Towards a Sustainable Disruptive Growth Model: Integrating Foresight, Wild Cards and Weak Signals Analysis

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Abstract

The paper introduces epistemological and methodological innovations for analyzing non-linear dynamics in sustainability systems, such as deforestation tipping points, exponential renewable adoption, and protests driving global reform. It focuses on adaptive resilience (e.g. decentralized grids stabilizing renewables) and topological models (e.g. network analysis of deforestation or policy diffusion). The study develops metrics to assess four dimensions of evolutionary change – context, people, process, and impact – supporting adaptive resilience and stability. In environmental systems, this may involve tracking early deforestation signals before tipping points, while in economics, it could mean analyzing how small policy shifts trigger market changes. It highlights Wild Cards and Weak Signals Analysis within the Sustainable Disruptive Growth Model (SD-Growth Model), enabling early detection of disruptions – such as AI breakthroughs or geopolitical shifts – so systems can anticipate, reorganize, and adapt effectively to shocks.

The research emphasizes constraints as key to resilience and stability amid disruptions. It integrates advanced analytical approaches to monitor and manage simultaneous information flows, ensuring efficient responses to shocks. The model also explores AI, machine learning, and explainable AI (XAI) in labor market dynamics, where predictive algorithms can identify trends and mitigate systemic risks. By combining quantitative metrics with strategic foresight, the framework equips decision-makers to preserve stability, sustain functionality, and adapt dynamically to change.

Keywords: research methods; forward planning; strategic planning; creative thinking; dimension reduction; horizontal scanning; foresight methods; disruptive dynamic; resilience.

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Introduction

The EEA-Eionet Strategy 2021–2030 highlights the growing role of foresight in the European Environment Agency's (EEA) work[1]. To address this, the Sustainable Disruptive Growth Model (SD-Growth Model) integrates foresight tools, Wild Cards, and Weak Signals Analysis to strengthen sustainability strategies. The model maintains four interdependent subsystems – context, people, process, and impact – to balance sustainable and disruptive growth. It examines disruptive dynamics from two key perspectives: (1) how equilibrium boundaries shift between stability and disruption, influencing system performance and triggering morphological changes (e.g. climate policies accelerating renewable adoption); and (2) the compatibility of metrics, which determines a system's adaptability and transformation (e.g. AI-driven early warning systems for deforestation). By integrating Wild Cards and Weak Signals Analysis, the model anticipates emerging disruptions and addresses deep uncertainties in sustainable systems, enabling more resilient and adaptive decision-making.

Uncertainty in modeling is central to the SD-Growth Model. Der Kiureghian and Ditlevsen (2009) classify uncertainties as epistemic (reducible through improved data or refined models) and random (irreducible). Accurately modeling epistemic uncertainty is crucial, as it can create dependencies among random events, impacting risk assessments (e.g., climate models predicting wildfire intensity). To address this, the model emphasizes Explainable Artificial Intelligence (XAI), ensuring that AI-driven systems remain transparent, interpretable, and trustworthy (e.g., XAI-based forecasts for labor market shifts). By bridging gaps in uncertainty, XAI strengthens reliability, adaptability, and informed decision-making within sustainability strategies.

Building on this, Marchau et al. (2019) describe deep uncertainty as arising when experts lack consensus on models, probability distributions, or desired outcomes (e.g., predicting economic recovery after financial crises). This concept aligns with the comparison of ecological and economic resilience, emphasizing phased recovery mechanisms to navigate uncertain scenarios (Bang et al., 2021). Osband (2023) categorizes indeterminacy across domains: randomness in mathematics, objective risk in economics, and aleatory uncertainty in machine learning (e.g. AI predicting market volatility). His assertion that "the variance of beliefs" reflects the value of new information underscores the SD-Growth Model's emphasis on adaptive management and informed decision-making.

The SD-Growth Model introduces three management frameworks – regular, disruptive, and boundary – linked to four archetypal topological modes: transient, capture, deep transient, and deep capture. These modes illuminate evolutionary phases and stability patterns in sustainable systems, offering insights into adaptive topological resilience. By incorporating stratified axes, the model extends the notions of parallelism, transversality, and concentration, enabling precise measurement of morphological changes and risk areas. These mechanisms facilitate development through foresight-driven scenarios, robust trajectories, and equilibrium boundary detection (Yang et al., 2020).

The SD-Growth Model introduces three management frameworks – *regular*, *disruptive*, and *boundary* – linked to four archetypal topological modes:

- Transient (e.g., short-term policy shifts impacting emissions)
- Capture (e.g., market dominance by a single renewable technology)
- Deep transient (e.g., temporary but severe economic recessions)
- Deep capture (e.g., long-term monopolization of AI infrastructure)

These modes reveal evolutionary phases and stability patterns in sustainable systems, offering insights into adaptive topological resilience. By incorporating stratified axes (e.g. layered socio-economic and environmental data), the model refines parallelism (e.g. simultaneous growth of multiple green industries), transversality (e.g. cross-sector policy interactions), and concentration (e.g. regional clustering of climate adaptation efforts). These mechanisms enhance foresight-driven scenario modeling, enabling robust trajectories and equilibrium boundary detection (Yang et al., 2020).

A comparative analysis of Evolutionary vs. Stable Models highlights the role of theories in understanding complex systems. Karl Popper's "Myth of the Framework" argues that theories help avoid biases and misconceptions, providing a foundation for objective analysis (Popper, 1994). His view on entropy and order – "randomness reflects our lack of knowledge of the prevailing order" – aligns with the SD-Growth Model's approach to managing uncertainty (Popper, 1992). This theoretical grounding strengthens the model's ability to address epistemic (e.g., data gaps in climate projections) and aleatory (e.g., unpredictable market fluctuations) uncertainties, making it a key tool for navigating disruptive dynamics.

The SD-Growth Model is applied through Horizon Scanning and Foresight, identifying emerging technologies and disruptive innovations that drive socio-technical transitions toward sustainability (Popper, 2023). These processes distinguish emerging futures by analyzing contextual drivers of change, enabling adaptive and resilient transformations. For example, Horizon Scanning tracks AI's role in green energy, reinforcing the value of strategic foresight in shaping sustainable futures.

[1] https://eea.europa.eu/en/about/who-we-are/eea-eionet-strategy, accessed 06.12.2024.

The model examines regular and disruptive dynamics using topological resilience to study adaptation and recovery in cyber-physical systems (Yang et al., 2020). It highlights:

- Clusters around behavioral trajectories (e.g., consumer shifts toward electric vehicles)
- Equilibrium boundaries (e.g., carbon pricing thresholds impacting emissions)
- Parallelism (e.g., simultaneous decarbonization of energy and transport sectors)

These insights refine the understanding of topological modes, improving risk detection and management. By linking adaptive topological resilience to real-world challenges, the model enhances sustainability strategies while maintaining systemic balance.

The Four-Dimensional Framework – covering Context, People, Process, and Impact – supports adaptive decision-making and aligns with sustainability, resilience, and foresight goals (Popper et al., 2017). By integrating theories, methodologies, and case studies, the SD-Growth Model provides a robust foundation for managing the complexities of sustainable disruptive growth. Wild Cards and Weak Signals help reveal actionable insights under deep uncertainty, while a multi-dimensional approach fosters cross-sectoral collaboration, essential for tackling interconnected modern challenges.

Overall, the SD-Growth Model strengthens our capacity to navigate uncertainty, promoting resilience and adaptability in the face of disruptive changes. Through foresight tools, theoretical grounding, and practical applications, it offers a comprehensive pathway toward sustainable development – demonstrating how resilience thinking, strategic foresight, and advanced modeling can pave the way for a more sustainable and adaptive future.

Strategic Foresight for Sustainable Innovation

The foresight process integrates reflection, networking, consultation, and discussion to refine visions and co-create strategies (Georghiou et al., 2008). Following the SMART Foresight Framework (Popper, 2011, 2012; Miles, 2013), its five phases – Scoping, Mobilizing, Anticipating, Recommending, and Transforming – help stakeholders navigate uncertainty and align efforts toward sustainable outcomes.

During Action Roadmapping Management, multi-criteria analysis evaluates practices, outcomes, and participants, ensuring strategies are sustainability-oriented. The four dimensions of the framework – Context, People, Process, and Impact – bridge the gap between visioning and actionable plans (Carayannis, Campbell, 2009, 2010; Martin, 2012; Miles et al., 2016; Martini et al., 2020).

The methodology merges the Foresight Diamond (Popper, 2008), topological approaches (e.g. differential systems, local stability), statistical methods (e.g. multivariate factor analysis), and sustainability metrics (e.g., ecological health, human vitality). These tools identify critical issues, including opportunities, risks, and pathways toward sustainable development.

By integrating Comparative Evolutionary Models with global case studies, the foresight process demonstrates its practical value in diverse contexts. This blend of analytical depth and real-world application equips stakeholders to handle uncertainty, boost resilience, and drive sustainable innovation.

Comparative Evolutionary Models

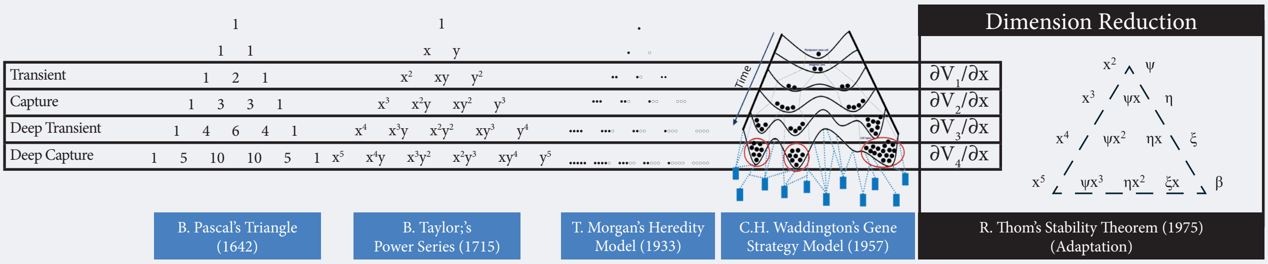
Researchers across disciplines have developed evolutionary models to understand dynamic systems. Notable examples include:

- Pascal's Triangle Model (1642): arranges binomial coefficients to illustrate combinatorial symmetry (e.g., predicting election turnout patterns)
- Taylor's Power Series (1715): uses polynomial approximations for system dynamics (e.g., tracking pandemic spread rates) (Bilodeau et al., 2010)
- Morgan's Heredity Model (1935): reveals chromosomes' roles in inheritance (e.g., tracing disease transmission pathways)
- Waddington's Epigenetic Landscape (1957): shows how environmental interactions shape evolutionary outcomes (e.g., mapping cultural shifts across generations)
- Thom's Catastrophe Theory (1975): focuses on dimension reduction to identify equilibrium zones (e.g., foreseeing economic crash thresholds) (Bilodeau et al., 2010)

These evolutionary models each rely on binary interactions – for instance, Pascal's Triangle with combinatorial pairs (1, 1), Taylor's Series with (x, y), or Morgan's inheritance model using white/black markers (○,●). Figure 1 presents five models, culminating in an extended version of Thom's approach, which introduces a triangular interaction zone (risk or threshold zone) showing how four parametric factors interconnect. The rows represent rates of change in the original catastrophe models, while co-diagonal separations illustrate dimension reduction via principal components. On the diagonal, independent momentum axes emerge along principal directions – shedding light on risk, equilibrium, and stability zones in line with Osband's (2023) indeterminacy framework. This comparative view helps to grasp system dynamics and key transitions across different evolutionary models. They reveal three primary dynamics:

- Horizontal Dynamics: competitiveness and system interactions
- Vertical Dynamics: growth-oriented, focusing on systemic development
- Central Dynamics: interplay of competition, harmony, risk, and stability (Waddington, 1957; Thom, 1975)

Figure 1. **Evolutionary vs Stable Models with Disruptive Dynamics**



Source: authors.

By integrating these perspectives, the SD-Growth Model links theoretical constructs with practical tools – such as foresight and morphological analysis to manage uncertainty, equilibrium boundaries, and system resilience.

Case studies further demonstrate the applicability of these models, showcasing how Wild Cards and Weak Signals Analysis can anticipate risks and seize opportunities, supporting sustainable growth. Together, these frameworks underscore the importance of combining theory and practice to tackle complex global challenges.

Case Studies, Innovative Practices, and the Topological Perspective

By combining topological and statistical methods with the Foresight Diamond, Horizon Scanning, and Foresight Processes, this study identifies constraints, breaking points, and 'weak signals' that hint at potential 'Wild Cards'. These insights feed into a risk-based management strategy addressing when and how systems may experience paralysis or disruption. Four topological modes – transient, capture, deep transient, and deep capture – are linked to the Four Management Dimensions, reflecting varying depths of change:

- *Transient mode* (e.g. temporary shifts in socio-economic preferences, Ahamer, 2020)
- *Capture mode* (e.g. sustainability-focused business models in Sweden's agri-food sector, Dehghannejad, 2021)
- *Deep transient mode*, involving sensitivity analyses of deeper systemic changes
- *Deep capture mode*, representing stable correlations among behavioral modes

This framework clarifies the topological significance of constraints, while 'weak signals' at different stages enable early detection of disruptive events.

Interconnecting Knowledge (iKNOW) for Weak Signals Analysis

The iKNOW Project explored how overlooked issues can shape or disrupt science, technology, and innovation (STI). It advanced Weak Signals research, defining these subtle, ambiguous "seeds of change" as early indicators of potential high-impact developments (e.g., Wild Cards, emerging challenges, or new opportunities). Although interpretation, importance, and impact are often uncertain, systematic monitoring reveals valuable insights for early intervention. In contrast, Wild Cards are low-probability yet high-impact events that can be unexpectedly disruptive (see Appendix). When combined with the SMART Foresight Framework, stakeholders can anticipate, recommend, and transform TEEPSES (technological, economic, environmental, political, social, ethical, and spatial) futures. This integrated approach embeds foresight into policy and strategy cycles, ensuring weak signals and wild cards inform strategic decisions and long-term resilience (Popper, 2011).

Figure 2 illustrates how Topological Analysis connects to the Policy & Strategy Cycle (Formulation, Realization, Learning) and the Issues Analysis Framework. A stratified behavioral function in a production-line scenario highlights four dynamic modes, from maximum output (A) to minimum arrival (C), with an inflection point (B). Decomposing equilibrium points isolates regular dynamics, showing how systems absorb shocks and maintain resilience (Yang et al., 2020). On the right, Figure 2 showcases the Issues Analysis Framework, emphasizing how different levels of uncertainty and interpretative biases influence Weak Signals Analysis, which is context dependent or situation-bounded (Popper et al., 2011; Ravetz et al., 2011). Four Wild Card trajectories emerge:

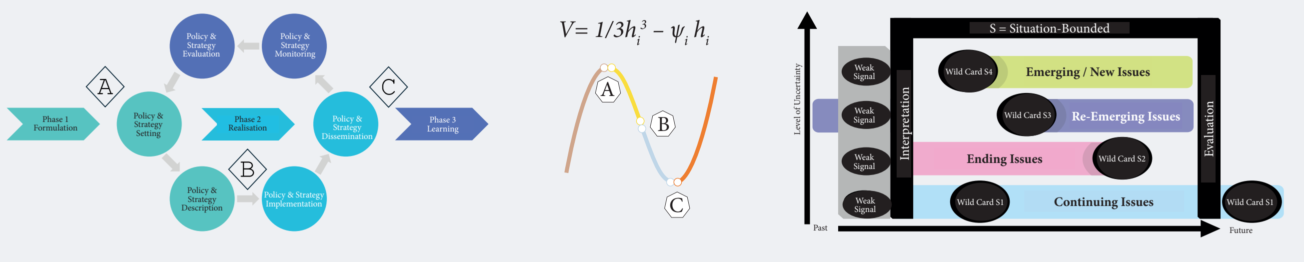
- Continuing Issues (e.g., cyber attacks)
- Ending Issues (e.g., market exit)
- Re-emerging Issues (e.g., global pandemic)
- Emerging Issues (e.g., new paradigm)

Evaluating process, people, and impact dimensions supports co-created action roadmaps, ultimately strengthening foresight and resilience in complex systems.

CASI Framework for Sustainable Innovation

The CASI Framework (CASI-F) – A Common Framework for Assessment and Management of Sustainable Innovation (SI) – has been applied across all EU Mem-

Figure 2. **Linking Weak Signals Analysis Framework with Disruptive Dynamics**



Policy & Strategy Cycle **Topological Analysis** **Issues Analysis Framework**

Source: authors.

ber States and in regions like Latin America (e.g. Uruguay) and the Middle East (e.g. United Arab Emirates). Figure 3 presents the CASI-F approach, an inductive method for SI assessment and management (top), alongside a network analysis of research and innovation (R&I) priorities distilled from 1,852 SI goals into 10 SI agendas (bottom) (Popper et al., 2017).

The CASI-F framework uses five steps to map innovations, prioritize cases, analyze issues, identify STI actions, and co-create roadmaps. In Step 5, these roadmaps span four dimensions – Context, People, Process, and Impact – across short-, medium-, and long-term timelines (Martini et al., 2020). By aligning these four CASI-F dimensions with four locally stable topological models, the study reveals topological constraints tied to equilibrium and depth. For instance:

- Transient (e.g. AI-driven climate adaptation pilots)
- Capture (e.g. local carbon sequestration projects)
- Deep transient (e.g. global circular economy expansions)
- Deep capture (e.g. region-wide decarbonization frameworks)

These perspectives guide STI foresight, revealing emerging trends, uncertainties, and prudent preparedness.

Four properties: Management Framework and Topological Modes

- *Intrinsic Property* focuses on transient context dynamics, influencing all process stages as systems shift from one state to another. Examples include nanotech safety alerts, e.g. coral reef conservation efforts (Bang et al., 2021), and iKnow Policy Alert (Popper et al., 2011).
- *Evolutionary Property* relates to capture topological modes, where stable attractors (basins) join two states at a shared boundary. This involves structure sensitivity, in which morphological constructs share internal properties, e.g. iKnow Policy Alert A39 on 'Nanotech robots caring for the elderly' (ibid). Contrasting scenarios highlight humility, adaptability, and persistence.
- *Transmuting Property* is defined by deep transient modes, emphasizing unexpected biases in impact and development pathways, e.g. iKnow Policy Alert A06 on food safety (ibid).
- *Imprinting Property* involves deep capture-emission dynamics, creating lasting impacts during sensitive periods. Examples include the global spread of a killer virus, e.g. iKnow Policy Alert 01 (ibid), illustrating how deep capture affects ecological systems (Hastings, 2004).

Summary

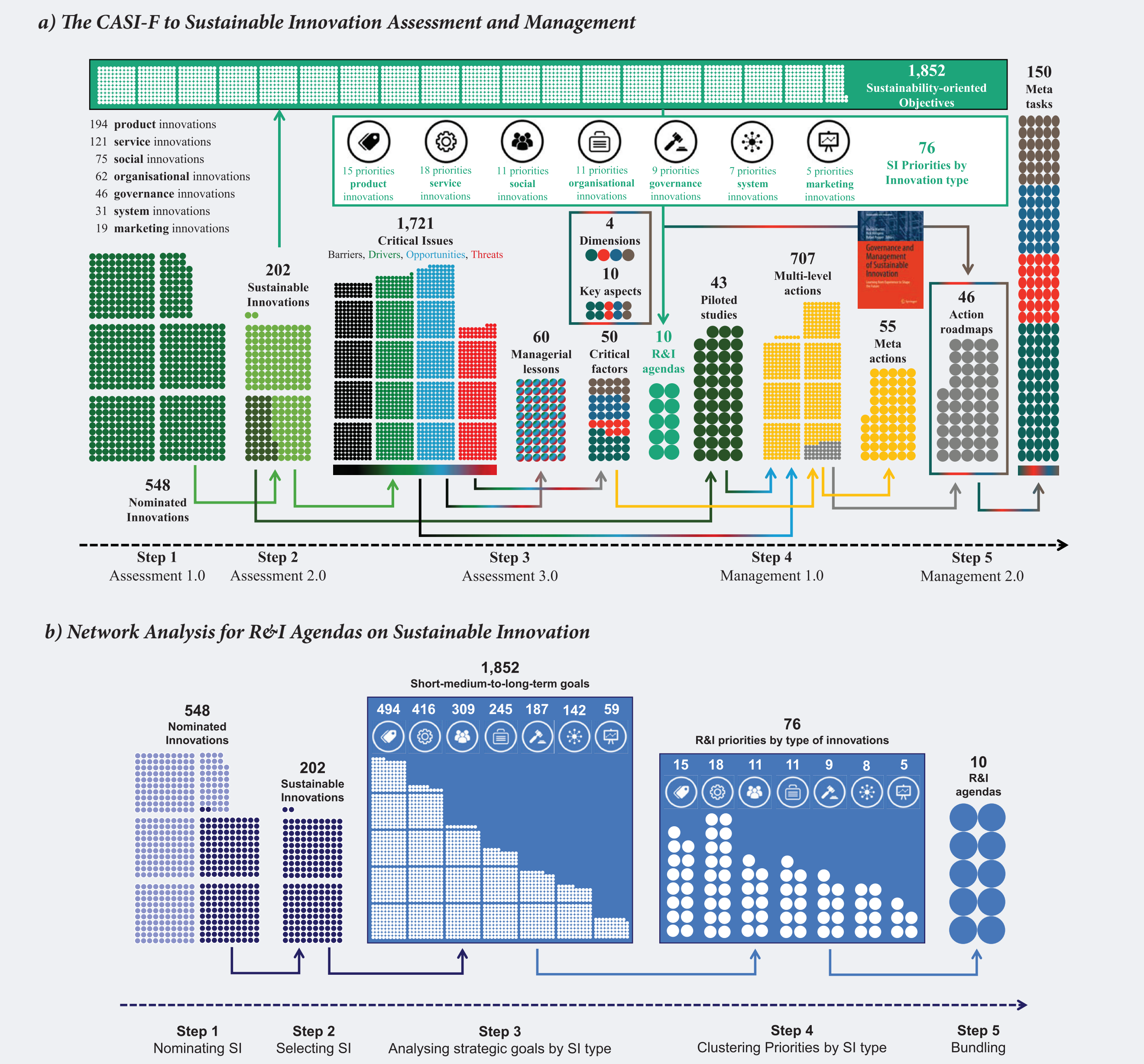
Analyzing the Specific Dynamics behind evolutionary processes is vital for managing uncertainties in both policy and business. By integrating Foresight, Wild Cards, and Weak Signals Analysis, we refine risk management (e.g. anticipating market volatility) and reliability (e.g. strengthening supply chains) through precise uncertainty categorization, paving the way for local sustainable disruptive growth.

We identify four levels of growth, each linked to a topological mode – transient, capture, deep transient, and deep capture – and three types of dynamics: regular, disruptive, and boundary. For instance, transient growth may involve brief policy changes that shift consumer demand, while capture might describe a new platform dominating a local market. A threshold zone separates macro (e.g. rapid currency devaluation affecting entire economies) from micro (e.g. DeepSeek's sudden disruption of the AI sector) disruptive behaviors. Finally, boundary dynamics concentrate critical information – such as system breakpoints or adjacency in complex networks – revealing where and when policymakers or businesses should intervene.

Dimension Reduction

We propose new methods for analyzing non-linear dynamics in sustainability systems, focusing on adaptive resilience and topological models. By applying dimension reduction techniques – including singular value decomposition (SVD), factor analysis, clustering, and policy bundling – we simplify large datasets into man-

Figure 3. **The CASI-F Framework and Network Analysis**



Source: authors.

ageable frameworks, eliminating noise and highlighting critical signals. This process clarifies four correlated subsystems linked to local stability, while revealing essential variables for understanding four stages of evolutionary change.

The SD-Growth Model integrates Wild Cards and Weak Signals Analysis to preserve local stability amid disruptive events, emphasizing constraints as a path to resilience. A practical example is the dimension reduction from 1,852 short-to-long-term goals to 76 R&I priorities and 10 R&I agendas, showing how quantitative, semi-quantitative, and qualitative methods can streamline complex data in sustainable innovation management. Arriving at the 10 SI R&I agendas involves aligning Context, People, Process, and Impact with the four locally stable topological models – Transient, Capture, Deep Transient, and Deep Capture. For instance, AI-driven climate adaptation pilots (Transient) emphasize shifting contexts; local carbon sequestration projects (Capture) highlight collaborative processes; global circular economy expansions (Deep Transient) affect long-term societal impacts; and region-wide decarbonization frameworks (Deep Capture) demonstrate embedded systemic change. This integrated viewpoint helps decision-makers balance resilience, innovation, and stability when designing R&I roadmaps.

Integrated Analytical Perspectives

Our analysis includes monitoring and transmitting simultaneous information, creating opportunities for artificial intelligence (AI), machine learning, explainable AI (XAI), and relatedness metrics (e.g., cosine similarity for job skill matching). These tools address labor market shifts and motivate the SD-Growth Model.

Achieving High Accuracy and Preserving Essential Information

Dimension Reduction is crucial for simplifying complex datasets while preserving key insights needed for sustainable innovation assessment and management. Techniques like singular value decomposition enable efficient data compression, ensuring that environmental, economic, and social variables can be analyzed together without information overload. In communication theory, reducing noise (Wiener, 1948) addresses the entropy problem (Shannon & Weaver, 1949) – the tendency toward disorder – so decision-makers can focus on relevant signals. Meanwhile, Deng entropy (Deng, 2016), based on Pascal's Triangle, measures uncertainty in basic probability assignments, and quantum computing merges physics, math, and computer science for more advanced information processing. Collectively, these methods enhance risk analysis, strategic foresight, and resource allocation, enabling policymakers and innovators to anticipate challenges and bolster resilience within sustainability systems.

In statistics, dimension reduction (e.g. factor analysis for specific variance) aims to maintain accuracy when analyzing high-dimensional data (Pearson, 2022; Spearman, 1904; Johnson & Wichern, 2014). In topology, it involves using canonical models to highlight independent main directions, clarifying complex interactions (Yang et al., 2020) and showcasing topological resilience (e.g. homeomorphisms for stability analysis).

Critical Discourse Analysis (CDA) and Action Research support the SMART Foresight Framework, employing dimension reduction to reassess advisors' mindsets about balanced preservation across all levels (Velasco, 2017). In linguistics, dimension reduction supports depth-based classification – covering lexical, semantic, morphological, and compositional effects (Pinker, 2007; Huang & Pinker, 2010).

Overall, these approaches integrate economics, topological methods, statistical analyses, and morphological insights, illuminating complex evolutionary frameworks for sustainable behavior change.

Towards a Sustainable Disruptive Growth Model (SD-Growth Model)

In the Four-Dimensional Management Framework, we combine Weak Signals and Wild Cards (WIWE) analysis across four phases:

1. *Stratified Dynamics* (e.g. equilibrium sets mapping tipping points)

2. *Behavioral Convergence* (e.g. eigenvalue shifts indicating system alignment)

3. *Equilibrium Stability Analysis* (e.g. boundary detection using potential functions)

4. *Sustainable Disruptive Growth* (e.g. dynamic change modeling using nonlinear differential equations)

Using topological modes, we link unexpected realities (seen as constraints) with abstract sensitivity levels. Each mode – transient, capture, deep transient, and deep capture – can be visualized as function graphs displaying varying degrees of singularity, shown through rates of change. This approach highlights how small signals or shocks can trigger significant transitions, guiding innovators and policymakers to manage and adapt their sustainability strategies effectively.

$v_1 = 1/3h_i^3, v_2 = 1/4h_i^4, v_3 = 1/5h_i^5, v_4 = 1/6h_i^6;$
$s_1 = h_i^2, s_2 = h_i^3, s_3 = h_i^4, s_4 = h_i^5.$

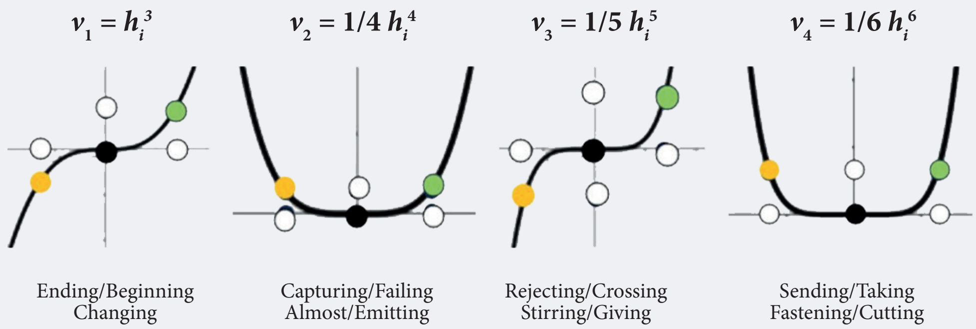
A stratified version of topological modes (e.g. layered phase transitions in markets) is introduced here. This approach treats each one-dimensional stratum of the mode's graph as a solution of a regular dynamical system, effectively splitting an initially singular, structurally stable system into two regular subsystems with unique, complete solutions. By applying differential systems in contact theory (e.g. modeling how supply and demand curves dynamically adjust in competitive markets), we can detect robust connections among stable solutions converging to the same closure point – an insight that proves useful in mapping innovation ecosystems and identifying dominant market strategies.

For transient topological modes in their canonical environments (e.g. unexpected shifts in economic equilibria), such robust connections emerge when multiple rates of change (1st, 2nd, 3rd derivatives) converge to their closure point from both sides. This implies curvature may switch concavity yet preserve slope and radius – with downward concavity (past dynamics) on one side and upward concavity (future outlook) on the other.

Figure 4 shows a stratified representation using analytical expressions v_k and rates of change s_k, for k=1 to 4. Each behavioral mode – *transient, capture, deep transient, deep capture* – is partitioned into two one-dimensional strata plus a zero-stratum (the closure point). Link points (yellow or green) lie near the zero stratum, indicating where behavioral dynamics shift. Two white link points reveal disruptive transitions (e.g. supply-chain breakdown leading to a new market normal). The i-th slope function (i-th derivative) is calculated at these points, and if left and right limits coincide, it signals a robust connection – key for systemic stability. Finally, the deep transient mode is more fragile, since rates of change vanish at zero up to the fourth order, showing non-zero behavior only at the fifth – underlining long-term vulnerabilities in complex innovation ecosystems..

In the Appendix, you can find details about the stratified axis ψ_i (e.g. layered policy thresholds) – also known as the Context Dimension Management Axis, which includes elements such as '*Momentum*', '*Foresight*', '*Resources*', and '*Mobilization*', all crucial for in-

Figure 4. **Topological Modes Graphics & Neighbourhood Dynamics**



Source: authors.

novation and strategic planning (Martini et al., 2020). The ψ_i -parametric family is represented by V_1. When the parameter is positive, the rate of change of the topological transient mode (e.g. quick shifts in markets) is linked to specific variance. This link highlights how shifts in a representative mode mirror key variation, essential for understanding disruptive dynamics in sustainable systems.

The relationship between specific variance and the transient topological mode is shown analytically in the Appendix. The singular set (e.g. boundary points of transformations), (Sv_1), representing the equilibrium set of the transient mode behavior, defines a nearby threshold zone, allowing concepts like parallelism, transversality, and concentration to explain transitions within this zone. Inside, the behavior compresses and reflects; outside, it expands and reflects. This duality illustrates how constraints affect the stability and evolution of complex systems, offering a framework to analyze and manage them in sustainable contexts.

The risk zone, bordered by singular points, holds the critical changes in behavior. Transversal transit through this risk zone, connects different behavioral states, aiding in identifying and managing potential risks and disruptive behaviors. Figure 5 (left) shows the threshold zone, defined by two symmetric curves γ_i, denoted by G($\gamma_i^{\pm}$), as explained further in the Appendix.

There are three transversality types – Regular (R), Disruptive (D), and Boundary (B) – which define transversal lines to the axis ψ_i. Specifically, $L_1(R)$, $L_{-1}(D)$, and $L_0(B)$ intersect the Regular (ψ_i=1), Disruptive (ψ_i=–1), and Boundary (ψ_i=0) points respectively. For instance, Regular transversality might reflect standard supply-demand adjustments, Disruptive transversality could manifest as abrupt AI-driven policy shifts, and Boundary transversality can denote cross-sector trade negotiations.

Figure 5 (middle) illustrates parallelism, concentration, and multi-fibration (e.g. parallel AI deployments, concentration of green investments, multi-fibration linking economic sectors). On the right, the figure shows parallel lines traversing the negative ψ_i axis – indicating disruptive dynamics. Three notable closure points capture *Momentum* (a maximal or unstable attractor), *Foresight* (a minimal or stable attractor), and an inflection point (tied to *Resources* and *Mobilization*). These points highlight how behavioral trajectories with robust connections tend to converge on shared destinations, emphasizing the need for higher-order contact coordinates to enable or reject connections across behavioral dynamics.

Five operations guide these transitions:
1. Symmetries (input/output vs. equilibrium) around a parametric neutral axis (ψ_i) (e.g. average CO_2 footprints), which measures variance (distance to a mean).
2. Expansion & symmetry away from equilibrium.
3. Compression & symmetry inside the threshold zone.
4. Robust connections aiding transmission of behavior.
5. Resilient trajectories with a quadratic rate of change.

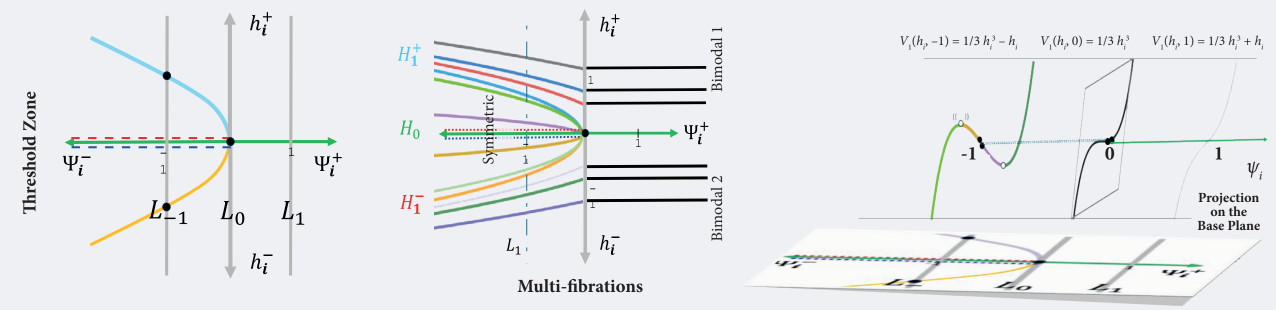
The SD-Growth Model helps form evolutionary clusters, tracing parts of behavioral trajectories to visualize potential arrival connections and spot synergy gaps (e.g. mismatched AI–climate policies). Laurett et al. (2021) used exploratory factor analysis in Brazil to gauge local views on sustainable development, focusing on natural agriculture variables. They found two main barriers – lack of information/knowledge and lack of planning/support, both echoing common obstacles to sustainability and synergy in complex systems.

Applications

Context Dimension Management and the Transient Mode

Transient Mode: A Key to Context Dimension Management. A stratified transient mode (see Figs. 4, 5) illustrates how dynamic systems undergo layered, multiscale changes. This process comprises four phases – two macro (e.g., production and distribution) and two intangibles (e.g., management and optimization). Within this framework, three key transition points emerge – a maximum, a minimum, and an inflection

Figure 5. **Transient Mode & Stratification by Equilibrium**



Source: authors.

point (see Fig. 2) – that act as connection layers between phases. Recognizing these critical elements is fundamental for sustainable innovation management, as it reveals how systems shift between stable and risky conditions. This insight enables policymakers and innovators to detect weak signals of disruption early, implement targeted interventions, and adapt strategies to maintain local resilience and stability.

Energy Applications: Harnessing Stratified Efficiency. In wind energy studies, the potential function measures average change over time (P = E/t). For example, a cylindrical mass of air (density ρ, radius R) passing through a vertical disc generates an average power of $P = 1/2\rho\pi R^2 v_w^{\ 3}$. This concept extends beyond physical scales to processes like diffusion, conduction, and transport in energy networks, where an "efficiency diameter" defines the largest cluster in fragmented systems (Aliprantis, 2011). We propose linking a local state variable, v_{rel} (velocity relative to mass density), to model a transient mode of behavior as $v_1(v_{rel}) = 1/3v_{rel}^{\ 3}$ – matching the average local power and integrating environmental analysis via specific variance (ψ_i). The function $V_1(\psi_i,v_{rel})$ reveals singular points and the topological resilience of behavior. In terms of sustainable innovation, this framework helps energy planners manage both stable and risky areas, ensuring robust connections (e.g. wind farm networks).

Communication Applications: Ensuring Robust Signaling. A maximum behavioral trajectory (e.g. peak user participation in digital systems) guides signal transmission between a source and a receiver. Figure 5 (right) illustrates a prototype of L_{-1} disruptive behavior in the variance-variable plane, generating four one-dimensional layers: two external (for source and destination messaging) and two internal (for operational systems). Topological resilience visualizes the zero-strata – key connection points – as stable links between phases. Equation (4) shows that the transient mode maintains robust contacts across phases, thereby enhancing communication reliability (e.g. in network traffic management for smart city projects).

AI Applications: Managing Complex Behaviors. The canonical environment of the layered transient mode provides detailed precision for AI systems (e.g., robotic coordination and recommendation algorithms). It robustly connects different behavioral phases around an equilibrium point (Figs. 4, 6), where the weaknesses of one phase are offset by the strengths of another, creating a dynamic capturing/emitting process. As shown in Fig. 6 (left, step 4), both parameters act as stable attractors that regulate the machine learning process, enabling adaptation or failure under stress (e.g., compression or distension in the model's variance and covariance parameters).

Quantum Applications: Leveraging Parallel Frameworks

Topological modes of behavior exhibit a twofold parallelism: within the threshold zone, they enable concurrency (e.g., multiple qubits operating simultaneously), and outside the threshold zone, they support task decomposition and simultaneous execution of smaller sub-tasks. This dual approach is crucial for managing complex sustainability initiatives, such as coordinated greenhouse gas reductions across multiple sectors, highlighting the value of topological modes for seamlessly orchestrating operations across diverse contexts.

Startup Ecosystem Applications: Orchestrating Growth Dynamics. Stratified transient modes help pinpoint constraints shaping early-stage venture cycles (e.g. pivot signals from founders, synergy cues among investors). By analyzing short bursts of innovation, we see how disruptive factors (e.g., new competitor entries or shifts in venture capital) escalate or stabilize. This approach fosters a robust ecosystem, ensuring sustainable expansions and long-term resilience in startup networks.

Data Requirements for Stratified Transient Mode Analysis. Effective application of stratified transient modes involves multifaceted datasets. In startup ecosystems, for example, funding data (e.g. investment rounds, valuations), accelerator or incubator metrics (e.g. applicant acceptance rates), and pitch-deck analytics (e.g. traction and user growth) provide quantitative indicators. Qualitative inputs (e.g. mentor feedback, founder surveys) capture contextual nuances, while hybrid data streams (e.g. regional policy changes, co-working space usage) further enrich analysis. By combining these diverse sources, organizations can detect hidden constraints, track evolving behaviors, and develop resilient strategies for sustainable growth.

Synthesis and Multi-Level Analysis. Overall, these application examples – spanning energy, communication systems, AI, quantum computing, and startup ecosystems – show how topological constraints and stratified transient modes guide sustainable innovation management. At the micro level, the SD-Growth Model pinpoints disruptive dynamics within threshold zones, highlighting wave-like behaviors tied to system depth. Beyond these zones, regular behaviors dominate at the macro level. Identifying equilibrium sets and topological constraints supports in-depth exploration of behavioral shifts.

When behavioral trajectories converge on a common closure point, their topological resilience drives collaborative innovation, vital for sustainable outcomes in complex systems. The Context Dimension is paramount, shaping how local environments – from community energy programs to startup hubs – can nurture robust clusters for long-term success. This approach depends on diverse data sources (e.g. sensor readings, financial metrics, mentor surveys) to detect hidden constraints, track evolving behaviors, and adapt strategies effectively for resilient, multi-scale growth.

People Dimension Management and Capture Mode of Behaviour

The People Dimension Management involves aspects such as ’aptitude’ (current skill sets) and ’attitude’ (behaviour and motivation) linked to innovation. These factors are essential in the foresight process, particularly during the mobilizing phase, which encompasses activities like contract negotiations and engaging target groups, helping to locate equilibrium points where cooperation and networking can stabilize.

Mobilizing represents the second phase of Foresight. identifying three key topological moments, two competing attractors which are minimum points (mP), namely: the ´aptitude´ a locally stable mP- attractor, the attitude a simultaneous mP-attractor; and, a neutral point (NP), together with a balance point between these two attractors (within the scoping phase, where cooperation and networking can stabilize). Near the center of balance, the two competing attractors (aptitude and attitude) have the opportunity to jump from one level to another, leading to a possible detection of those ‘key moments’ for leaps in development or disruptive innovation; connected by two fundamental aspects: financing and foresight mobilization, where ´cooperation and networking´ could attain a locally stable cluster equilibrium.

The capture topological mode represented by Figure 6 (the second function, Appendix, Table A1), exhibits its behavior inside a parametric family of behavioral functions; depending on two parametric factors representing. The figure right shows its complexity and restrictions through the equilibrium analysis. The left figure is divided into two zones: non-disruptive behavior, represented by the line L_1, and disruptive behavior, represented by the line L_{-1} transverse to a cusp curve; and the line L_0, the boundary between two types of behavior.

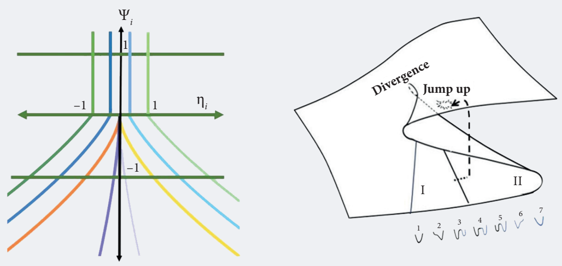
An equilibrium analysis similar to the Context Management Dimension, allows defining the set of the singular points which are distributed in the form of a curved cusp with bifurcation pont at zero. The transversal factor, η_i, incorporates a new measure, which shows how the trajectories of behavior can preserve harmonious parallelism of the ψ_i axis, which exhibits a bimodality in its transversal transit through the η_i axis. This bimodality illustrates how constraints (the cusp curve as boundary of a ’threshold zone’ or risk zone) impact the stability and evolution of complex systems with a parallelism induced by a threshold zone.

The Figure 6 right, show the lifting of the bimodal plane; at the bottom the image shows seven waves numbered from one to seven, representing a strategic cycle that allow crossing the area through a resilient path, monitoring the Weak Signals of the behavior function, as in the case of 2. The cicle shows how two behaviour attractors (the attractor (1) and the attractor (7), when the function V_2 take minimum value, change progressively from one mode to another, passing for stability (4), in whose proximity the occurrence of a jump to the top layer, could be favorable, for possible innovation (and after, going to the right), or catastrophic shock (returning to the left and generating a cycle falling down and jump up again.

A natural jump up occurs on the seventh step, hence the importance of identifying the proximity of the equilibrium sets; also, the parallelisms analysis, concentration analysis and the visualization of trajectory linked to robust connections and risk analysis. Barunik and Vosvrda (2009) adapted representative of the capture topological mode to stock market data, explaining the fall of the stock markets, using data from the US stock markets.

The Dimension People equilibrium dynamics is linked to stable attractor points and jumps between different behaviour modes. The “jump up-capturing” archetype (Figure 6 emphasizes conditions for disruptive innovation, balancing aptitude (knowledge and research) with attitude (experience and tradition) then, enhancing the depth of morphological change processes is encouraged by the emergence of Cluster Grouping and Cooperation, on the (context, people) plane, with (ψ_i, η_i), parametric coordinates references (Masini, Vasquez, 2000). There can be grouping alignations with the spectrum of knowledge states (certainty-risk-uncertainty-ambiguity), consistent in the cooperative behaviour emerging at the bifurcation point (0, 0); cooperative cluster with recognise specific properties and risk dynamic (Vasquez, Ortegón, 2006).

Figure 6. **Capture Topological Mode. Stratification & Outlier Points**



Source: authors.

The resulting stratified surface contracts near zero, revealing two symmetric cusps influenced by ξ_i. When ξ_i shifts, the system can undergo a behavioral change, marking critical thresholds for process-driven innovations.

Case Study on Aphid Population (Wu et al., 2014). An example from ecological management highlights how monitoring equilibrium zones is essential in dynamic systems. Let h_i be Aphid population density, ψ_i an environmental control factor, η_i the crop condition (carrying capacity), and ξ_i a predator factor. A representative unfolding function captures how state variable h_i behaves under control conditions, influencing morphological changes in pest management – much like deep transient modes in innovation processes.

Applications in Startup Ecosystem Orchestration. For startups, the deep transient mode spotlights prolonged shifts in processes – for example, a multi-stage pivot driven by new market insights. *Catalysts* might be accelerator programs and angel investments, while *Fosterers* could be industry partnerships and user community growth. By tracking parametric shifts (ψ_i,η_i,ξ_i), founders can spot cusp points that signal slow-building transitions, helping them fine-tune product rollouts or scale more sustainably.

Data Requirements for Deep Transient Mode Analysis. To understand deep transient modes in process management, mixed data are crucial: *Quantitative*: Longitudinal metrics (e.g., implementation timelines, R&D spending, customer retention rates); *Qualitative*: Stakeholder feedback, expert interviews, field observations capturing persistent challenges or gradual cultural shifts; and *Hybrid*: Policy updates, organizational network measures, pilot project outcomes that help correlate slow-moving changes with faster pivots. Such integrated datasets reveal extended transitions and underlying biases, enabling adaptation in sustainability-driven innovation processes.

Synthesis and Multi-Level Analysis. In deep transient mode scenarios, prolonged shifts can either strengthen or disrupt innovation trajectories. At the micro level, analyzing catalysts and fosterers pinpoints local changes (e.g. team reorganization, ongoing pilot ex-

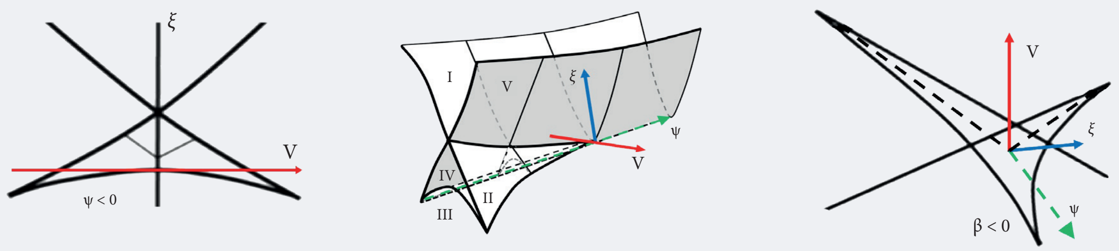
Process Dimension Management and the Deep Transient Mode

Deep Transient Mode: A Key to Process Dimension Management. A *deep transient mode* emerges when systems experience longer-lasting transitions – often involving complex changes that unfold gradually before stabilizing. Recognizing this mode is crucial in Process Dimension Management, which addresses *Catalysts* (factors initiating and implementing innovation) and *Fosterers* (elements consolidating and diffusing innovation). By identifying deep transient behaviors, managers can guide innovation processes through prolonged shifts, ensuring resilient and sustainable transformation over time.

Process Dimension Management. In this dimension, function V_3 defines a canonical neighborhood of the deep transient mode, while its slope function $s_3(h_i)$ (linked to the fourth statistical moment) captures innovation's rate of change. A bias factor ξ_i introduces a third parametric axis – in addition to ψ_i and η_i – allowing growth within an equilibrium zone. Figure 7 illustrates these parametric axes at the center, showing a curvilinear polygon sliding along ψ_i and displaying two behaviors:

- Regular (ψ_i>0, e.g. ψ_i=1)
- Non-regular (ψ_i<0, e.g. ψ_i=−1)

Figure 7. **Depth Transient and Capture Modes & Dynamic**



Stratified 3-depth curve

3-depth curve moving on axis Ψ

Stratified 4-depth curve

Source: authors.

periments) that slowly reshape process outcomes. At the macro level, cusp analyses and contracting surfaces guide policy interventions, financial backing, or ecosystem partnerships aimed at sustaining long-term innovation growth. Recognizing these deep transient patterns bolsters Process Dimension Management, ensuring continuous adaptation and resilience across complex innovation landscapes.

Capture Mode and High-Precision Monitoring

Deep Capture Mode: A Key to Impact Dimension Management. A deep capture mode emerges when long-term, transformative change takes root in a system, culminating in significant, stable shifts across multiple parameters. Recognizing deep capture is critical in Impact Dimension Management, which addresses '*Transformation*' (positive changes in the quadruple helix of science, innovation, and society) and '*Sustainability*' (environmental, societal, economic, governance, and infrastructural advancements). By spotting deep capture patterns, decision-makers can direct high-precision monitoring toward long-lasting impacts in complex socio-technical systems.

Impact Dimension Management. In this dimension, function V_4 defines a canonical neighborhood of the deep capture mode, while its slope function, $s_4(h_i)$ (related to the fifth statistical moment), measures the rate of change in agreeing and impacting processes. A new butterfly factor (β_i) introduces a fourth axis alongside ψ_i, η_i, and ξ_i, generating stability in an equilibrium zone. For $\beta_i<0$, the maximal trajectory passing transversally to ψ_i marks the boundary of the shock wave – sometimes termed a "pocket organization" in semantic interpretations.

Case Study – Risk Analysis and Policy Recommendations. Zhu et al. (2023) applied a capture topological mode to investigate China's zirconium industry (2005–2021), revealing an "early warning" state tied to political turbulence and technological advances. Their work illustrates how deep capture insights can inform policy proposals that strengthen sustainability in vulnerable industries.

Applications in Startup Ecosystem Management. For startups, a deep capture mode highlights long-term impact (e.g. systemic shifts in market positioning or industry-wide alliances). When transformation occurs – encompassing quadruple helix actors such as universities, industry, government, and society – founders and investors can analyze β_i to detect shock wave boundaries. Identifying pocket organizations or hidden networks may guide sustained growth strategies (e.g. global expansions or circular economy initiatives).

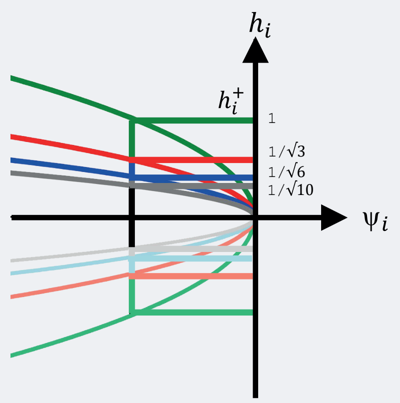
Data Requirements for Deep Capture Mode Analysis. Effective deep capture assessment demands comprehensive datasets: *Quantitative*: Longitudinal policy metrics, macro-level market data, environmental impact scores; *Qualitative*: Stakeholder interviews (society, government), expert panels on technological adoption; and *Hybrid*: Cross-sector collaborations (e.g. academia-industry partnerships), funding flows that reflect multi-helix engagement. These inputs pinpoint equilibrium sets, shock wave boundaries, and butterfly factor dynamics, ensuring risk analysis and policy adaptation align with deep, transformative change.

Synthesis and Multi-Level Analysis. In deep capture mode scenarios, long-term transformations become anchored in impact-oriented dimensions, driving substantial shifts across entire sectors or regions. At the micro level, analyzing butterfly factor (β_i) and equilibrium zones reveals organizational readiness (e.g. pocket organizations fostering breakthrough innovations). At the macro level, shock wave boundaries outline where policy interventions or stakeholder cooperation can secure sustainable advantages. Recognizing deep capture patterns fortifies Impact Dimension Management, enabling high-precision monitoring and systemic resilience in complex, ever-evolving innovation ecosystems.

Energy: A Key Driver for Sustainable Disruptive Growth

Within the four Management Dimensions – *Context*, *People*, *Process*, and *Impact* – energy systems provide a powerful example of how topological modes shape sustainable innovation management. As illustrated earlier with wind power (mass of air at average velocity), energy-related contexts highlight key risk exposures and resilience strategies, echoing Cherp and Jewell's (2014) "four A's of energy security" (availability, accessibility, affordability, acceptability) and the vulnerability arising when vital energy systems intersect with critical social functions. According to Americo et al. (2023), clean technologies (wind, solar, electric vehicles) pose

Figure 8. **The (h_i, ψ_i)-plane Stratified by Depth of Change**



Source: authors.

opportunities and challenges for fossil-fuel producers and metals/minerals suppliers, demanding long-term adaptation across local and global networks.

Figure 8 demonstrates how the four dimensions interact – *Context* frames resource availability, *People* drive skills and motivation, *Process* underpins system development, and *Impact* reflects transformation. This stratification reveals zones of energy change where threshold overlaps define stable or disruptive behavior. Behavioral clustering at close distances (e.g. regional cooperatives or innovation alliances) fosters cooperative pathways, parallelism in roles, and concentration of efforts. The four structurally stable behavioral models (depicted in Figure 8 at $\psi=-1$) each link to a distinct dimension; together, they enable anticipation of system requirements for scalable or disruptive growth.

Moreover, these dynamics mirror market liquidity and resilience principles. Effective energy markets share traits with well-functioning financial markets – they involve diverse participants, reliable price discovery, and robust trading mechanisms (Markets Committee, 2019). Adequate liquidity – or energy supply flexibility – supports timely transactions and efficient adaptation under uncertainty (Logan, Bindseil, 2019). This parallel extends to startup or innovation ecosystems investing in renewable projects, where stakeholders with varied commercial interests must coordinate to ensure both resilience and disruptive potential, thereby advancing sustainable and transformational energy solutions.

Measuring Behavioral Relationships and Economic Complexity

Building on the Context Dimension Management discussed earlier (momentum and foresight points), a system's future arises from its current momentum and management negotiations across threshold zones, bridging two distinct states to reach foresight visions. One context measure calculates the distance between two canonical behavioral trajectories – for instance, $(h_i,\psi_i) \mid \psi_i=a$ and $(h_i,\psi_i) \mid \psi_i=b$ – where the rate of change might be $h^2+\psi$. The difference in rates of change is $|a-b|$, yielding a behavior-specific distance for Context, People, Process, or Impact strata.

Hidalgo and Hausmann (2009) introduce an economic complexity framework linking countries, their capabilities, and the products requiring those capabilities. Under the SD-Growth Model, these could represent a source (ψ_i,η_i,ξ_i) and target (ψ_i,η_i,ξ_i), reflecting ideal connections. The distance between two behaviors is then the mean difference of these ideal points. Axis ψ_i can signify momentum-foresight (Context), η_i captures skill or attitudinal leaps (People), and ξ_i reflects innovation bias (Process), influencing the overall impact on production or growth. In a startup ecosystem, these dimensions help entrepreneurs identify capability gaps and potential pivots – bridging the gap between localized production and scalable solutions. Future work will explore how these ideal model connections inform synergies and cluster formation across context, people, process, and impact dimensions.

Key Outputs

The SD-Growth Model offers a structured framework for analyzing non-linear dynamics in sustainability. Integrating topological, statistical, and morphological analysis, it addresses disruptive, regular, and boundary behaviors. By focusing on context, people, process, and impact dimensions, it enables more resilient, adaptive, and innovative strategies across complex systems, ensuring sustainable long-term transformations.

Dimension Reduction and Topological Frameworks

TThe SD-Growth Model employs four stratified measurement axes – linked to the *transient*, *capture*, *deep transient*, and *deep capture* modes – to track morphological changes by depth. Each axis detects regular, disruptive, or boundary behavior, linking back to *Context*, *People*, *Process*, and *Impact* dimensions. By reducing complexity, the model pinpoints essential behavioral shifts for sustainable innovation management (e.g. identifying sudden AI disruptions or pivot moments in startup ecosystems).

Behavioral Convergence Across Dimensions. Through diverse case analyses, the SD-Growth Model highlights converging trajectories that share robust connections and display adaptive or recovery capabilities, eventually approaching a common focal point. Recognizing these higher-order contact coordinates is crucial for aligning resources and fostering collaboration across the *People* (skills, motivation) and *Process* (catalysts, fosterers) dimensions, thereby enabling or rejecting specific behavioral connections.

Stratified Dynamics: Macro and Micro. The SD-Growth Model differentiates macro-dynamics (outside threshold zones) from micro-dynamics (within threshold zones). Macro-dynamics often reflect stable developments (e.g. steady market growth), while micro-dynamics capture disruptive or wave-like changes (e.g. small-scale energy cooperatives confronting local risks). This stratification supports policymakers and innovators in targeting interventions precisely where volatility or opportunity is greatest.

Equilibrium Stability and Threshold Zones. At the micro level, the model reveals disruptive dynamics emerging in risk zones, with varying amplitudes tied to system depth. Macro-level behaviors outside these zones remain regular. By identifying equilibrium sets and topological constraints, the SD-Growth Model offers methodological guidance for analyzing behavioral shifts in fields like data analytics, artificial intelligence, astrophysics, and startup ecosystem management. Recognizing these threshold zones is vital for preventing instability or capitalizing on disruptive innovation.

Advancing Sustainable Growth. By blending management frameworks (human-society and foresight processes) with morphological, statistical, and topological analyses, the SD-Growth Model underscores the importance of *Context* in defining local environments that foster cooperative relationships. This facilitates sustainable growth and local stability, effectively bridging morphological changes with potentially disruptive yet transformative innovations.

These five features demonstrate the analytical depth and strategic insights provided by the SD-Growth Model in understanding resilient systems, behavioral dynamics, and their implications for sustainability and innovation theory.

Methodological Contributions of the SD-Growth Model

The SD-Growth Model presents a multidimensional framework analyzing *context*, *people*, *process*, and *impact* together, enabling a holistic understanding of how sustainability and innovations evolve over time and space. By stratifying behavioral trajectories into depth-based phases (e.g. *transient*, *capture*, *deep transient*, *deep capture*), it pinpoints critical transformation points and reveals resilience dynamics in complex systems. Using topological and statistical tools, the model examines morphological changes, identifies equilibrium states, and detects disruptive behaviors linked to sustainability goals. Its dimension reduction techniques simplify high-dimensional data, focusing on essential parameters that influence socio-sustainable processes – a crucial asset for startup or innovation ecosystems exploring new markets or technological breakthroughs. By bridging biological, statistical, and epidemiological frameworks, the model broadens sustainability analysis and offers fresh perspectives on topological resilience and emerging disruptive innovations.

Epistemological Contributions of the SD-Growth Model

Adopting a four-dimensional perspective (*Context*, *People*, *Process*, *Impact*), the model underscores the interconnectedness of factors shaping sustainable disruptive growth. Its depth-based approach moves beyond surface-level observations, uncovering underlying forces and emergent properties within adaptive systems. By stratifying the evolution of sustainable behaviors, the model clarifies how these systems maintain topological resilience and stability in the face of external shocks – an insight especially relevant for innovators managing long-term change. Integrating biological, statistical, and topological concepts strengthens this interdisciplinary stance, revealing the mechanisms by which disruptive innovations arise in sustainable contexts. In doing so, the SD-Growth Model expands the theoretical foundations of sustainability studies, promoting a forward-looking view on transformation and evolution that deepens our understanding of systemic behaviors and the drivers behind radical innovation.

Conclusions and Practical Implications

By incorporating Context, People, Process, and Impact dimensions, this paper's insights offer policymakers and innovators a multi-dimensional lens to shape sustainable innovation ecosystems and enhance resilience. Understanding depth analysis and stratified behavioral dynamics enables targeted management of innovation processes, identifying key transformation points, optimizing resource allocation, and creating environments conducive to disruptive growth.

Integrating biological, statistical, and topological frameworks supports network analysis and strategic planning in socio-technical systems, revealing key actors, network dependencies, and systemic shifts central to ecosystem resilience (e.g., adaptation in renewable energy cooperatives or cross-sector startup collaborations). Recognizing risk zones and robust connections enhances risk management, helping stakeholders anticipate disruptions and devise adaptive strategies. Likewise, AI-driven analytics can leverage these insights for scenario simulations, sustainability planning, and evidence-based decision-making aligned with sustainable innovation principles.

Imagine you are piecing together a huge jigsaw puzzle where each piece keeps changing shape and size every time you try to fit it in. The four dimensions – *Context*, *People*, *Process*, and *Impact* – act like the puzzle's edges, giving you a sense of where to start and how everything might link up. Meanwhile, the four topological modes – *transient*, *capture*, *deep transient*, and *deep capture* – are special pieces that unlock new connections, revealing unexpected patterns or hidden shortcuts in the bigger picture. Even when it seems impossible, this paper shows which pieces fit, which to rotate, and which to save for later, making the puzzle manageable and exciting. In doing so, it provides a groundbreaking blueprint for navigating the ever-evolving jigsaw of sustainability, innovation, and disruptive transformation – applicable to all fields, from science and technology to the humanities.

Further Research Areas

Dynamic Network Analysis. Future work could integrate depth analysis and stratified dynamics into network-oriented methods, examining how topological changes over time influence sustainability outcomes. This might involve studying behavioral patterns in innovation clusters, tracking persistence of stratified states, and gauging long-term resilience against disruptions.

Multi-Level Governance and Complexity. Applying the SD-Growth Model to multi-level governance structures can clarify how local, national, and global policies interact in driving innovation diffusion and policy effectiveness. Research might explore vertical (national–local) and horizontal (cross-sector) integration, revealing synergies or tensions that affect ecosystem resilience.

Integration of Sustainable Behavioral Strategies. Investigating how social norms and individual choices shape innovation adoption can deepen our understanding of sustainable behavior. This includes identifying decision-making biases, mapping collective behavior shifts, and tailoring interventions for increased uptake of green technologies, ethical entrepreneurship, or circular economy models.

Futures Prosperity Index (FPI) or Model (FPM). Building on the SD-Growth Model's multidimensional focus (context, people, processes, impact), future work could develop a Futures Prosperity Index (FPI) or Futures Prosperity Model (FPM). This would integrate the following four factors – environmental sustainability, social and health wellbeing, innovation competitiveness, and fiscal/governance resilience – into a composite measure.

Extreme-Scenario Testing and Foresight. Employing future-proof methods (Popper, Towpik, 2024; Popper, Popper, 2024) within the SD-Growth Model allows strategies to be tested against uncertain and disruptive scenarios, particularly those affecting public funding for research and innovation. This approach strengthens policy robustness and refines innovation design, equipping decision-makers to meet frontier challenges in rapidly evolving fields.

Finally, extending these methodologies beyond sustainability – to fields like ecology, sociology, political science, and economics – can help validate and refine their applicability, fostering greater coherence and synergy in tackling complex global challenges.

Limitations

A key limitation is the availability and quality of data for depth analysis and stratified behavioral dynamics. Overcoming this may require new data collection methods or leveraging AI and machine learning for robust synthesis. Similarly, the sustainability and practicality of the models can be challenging, especially when interpreting and applying results to real-world scenarios. Researchers might develop simplified frameworks or visualization tools to help stakeholders grasp ecological dynamics.

Another limitation is generalizing findings across diverse ecological contexts and regions. Validating these methodologies in varied socio-ecological environments and institutional settings is essential to confirm robustness. Ethical and policy issues also arise when predictive analytics and algorithmic models influence governance – fairness, transparency, and unintended consequences must be assessed. Interdisciplinary collaboration is vital; bridging disciplinary gaps and harmonizing methodologies can significantly advance sustainability research.

Moreover, the complex topological modes (transient, capture, deep transient, deep capture) may hinder adoption if stakeholders lack technical expertise. Overlapping threshold zones can create ambiguous signals, complicating decision-making. While Wild Cards (low-probability, high-impact events) are partly addressed by Weak Signals Analysis, true Black Swans (rare, unforeseeable disruptions) may exceed the model's scope. Sector-specific nuances – from quantum computing to startup ecosystems – might require tailored adaptations. Finally, longitudinal datasets capturing shifts in Context, People, Process, and Impact are essential to maintain the model's accuracy in fast-changing environments.

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Appendix 1. Topological Stability & Non-Regular Dynamic

The Stratified Axes

The stratified axes, e.g., ψ_i, represents each stratum, the positive (resp. negative) as image of the real line using exponential function. Similarly, the real axis of potential function.

$$Axis(h_i) = \{-e^{\lambda_h}\} \cup \{(0,0)\} \cup \{e^{\lambda_h \cdot}\}$$

The Local Stability Theorem

Using a stratified version of the theorem, we decompose the behavioural functions into strata. The analytical expression of the equations allows demonstrating the relationship between the statistical moments, especially the specific variance with the equations shown in the table A1.

Theorem. If a process, controlled by no more than four real factors or parameters, can be described by minimizing or maximizing a function with one explanatory variable, then any singularities will be like those appearing in any of the following archetypal models, where h_i represent a density variable in a i locality and ψ_i, η_i, ξ_i and β_i are real parameters (Thom, 1975).

Table A1: Germs of Functions and their Unfolding

Germ of function	Universal unfolding of function
$v_1 = 1/3h_i^3$	$\mathcal{V}_1 = 1/3h_i^3 + \psi_i h_i$
$v_2 = 1/4h_i^4$	$\mathcal{V}_2 = 1/4h_i^4 + 1/2\psi_i h_i^2 + \eta_i h_i$
$v_3 = 1/5h_i^5$	$\mathcal{V}_3 = 1/5h_i^5 + 1/3\psi_i h_i^3 + 1/2\eta_i h_i^2 + \xi_i h_i$
$v_4 = 1/6h_i^6$	$\mathcal{V}_4 = 1/6h_i^6 + 1/4\psi_i h_i^4 + 1/3\eta_i h_i^3 + 1/2\xi_i h_i^2 + \beta_i h_i$

The first function is solution of a differential equation defined by the specific variance, since the rate of change of the behavioral functions coincides with the specific variance. The diagram relates the behaviors in the zero environment. The following diagram shows the relation The specific variance as the rate of change of the first function defined in the stability theorem, for the case of a positive parameter.

$$\begin{tikzcd} \mathrm{G}(\tilde{v_1}) = \{(h_i, 1/3h_i^3), h_i \in \Re^*\} \arrow[r, "H_\epsilon"] \arrow[d, "\frac{\partial}{\partial h_i}"'] & \mathrm{G}(\tilde{\mathcal{V}_1}) = \{(h_i, 1/3h_i^3 + \epsilon h_i), h_i \in \Re^*\} \arrow[d, "\frac{\partial}{\partial h_i}"] \\ \mathrm{G}(\tilde{s_1}) = \{(h_i, h_i^2), h_i \in \Re^*\} \arrow[r, "\tau_\epsilon"] & \mathrm{G}(\tilde{S_1}) = \{(h_i, h_i^2 + \epsilon), h_i \in \Re^*\} \end{tikzcd} \tag{1}$$

Transient model & non-regular points

The threshold zone, defined by two graph, and the bifurcation point (0, 0):

$$G(\gamma_i^+): \quad \gamma_i^+ = (\sqrt{-\psi_i}, \psi_i), \psi_i < 0; \quad G(\gamma_i^-): \quad \gamma_i^- = (\sqrt{-\psi_i}, \psi_i), \psi_i < 0 \tag{2}$$

Parallelism in the Risk Zone: compression & expansion

The threshold zone opens up space, like the basing of a river, and induces new notions of parallelism and transversality in the variable-parameter plane. New parallelism we defined using a δ compression, for $0 < \delta < 1$, denoted by c_δ, and δ expansion for δ greater than zero, denoted by e_δ, and given by:

Table A2: Transient Topological Mode. Morphological Changes and Key Information.

Slope function: $s_1 = h_i^2$	**Behaviour:** $v_1 = 1/3h_i^3$	**Unfolding:** $\mathcal{V}_1 = 1/3h_i^3 + \psi_i h_i$	
Singular set (Sv_1)	**Bifurcation set** (v_1)	**Outlier set** (Ov_1)	**Code marks on** $\{\psi_i\}$
$\frac{\partial \mathcal{V}_1}{\partial h_i} = h_i^2 + \psi_i = 0$	$\{\frac{\partial^2 \mathcal{V}_1}{\partial h_i^2} = 0\} \cap S_{\mathcal{V}_1}$	$\pi_{\psi_i} : p \in S_{\mathcal{V}_1} \mapsto \psi_i$	$(-\sqrt{-\psi_i}, \psi_i), \quad \psi_i < 0$
$\{(\mp\sqrt{-\psi_i}, \psi_i)\}$	{(0, 0)}	$h_{\psi_i} = \pm\sqrt{-\psi_i}$	$(0, \psi_i), \quad (\sqrt{-\psi_i}, \psi_i)$

$$c_\delta \gamma_i(\psi_i) = (\sqrt{-\psi_i \delta}, \psi_i); \quad e_\delta \gamma_i(\psi_i) = (\sqrt{-\psi_i + \delta}, \psi_i). \tag{3}$$

The Maximal Stratified Trajectory of Behaviour & Robust Connection

The plane (stratified by non-regular points) is lifted without non-regular points, denoted E^2, to its natural extension to the 3-space, $E^3 = E^2 \times \Re$. The natural projection of each point on its base allows to define a fibered manifold $M = (E^3, \tilde{\pi}_i, E^2)$, and a lifting of E^2 using the function v_1, i.e., a section η, of the bundle M: given by:

$$c^3\eta : (h_i, \psi_i) \in E^2 \mapsto (h_i, \psi_i), 1/3h_i^3 + \psi_i h_i, h_i^2 + \psi_i, 2, 0) \in C^{3,1}M). \tag{4}$$

We define an integrable differential system of order three, using a a regular submanifold $W \subset C^{(3,1)}M$ of the contact manifold of order 3 and dimension 1 of the bundle M. (Villarroel, 1995). Then, robustness connection can be defined, introduced, converting the behavioral trajectories,namely the ´R-pseudomanifolds´, where R is a parametric group defined by a maximal solution of a differential equation; the notion is related with G-pseudomanifold, introduced by R. W. Popper in the case of G being a compact Lie group acting on pseudomanifolds (Popper, 2000).

Capture Mode & Parallelism

Similarly, the parallelism in the 'capture mode' linked to 'people' is defined by virtue of the coexistence of two modes of behavior, analyzed in the 'capture mode' section.

$$\gamma_1^+(\psi_i) = (\psi, \sqrt{-4/27\psi_i^3}), \quad \gamma_1^-(\psi_i) = (\psi_i, -\sqrt{-4/27\psi_i^3}), \quad \psi_i < 0.$$

The depth transient and capture behavior modes are analyzed by decomposing the respective plane by singularities. The notions of parallelism and transversality modes of behavior depth transient and capture are more complex since as the depth increases the dimensions involved increase.

Appendix 2. Key Concepts

Critical Issues Analysis (CIA) is a multidisciplinary, systematic method for identifying, evaluating, and prioritizing issues that significantly influence the technological, economic, environmental, political, social, ethical, and spatial (TEEPSES) dimensions of a given context, particularly in relation to sustainable innovations. This approach integrates diverse inputs from creativity-based, interaction-based, evidence-based, and expertise-based methods to assess, in a structured manner, the potential impact and uncertainty of key drivers of change. By doing so, CIA offers a comprehensive framework for tackling complex, multifaceted challenges, enabling decision-makers to prioritize issues that demand immediate attention for effective management and strategic action.

SMART Foresight is a structured, participatory, forward-looking, and policy-driven process designed to actively engage key stakeholders in a comprehensive set of activities. These activities encompass Scoping, Mobilizing, Anticipating, Recommending, and Transforming (SMART) potential futures across technological, economic, environmental, political, social, and ethical (TEEPSE) dimensions.

Horizon Scanning (HS) is a structured, ongoing activity designed to "monitor, analyse, and position" (MAP) emerging and frontier issues that are relevant to policy, research, and strategic agendas. The issues identified through HS include new or emerging trends, policies, practices, stakeholders, services, products, technologies, behaviours, attitudes, as well as unexpected events (Wild Cards) and early indicators of change (Weak Signals).

Wild Cards are low-probability, high-impact events that are both unexpected and disruptive (e.g., the 9/11 attacks, environmental catastrophes, or technological failures). These events may also emerge through serendipitous discoveries in scientific research (e.g., Penicillin, Dynamite, Viagra, Graphene). Wild Cards can be classified into three categories: nature-related surprises, unintentional human-induced events, and intentional human-induced events. In foresight and forward-looking research, Wild Cards are increasingly recognized as critical factors for understanding future uncertainties.

Weak Signals are subtle, ambiguous indicators or "seeds of change" that offer early insights or "hints" about potential future developments, such as Wild Cards, emerging challenges, or opportunities. These signals are inherently subjective, often shaped by the mental frameworks and interpretations of individuals working with limited information on emerging trends, developments, or issues within a specific temporal and contextual setting. The "weakness" of these signals corresponds to the degree of uncertainty surrounding their interpretation, importance, and potential impacts over the short, medium, or long term. Weak Signals are often indistinct observations that serve as early warnings of possible future events with the potential to be highly transformative or "game-changing".

Scenarios are structured narratives that systematically explore potential future developments by analysing trends, uncertainties, and expert insights. Constructed through methodologies such as desk research, workshops, and computational modelling, scenarios generate plausible and internally consistent future states. They may integrate expert opinions or reflect the collective perspectives of stakeholder groups, facilitating the mapping of alternative futures and guiding decision-making by elucidating potential risks, opportunities, and pathways for action. Classic approaches to scenario development include the 2x2 Approach, which uses a matrix based on two critical drivers; the Archetype Approach, which examines scenarios characterized as "better than expected", "worse than expected", and "different than expected"; and the Success Scenarios Approach, which delineates a credible and desirable future. Additionally, semi-quantitative techniques that leverage artificial intelligence, data analytics, cross-impact analysis, and morphological modelling are gaining importance in scenario development, providing innovative frameworks for addressing complexity and uncertainty in strategic foresight and planning.

Action Roadmapping (AR) is a structured methodology for coordinating and executing actions at the strategic, tactical, and operational levels to achieve innovation objectives. It aligns stakeholders and systematically addresses four key dimensions: Context, People, Process, and Impact, each comprising ten critical aspects that drive sustainable innovation. At the strategic level, AR guides top decision-makers from government, industry, civil society, and academia (the quadruple helix) to establish momentum, build foresight, and mobilize resources. Tactical actions translate these objectives into specific interventions, such as funding programs and partnerships, equipping stakeholders with the necessary skills and resources. Operational actions, led by front-line actors like policymakers and researchers, focus on executing tasks that drive innovation and its diffusion. AR ultimately emphasizes long-term impact, fostering systemic transformation and ensuring sustainability across environmental, social, and economic dimensions. By integrating actions across all levels, AR supports a cohesive and adaptive approach to innovation (Popper, 2008).