1992). Holism emphasizes the importance of the whole system and the interdependence and feedback of its parts rather than focusing on individual components or contributions in isolation. In the context of innovation, this means recognizing that new ideas and technologies do not exist in a vacuum. Instead, they manifest from ever-changing and evolving states of previous innovations and knowledge. The principle of Holism, in terms of complex feedback of interacting elements, provided the insights into the complex and dynamic nature of a multi-model simulation of innovation researched that lead to the framework of knowledge diffusions relationship with citation patterns shown in Fig. (3).

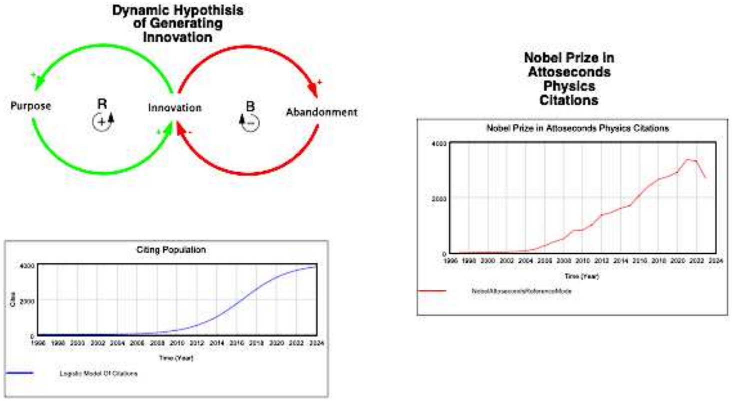


Fig. (3). Theory of Knowledge Diffusion using Citation Correlation: Shows how citations are dynamically connected leading to a S curve function which simulates real world research adoption of Nobel Prize awarded work in Attosecond Physics.

This framework of knowledge diffusion led to the development of a Causal loop diagram that was used to analyze the relationships between variables of research citations, as shown in Fig. (4) (Y. et al., 2023). The causal loop diagram gives insight into complexity's implications for understanding innovative phenomena (Larsen et al., 2014). The behavior of the dynamics of innovation and the workings of feedback was framed in terms of causality. Unlike static linear diagrams that assume constant relationships between variables, dynamic causal loops consider the interplay of multiple factors over time, allowing for a more realistic representation of reality.

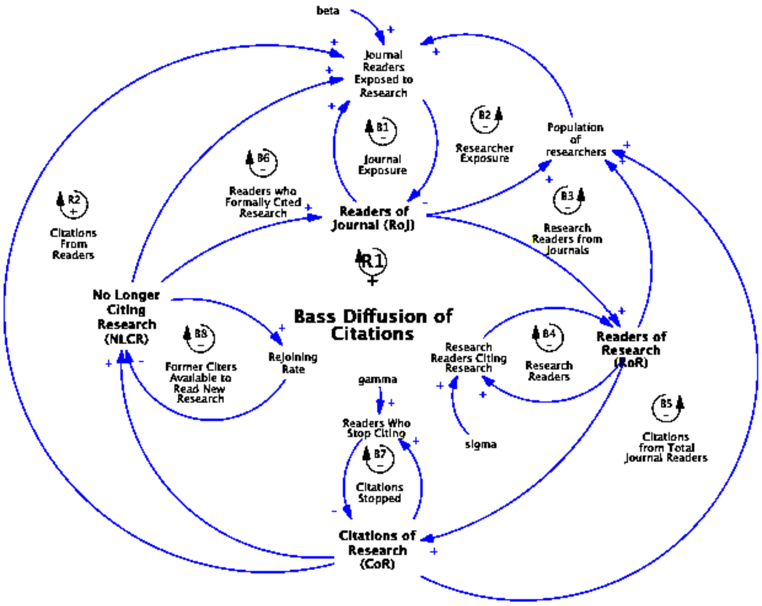


Fig. (4). Causal loop Diagram of Citation Generation from Research: Identifies the interactions of the variables, identifies the balancing and reinforcing loops, and captures the theory of how citations are generated from research.

2.5 *Bayes Causal Inference in Systems Dynamics:*

The causal loop diagram in Fig. (4). was used for Bayesian causal inference analysis to model and simulate the factors, change in purpose, structure, and behavior as the cause of innovation. Other factors like motivation, expertise, and mental capacity were not included but they will be incorporated in later studies. The Bayes conditional probabilistic model was used to determine the reverse probability of innovation given citation from the forward probability of citations given innovation, the probability easily calculated from observational data (Berrar, 2018). This gives more accurate predictions of future outcomes based on the data of citations over time (Rouder

& Morey, 2019). The Bayes Theorem for inferring innovation is shown in Equation (8):

$$\mathrm{P}(\text{Innovation}|\text{Citations}) = \frac{\mathrm{p}(\text{Citations}|\text{Innovation}) \times \mathrm{p}(\text{Innovation})}{\mathrm{p}(\text{Citations})} \tag{8}$$

The equation calculates the probability of innovation given the probability of Citations equal to the probability of citations given the probability of innovation multiplied by the probability of innovation divided by the probability of citations. The denominator, p(Citations) is the total sum of all the probabilities of being cited that can happen. The probability of citations happening given the probability of Innovation is known from observational data. This was calculated from time series data gathered using bibliometric analysis from Web of Science of Nobel Prize research citations and is expressed as the odds ratio in Equation (7). Probability mass functions (PMF) were built for citation and publication values that occur over time. In the Bayesian rule formula, these PMFs were summed and used as cumulative distribution functions (CDF) (Rouder & Morey, 2019). It should be noted that the probability associated with the CDFs has a distribution in which specific amounts of error exist. The error bars associated with the CDF were not included in this study, but they will be in a later paper.

3. Dynamic Models

The use of conditional probabilities, in the dynamic models in this paper, was employed for simulation. A dynamic Bayesian model was constructed to simulate the citation response of researchers adopting innovations (Friston et al., 2022). The Bayes probability was then used in a dynamic model of generating citations from innovations. The model starts by considering various factors that influence citation rates, such as the paper's field of study, the number of researchers that could adopt the research, and the novelty of the research in the field. These variables are then assigned initial probabilities based on historical citation data. The model can dynamically update these probabilities as time progresses, and new citations are received. This allows the model to adapt to changes in the research landscape and the paper's perceived relevance. For instance, the model can adjust the probabilities if a paper receives citations faster than expected.

Conversely, if a research paper's citation rate slows, the model accounts for this by continuously updating the response to new data. Thew dynamic model of probability provides a more accurate and nuanced simulation of a research paper's citation response. The dynamic model representing citation generation and Bayesian dynamics is shown in Fig. (5). The model predicts a citation population of 35200 compared to the population from data of 35223. This gives a confidence of 99.9% to representing the citing population. The dynamic Bayesian Conditional Probability model is shown in Fig. (6).

A "Susceptible, Exposed, Infectious, Removed" (SEIR) model, initially developed for studying infectious disease dynamics, was adapted for understanding information diffusion in research social networks and communities (Annas et al., 2020). In this context, the SEIR model was used to simulate the spread of information through various stages: susceptible individuals (S) who have not yet been exposed to the information, exposed individuals (E) who are aware of the information but have not fully adopted it, infected individuals (I) who have embraced the information and actively share it, and recovered individuals (R) who have already passed on the information to others or lost interest in it. By assigning appropriate parameters to each stage, such as the transmission rate of information, the incubation period for adoption of information, and the rate of recovery from the information, this model simulated and predicted information propagation within a relevant population. In epidemiology, the primary reproduction number, often denoted as R^0 and pronounced "R naught," is a metric to describe the contagiousness of an infectious disease within a population. It represents the average number of people that one infected individual is expected to transmit the disease to in a completely susceptible population. The value of R^0 is dimensionless, providing insights into the potential spread of an infection and the intensity of interventions required to control it. For the research described in this paper, the reproduction number equivalent to R^0 is the Innovation Potential number or ($IP^{0)}$. The IP^0 is calculated from researchers adopting innovative research divided by researchers abandoning innovative research. An IP^0 value greater than 1 indicates that each researcher will, on average, pass the knowledge to more than one other person while publishing their research, suggesting that the innovation will likely spread through the relevant research population.

Conversely, an IP^0 less than 1 implies that the research will transmit to fewer people than the number of current adaptors of the knowledge, leading to a decline in publications and potentially the eventual disappearance of the research knowledge from the relevant population. When IP^0 equals 1, it signifies a stable state where each researcher cites and publishes the innovation to researchers in the relevant community, maintaining a steady number of individuals citing the innovation over time.

A system of Ordinary Differential Equations (ODE) models the application of new knowledge and time into an innovation metric (Hassan et al., 2015). This mathematical model is used to understand the spread of information in a population. The model divides the population into four categories: readers of scientific journals (RoJ), Readers of Specific Research (RoR), Citer of Specific Research (CoR), and No Longer Citers of Research (NLCoR).

The researchers adopting innovations (RoJ), read and subscribe to a particular journal. Researchers exposed to adopting (RoR), are individuals exposed to a particular science or technology research paper of interest. Researchers who adopt innovation (CoR), use the knowledge to build upon their research initiatives and cite the innovation. Researchers in the community of interest (NLCoR), are individuals who no longer cite the research and have found more relevant research to use or cite. An innovation adoption model was developed with these variables. The model, shown in Fig. (5), is represented by this system of ODEs:

$$d(RoJ)/dt = -\beta *(RoJ)*(CoR) \tag{9}$$

$$d(RoR)/dt = \beta *(RoJ)*(CoR)- \sigma *(RoR) \tag{10}$$

$$d(CoR)/dt = \sigma *(RoR)- \gamma *(NLCR) \tag{11}$$

$$d(NLCR)/dt = \gamma * (NLCR) \tag{12}$$

The model assumes that the population is homogeneous and that the rate at which individuals move between the different categories is proportional to the number of individuals in each category. The Bayesian conditional model using odds ratios, shown in Fig. (6), simulates the odds of being cited from past citation patterns. This allowed predictions of the future spread of knowledge and estimates of whether information from published research papers is being adopted or discarded.

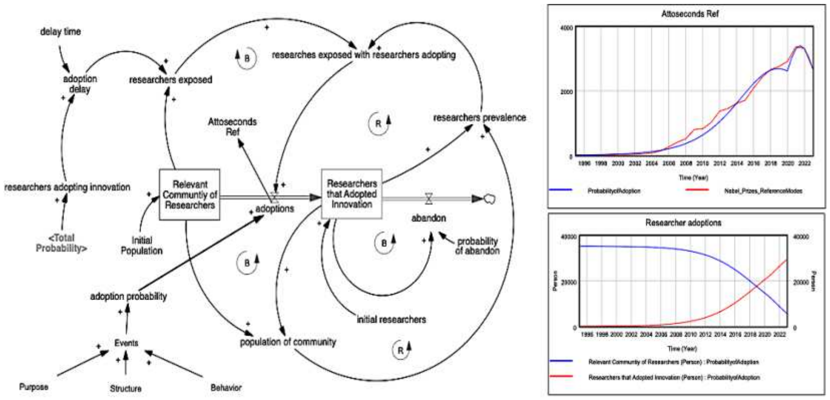


Fig. (5). Dynamic Model of Generating Citations from percentage change in Purpose, Structure and Behavior.

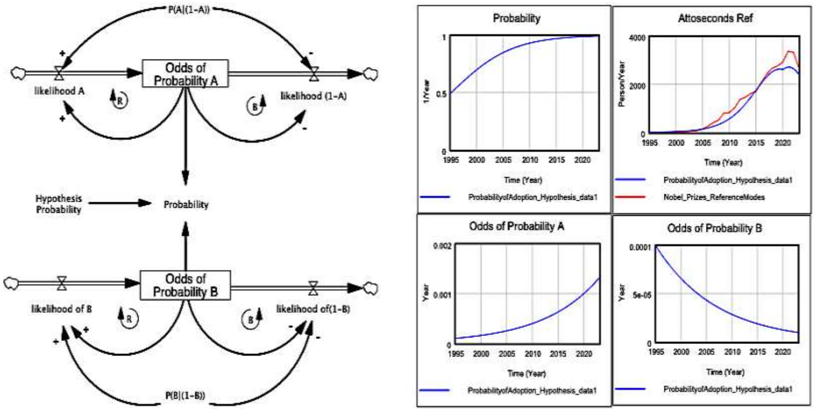


Fig. (6). Dynamic Model of Bayes Conditional Probability

4. Data Analysis

Analysis of citation patterns of past innovations to gain a systemic archetype understanding of the citation rates of innovative science and technology research was performed (Bünemann & Seifert, 2024). The patterns of citations for Nobel Prize researchers were used in the dynamical systems models. The model was used to give probabilistic predictions of the effect of changes in Purpose, Structure, and Events on present and future possible innovative scientific research efforts. The model shows the measure of the diffusion of knowledge as a measure of citation rate changes and the assimilation of that knowledge over time while quantifying the uncertainty in innovation. The Logistic function archetype is a common systems behavior archetype where the population, represented by a stock, of a resource grows exponentially until it equals the system's carrying capacity. This archetype was modeled and used for data characterization due to its universal acceptance of simulating growth. This archetype is characterized by an initial period of exponential growth, followed by a period of slow change, eventually leveling out, where the stock or population equals the environment's carrying capacity. This can be seen in Fig. (7).

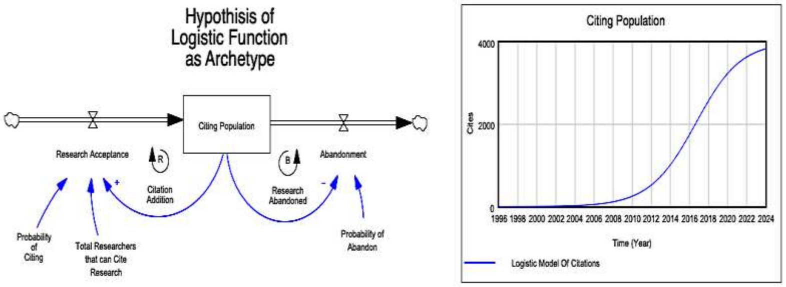


Fig. (7). Logistic Function model only used for Systems Thinking architype of data and graphs of Citations.

This simulation models the spread of knowledge as a correlation of citations within a relevant population of researchers in a specific field over time (Mazloumian et al., 2011). Observational data correlated with this model is shown in Fig. (8), which is the total population citations of the Nobel Prize in Physics research awarded to three physicists: Pierre Agostini at Ohio State University in Columbus, Ferenc Krausz at the Max Planck Institute of Quantum Optics in Garching, Germany, and Anne L'Huillier at Lund University, Sweden, for their research into attosecond pulses of light (Dombi & Schultze, 2023) (Paul et al., 2001) (Krausz & Ivanov, 2009).

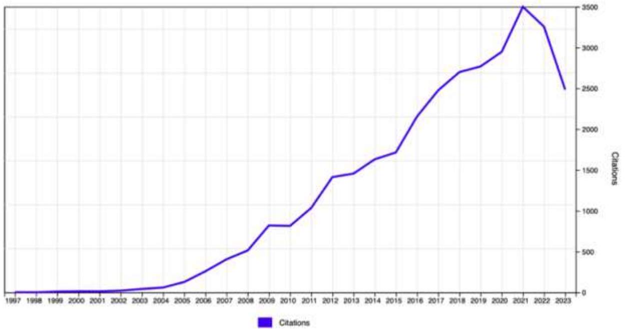


Fig. (8). Graph of Citations over time for Nobel Prize in Physics for Attosecond Laser Pulsers.

Similar patterns of citations, after Nobel Prizes were given in Chemistry 2023 and Physics 2022 are shown in Fig. (9). and

Fig. (10). (Wegner & Resch-Genger, 2024)("Nobel Prize in Physics Awarded to Arthur Ashkin, Gérard Mourou, and Donna Strickland for Laser Physics Techniques (Optical Tweezers and Chirp Pulse Amplification)," 2018).

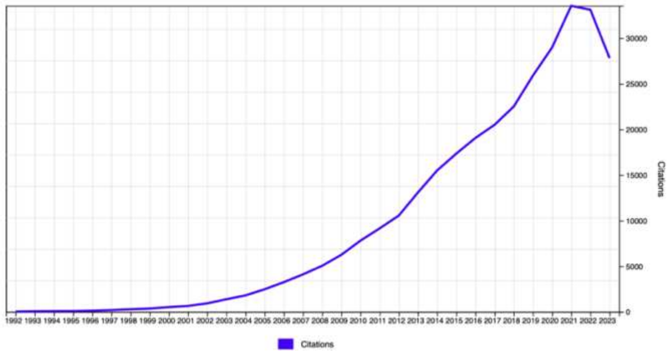


Fig. (9). Nobel Prize in Chemistry for quantum dots, nanoscale crystals that interact with light in unusual ways.

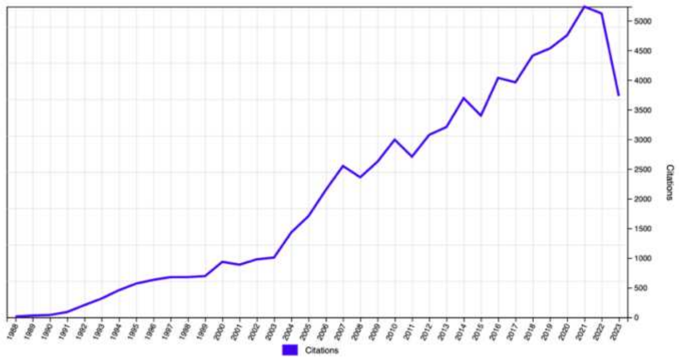


Fig. (10). Citations of Nobel Prize in Physics for in Chirped Pulse Amplification of Ultra Short Pulse Laser systems.

5. Results

Causation of Innovation as inferred from Citation Patterns:

Initial investigations were carried out using Causal Impact analysis of Nobel prize research publications on the population of research publications in their respective field (Nogueira et al., 2022).

The CausalImpact package in R Studio is a powerful tool for conducting observational studies on time series data, mainly when randomized experiments are not feasible. It employs Bayesian structural time-series models to estimate the causal effect of an intervention on a time series. For instance, it can assess the impact of a marketing campaign on daily clicks or sales (Yao et al., 2021). The package constructs a counterfactual prediction of what would have happened without the intervention, allowing for a comparison with the actual outcome. This is achieved using a control time series not influenced by the intervention to model the expected evolution of the response metric. The influence on relevant population citations was analyzed for Nobel prize winner Dr. Anton Zeilinger (Bouwmeester et al., 1997). His Nobel prize was for “experiments with entangled photons, establishing the violation of Bell inequalities and pioneering quantum information science.” His Nobel prize research paper is titled “Experimental quantum teleportation.” From 1997 to 2023, this paper received 4177 citations as referenced from Web of Science data. The impact of this research, measured by citation patterns in Entanglement Physics, was performed using R Studio’s CausalImpact statistical analysis tool and is shown below in Fig (11).

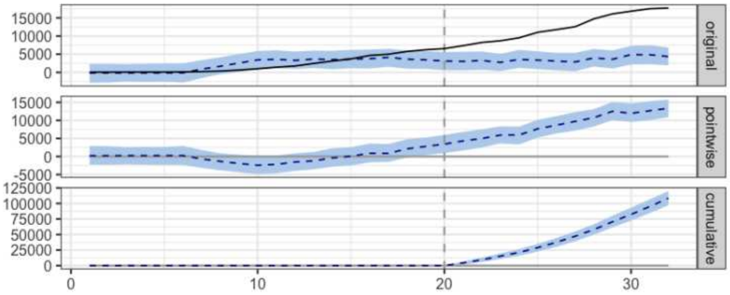


Fig. (11). Causal Impact analysis of Nobel Prize research in entangled photons on population of researchers publishing entangled photon research.

The three graphs in Fig. (11). visually represent the process of inferring the causal impact of the research paper “Experimental quantum teleportation” through counterfactual predictions in citations in entanglement Physics. The top graph is the simulated trajectory showing treated and untreated citation patterns with counterfactual predictions. The dashed line shows what would have happened if the Nobel Prize research paper had not been published, and the solid line shows what happened after the Nobel Prize research was published. The middle graph, pointwise, shows the inferred causal impact, illustrating the difference between observed data and counterfactual predictions. The bottom graph, the cumulative impact plot, demonstrates the summed effect of the Nobel prize research over time. Additional elements of shaded areas are for uncertainty, and vertical bars are for when specific events occur. The results of the causal impact analysis is shown in Table (2):

With Posterior tail-area probability p: 0.00103 and Posterior prob. of a causal effect: 99.89723%. The causal impact analysis shows that Nobel Prize research influences research within its field.

Due to the probabilistic significance of Nobel prize research on a relevant community of researchers' adoption of information, a dynamic model was developed using Vensim modeling software to show the effect of the change in the structure of elements, purpose, and behavior of previous innovative research on generating new innovations. The first step was to match Nobel prize research as a model validation reference for the dynamic model to serve as a benchmark for accuracy, ensuring the model's output aligns with established data patterns and behaviors, essential for validating the model's predictive capabilities and reliability. This is shown in Fig (12).

The reference, shown as the blue curve, is the citation

Table (2). Shows statistical analysis from the CausalImpact simulation of the effect of Nobel prize research on a relevant populations citation rate.

Posterior Inference Results {CausalImpact}		
	Average	Cumulative
Actual	12672	152061
Prediction (s.d.)	3635 (495)	43624 (5940)
95% CI	[2687, 4644]	[32250, 55724]
Absolute effect (s.d.)	9036 (495)	108437 (5940)
95% CI	[8028, 9984]	[96337, 119811]
Relative effect (s.d.)	254% (52%)	254% (52%)
95% CI	[173%, 372%]	[173%, 372%]

pattern of “Experimental quantum teleportation” by Anton Zeilinger, Nobel prize winner, et al. A correlation value of 0.9917 was obtained between reference data and model predictions.

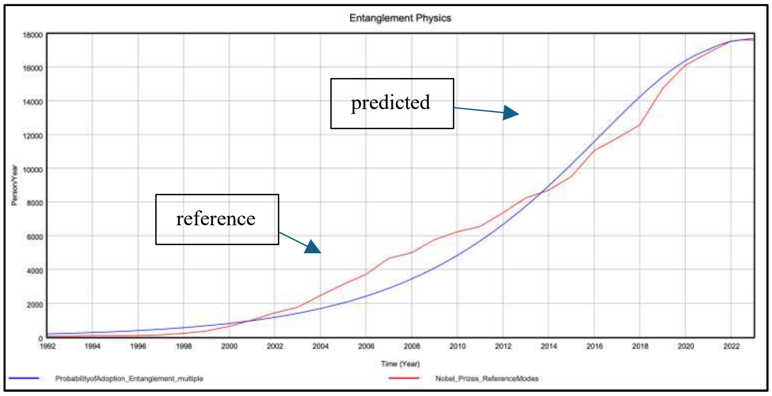


Fig. (12). This graph shows the Dynamic Model reference simulation of Citations in Entanglement Physics to validate to correct predictions of the dynamic model. Settings for the model are Hypothesis Probability 60% of being Cited with no changes in Purpose, Structure, or Behavior. This shows the model can simulate citation patterns.

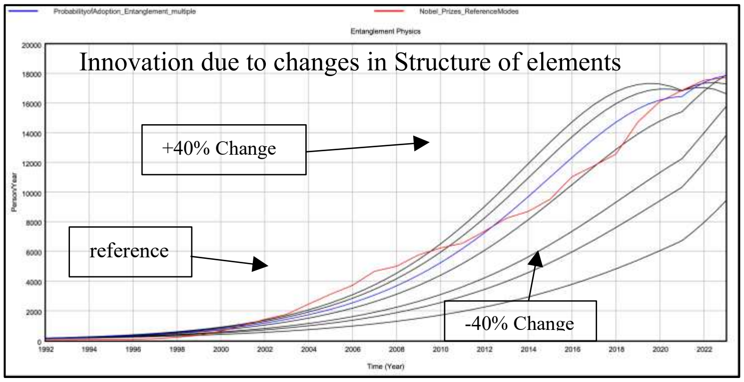


Fig. (13). This graph shows the Dynamic Model with reference in red, Hypothesis probability 60% of being cited with changes in Structure varying from +40% to -40%, and no change in Purpose or Behavior.

Fig. (13). shows the predicted citation patterns for a 40 percent positive change in the structure of the elements of the innovation in entanglement physics and the citation pattern with a 40 percent negative change, i.e., approaching no change in the innovation of entanglement physics. Fig. (14). shows multiple curves for changes in 40 percent changes in Structure and Behavior, both positive, i.e., more change, and negative, less change. Fig. (15). shows what Nobel research citation patterns would be over time with a 40 percent change in Structure, Purpose, and Behavior. The model predicts that if there were a positive change in Structure, Purpose, and Behavior of 40 percent, the peak of adoption of the innovation would occur eight and a half years earlier with 5777 more researchers adopting the innovation.

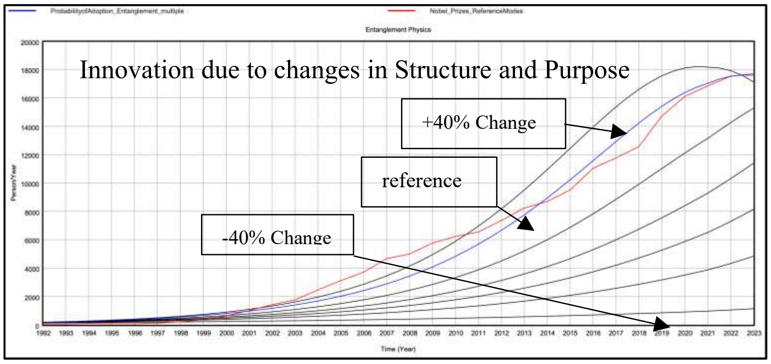


Fig. (14). This graph shows the Dynamic Model with reference in red, Hypothesis probability 60% of being cited with changes in Structure and Purpose varying from +40% to -40%, and no change in Behavior.

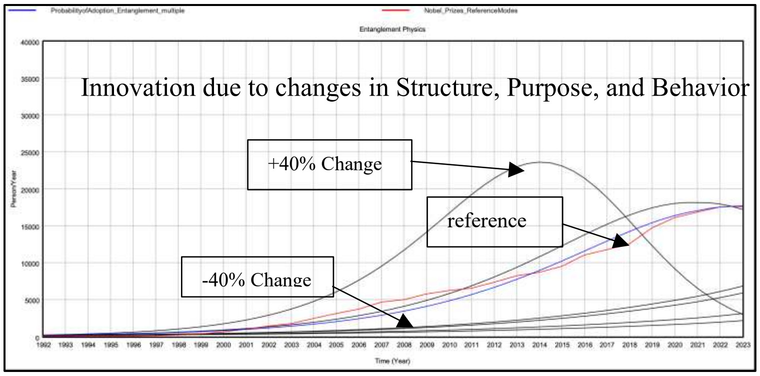


Fig. (15). This graph shows the Dynamic Model with reference in red, Hypothesis probability 60% of being cited with changes in Structure, Purpose, and Behavior varying from +40% to -40%.

5.1 *Sensitivity analysis:*

Vensim's sensitivity graph allows the understanding of the variability in the system dynamics models. By running multiple simulations with varied parameters, Vensim displays the results in a sensitivity graph that shows confidence bounds or multiple traces for a given variable. This was useful for identifying possible outcomes and understanding how different assumptions impacted the model's predictions. The percentile bands in the sensitivity graph represent the distribution of outcomes at each point in time, providing a visual representation of uncertainty. The 95% confidence band, shown in blue, 75% confidence band, shown in green, and 50% confidence band, shown in yellow, indicate the model's confidence for citation pattern influenced by Nobel prize research. Researchers' changing structure, purpose, and behavior in entanglement physics leads to new innovations. As indicated by Fig. (16). 75% of the simulation runs resulted in a value within that band.

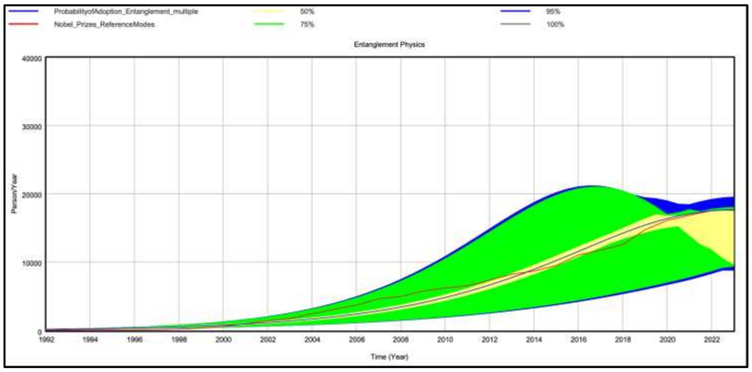


Fig. (16). This graph shows the Sensitivity analysis of the Dynamic Model with reference in red, Hypothesis probability 60% of being cited with changes in Structure, Purpose, and Behavior varying from +40% to -40%.

Confidence Bands Interpretation: Light Green (25%) to Dark Blue (100%) Intervals: represent uncertainty in publication predictions. The spread widens over time, particularly after 2016, indicating increasing uncertainty in forecasting research outputs due to the plateau and subsequent drop. The core model line (red) stays mostly within the 50–75% range, showing good fit until the recent years where actual publications may be diverging more strongly from previous trends. Vensim's Sensitivity2All feature was used to identify the most sensitive constants within the model. It is shown in

Fig (17) where the Hypothesis Probability, Purpose, Structure, and Behavior variables are shown to be the most sensitive parameters in the model.

Fig. (17). This graph shows the Sensitivity analysis of the variables in the Dynamic Model. Top four variables generate the most change in the model.

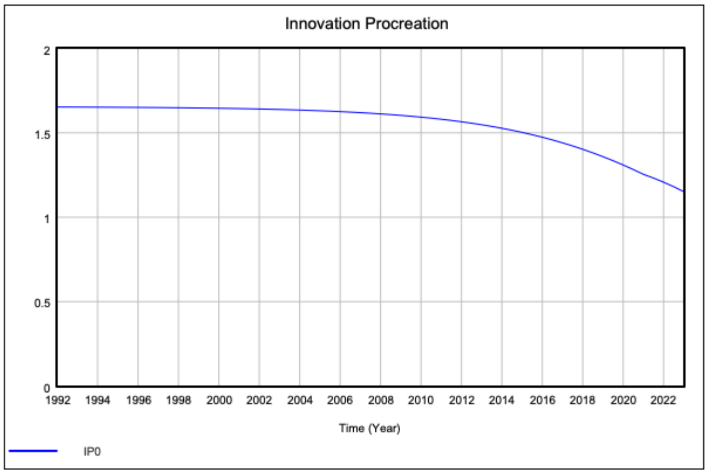


Fig. (18). This graph shows the concept of Innovation Procreation number for Nobel prize research in entanglement physics. It is analogous to the reproduction number R0 in epidemiology.

5.2 *Naval Applications*:

Naval radar research is ideal for learning how citation patterns reflect innovation and for calculation of IP^0. The Naval radar research area was examined due to its documented high-impact technology. It is technically rich and historically grounded. Analyzing this community's citation history can help the Naval RDT&E understand how ideas grow into future capabilities. A dataset of published radar research with citations tracked annually from 1900 to 2024 was used. The core metric of interest was citation activity over time for each paper. Total citations and average citations per year highlighted the most influential work. Fig. (19) shows that many papers begin gaining citations in large numbers during the 2000s and 2010s. Some citation lines rise rapidly, peaking between 2010 and 2020. This could reflect periods of intensified research. Each faint line on the graph represents a single paper, tracking how often that paper was cited in academic and technical literature each year.

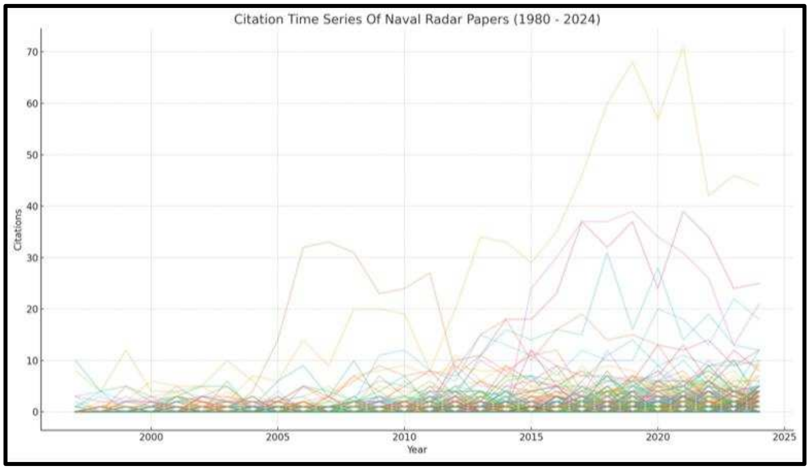


Fig. (19). Shows yearly citation activity for each individual research paper related to Naval Radar technologies, based on data collected from 1980 through 2024.

Fig. (20). Shows Annual Citation Totals for naval radar research from 1997 to 2024**.**

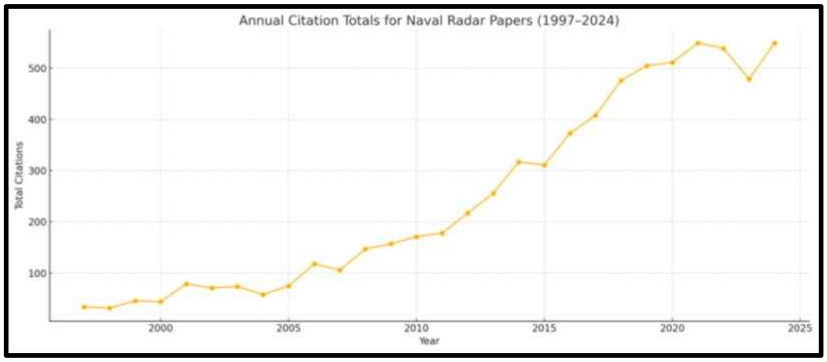
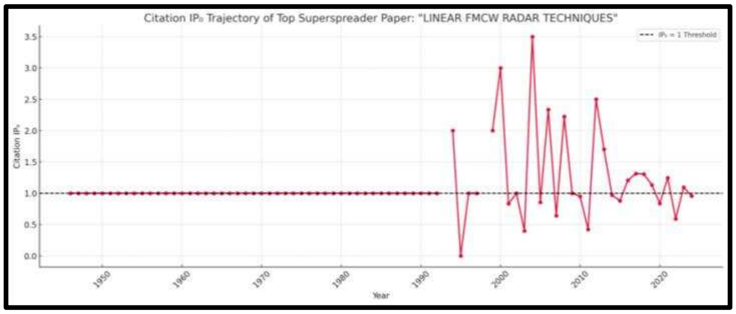


Fig. (20) shows how often naval radar research papers were cited each year, from 1997 to 2024. Each point on the line represents the total number of citations received by all papers in that year. It reveals how interest and influence in the field have changed over time. Fig. (21) Shows the Citation Impact Propagation Index (IP_0) which is analogous to the epidemiological concept Reproduction Number (R_0). The IP_0 is used for predicting innovation influence. It represents how one research paper influences the generation of future research, the rate at which a paper's ideas spread in a relevant research community.

Fig. (21). Shows how many *new citations* are generated by previous citations



During the first sustained spike above $IP_0 = 1$, the research shows an innovative moment. When IP_0 first rises significantly above 1, it marks the start of influencing citation behavior through adoption. This spike puts the paper on the radar of other researchers. It also indicates that successive citation behavior, where citing authors amplify awareness will begin. The effect is compounded if multiple high-IP_0 years follow.

6. Discussion and Conclusions

This paper has shown an innovation life cycle and evolution paradigm by observing recent trends in research citation and publication data. A new method for predicting innovation, a dynamic model, for predicting innovations using patterns of citations that indicate innovative research programs. The IP^0 metric was developed and is directly affected by changes in innovation structure, purpose, and or behavior. Dynamic models were created to simulate how changes in purpose, structure, or behavior affects citation rates.

Table (3) shows the subjective interpretation of different citation and publication analysis methods. It compares the different metrics and highlights how each metric varies in the depth and completeness of the qualitative information it provides, from simple counts to more nuanced measures of impact and innovation.

Dynamic time series model-based innovation analysis was proposed and researched in this paper. The dynamic model showed how altering the purpose, structure, and behavior alters the event or outcome, as defined by the Purpose Systems Principle, of how past innovations can lead to new research and possible new innovations. Changes in the purpose, structure, or behavior of existing research can open pathways to new applications, improved efficiencies, and functionalities that were not envisioned in earlier innovations. Such changes stimulate creative thinking and push the boundaries of what is possible, expanding the frontiers of knowledge. Building on this concept, the dynamic systems model developed in this paper offers a new metric for identifying innovative science and technology research using citation data. Because the rate of knowledge generation is critical to both economic growth and military power, it is essential to use methods that account for the time-dependent nature of innovation. This is something current approaches fail to capture. Fig. (18). shows the innovation potential for Nobel prize research in the field of entanglement physics.

Table (3). Show different metrics used for qualitative analysis of impact and productivity of innovative research. An IP0 value greater than 1 indicates that researcher will pass to more than one other person suggesting that the innovation will likely spread through the relevant research population.

Citation involved Innovation Metrics:	Accounts for short-term and long-term impacts	Indicates impact or influence	Leads to actionable insights	Counts number of publications and total citation	Factors Dynamic Complexity
Citation Count[3]	☑	☑		☑	
h-Index[4]		☑			
i10-Index[5]			☑		
Field-Weighted Citation Impact (FWCI)[6]		☑	☑	☑	
Citations Per Publication (CPP)[7]	☑	☑	☑	☑	
Highly Cited Papers[8]		☑		☑	
Number of Publications[9]				☑	
Disruption Index[10]	☑	☑	☑	☑	
New Systems Thinking Innovation Metric IP^0	☑	☑	☑	☑	☑

It is well above 1 for nine years, meaning the innovation is consistently being adopted, but it starts to decline after the year 2008, meaning the Nobel prize research is adoptable as new knowledge. It is still above 1 in the year 2023.

The United States Navy faces a paradox in its science and technology (S&T) sector, characterized by both remarkable advancements and concerning trends from advisories that threaten to outpace US innovation. The governance of RDT&E investment is crucial for sustaining long-term economic growth and military power, necessitating a shift from profit-maximizing strategies. Rapid advances in technology are often mistaken for

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continuous breakthroughs, overshadowing the lengthy early phases of innovation that will impact military power in the future. A unique constraint in modeling Naval innovation is the impact of security classification on bibliometric data. As a technology matures from a 'scientific concept' to a 'naval application' (e.g., advanced radar signal processing), it often transitions from open-access journals to Controlled Unclassified Information (CUI) or classified status.

The power of the dynamic models described for this paper are the ability to deduce the cause, a change in structure, purpose, and behavior, from the effect, increased citations, to give the probability of innovation for Naval application. In scientific discovery and engineering, the alteration of an element's structure, the redefinition of its purpose, and the modification of its behavior are fundamental processes that drive innovation. Although the laws of physics explain much of the world around us, we still do not have a realistic description of causality in a truly complex hierarchical structure (Ellis, 2005). This paper attempts to do so using Systems Dynamics, Systems Principles, and Systems Thinking. Naval engineering has evolved through cycles of bold experimentation and slow refinement. The transition from sail to steam, the development of nuclear propulsion, the rise of naval aviation, and the integration of networked systems followed unique innovation paths. Lessons from this history show that innovation depends on structure, feedback, and timing. The dynamic models created for this paper may allow these factors to be tested virtually.

This study presented a System Dynamics framework to model the diffusion of foundational knowledge within the Naval innovation ecosystem. By utilizing Nobel Prize-winning research as a validated proxy for high-impact discovery, we have demonstrated how technical "shocks" permeate scientific populations.

The findings in this study suggest that the innovation pipeline begins with the creation of knowledge that is tracked through the maturation of citations. It was noted that the ultimate success of an innovation for Naval applications is dependent on its transition across organizational and security boundaries.

Citations serve as a critical validation signal that reduces perceived risk for investment decisions. They must be understood as a lagging indicator of scientific maturity rather than a leading indicator of fleet integration. By quantifying knowledge diffusion, this model could provide Naval leadership with a baseline for understanding how foundational breakthroughs eventually populate the beginning of the pipeline and provide the technical certainty required to bridge the

"Valley of Death" and deliver decisive capabilities to the warfighter.

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Data availability statement:

Data sharing does not apply to this article, but quantitative datasets were generated and analyzed from the World of Science, Nobel Prize.org, B

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