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A HYBRID FRAMEWORK INTEGRATING COMPUTATIONAL THINKING INTO STRATEGIC FORESIGHT

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Abstract— *In the era of accelerated technological dislocation and complicating global interdependencies, organizations must anticipate rather than merely react to change. Strategic foresight has had a long time offering the conceptual and methodological foundations for projecting alternative futures; however, its qualitative orientation regularly shortens analytical perception and systemic validation. This article proposes a novel hybrid method that integrates computational thinking (CT) into strategic foresight methodology. Relying on the core CT concepts of decomposition, abstraction, algorithmic design, and iterative testing, the new methodology enhances traditional foresight methodologies by adding formal modeling and simulation-based investigations. This enables better mapping of interdependencies among systems, sensitivity analysis of main variables, and analysis of emergent behavior in future systems.*
To illustrate the conceptual validity of this approach, an exploratory case on the global energy transition is presented. This case demonstrates how CT enables the operationalization of esoteric foresight challenges through the facilitation of systemic mapping, computer simulation, and iterative refinement of strategic alternatives. The proposed framework is intended to augment the credibility and transferability of foresight outcomes while maximizing participatory engagement through model transparency.
The paper contributes to the new research on computational foresight in mediating qualitative study and quantitative simulation, offering both conceptual foundation and methodological stream for developing more scientific and robust foresight systems.

Keywords—*computational thinking, complex systems, decision-making, hybrid framework, scenario planning, strategic foresight.*

I. INTRODUCTION

The twenty-first century is marked by growing uncertainty, complexity, and interconnectedness of world systems. The accelerating speed of technological change, pressures from the environment, economic turmoil, and sociopolitical upheavals is remaking the context within which organizations and institutions have to survive. With the unstable conditions, possessing the ability to map potential futures as well as create adaptive strategies is the signature ability of adaptive governance and competitive sustainability. As a result, strategic foresight has once again re-appeared as a policy and a managerial tool, offering organized processes for forecasting possible, probable, and preferable futures.

Strategic foresight is literally a structured and participative process for sensing early warnings of emergence, making sense of patterns of change, and crafting robust strategic reactions in conditions of deep uncertainty. It incorporates a set of qualitative and quantitative techniques—such as scenario planning, horizon scanning, Delphi surveys, and system dynamics modeling—that allow decision-makers to overcome short-term limitation in thinking and imagine long-term implications. Foresight is always methodologically diverse, but fundamentally it is about learning from the future in order to steer action in the here and now.

As decision contexts grow more complicated, however, foresight practices are faced with mounting methodological and epistemological hurdles. Traditional foresight techniques rely heavily on qualitative methods placing strong premiums on expert judgment and creative search. Though very useful for generating discussion, these procedures lack formal analytical design, lucidity, and replicability. The discursive and narrative character of the majority of foresight exercises makes them difficult to evaluate, compare, or replicate, thereby limiting their credibility and institutional acceptability in decision-making contexts that are evidence-based.

An attempt has been made by practitioners and researchers in recent years to go beyond these limitations by incorporating more analytical and data-intensive methods into foresight. System dynamics, agent modeling, network analysis, and machine learning have been employed as methods of enhancing the rigor and predictive capability of foresight research. Although these methods enrich the foresight toolbox, they are more often introduced as standalone tools or technical add-ons rather than as foundational cognitive models. There remains a conceptual chasm between the humanistic, intuitive nature of foresight and the mathematical, computational nature of modeling.

This disintegration points to a fundamental literature gap : while foresight increasingly acknowledges the merit of complexity and information, it doesn't yet fully enjoy a transparent theoretical framework incorporating computational thinking as a whole throughout the entire foresight process. In short, foresight not only needs computational tools but also a computational way of thinking. The emerging research area of Computational Thinking (CT) offers a possible paradigm to fill this gap. Formulated by Wing (2006) and expanded upon by Shute et al. (2017) and Grover and Pea (2013), CT is a set of procedural and cognitive skills that enable one to express problems and solutions in representation forms that can be carried out by computational machines. CT involves four principles—decomposition, abstraction, algorithmic design, and iterative simulation—and these four collectively give rise to systematic reasoning about dynamic, complex systems.

Using computational thinking in strategic foresight has a number of potential benefits. First, decomposition of complex socio-technical systems into tractable fragments, showing causal structures and interdependencies. Second, abstraction allows one to identify generalizable patterns and structures in situations. Third, algorithmic design provides a logic to translate qualitative stories of foresight into formal models that are able to be simulated, tested, and iteratively refined. Ultimately, iterative simulation facilitates adaptive learning through ongoing feedback, which adds to the robustness of strategic options. Taken together, these mechanisms make foresight a dynamic, computationally supported process of anticipatory governance.

Research Gap and Objective.

As much as there has been growing interest in applying computational tools, so far, relatively few studies have explored systematically how computational thinking can reframe the epistemological and methodological foundation of foresight in itself. There is no coherent framework in current literature combining CT as a core design principle and not an auxiliary tool. Filling this conceptual loop entails refocusing foresight as a hybrid system including qualitative interpretation and collective intelligence complemented by formal analytical modeling and computational experimentation.

Purpose and Contribution.

The goal of this paper is to develop and conceptually validate a hybrid foresight framework that embeds computational thinking principles throughout the entire cycle of the foresight process. The Hybrid Foresight–CT Framework, as envisioned, transforms foresight from a linear process of sense-making, modeling, simulation, and learning into an iterative loop. Conceptually, it adds to the emerging field of computational foresight by introducing CT as a cognitive bridge between the creative and analytical dimensions of future studies. In application, it gives policymakers, strategists, and researchers a unifying method to craft and test strategies in complex, data-rich, and risky systems.

Through the definition of foresight as social learning process as well as computationally augmented system, this study presents an integrative vision of how anticipatory intelligence can unfold in the complexity era.

II. LITERATURE REVIEW

A. Strategic Foresight as a Foundation for Anticipatory Governance

Strategic foresight is now an essential process in managing uncertainty and complexity in modern socio-economic systems. In the midst of turbulence, volatility, and nonlinearity of the present times, foresight enables organizations and governments to expand their time horizon and foresee long-term change. As the systematic investigation of possible, probable, and preferable futures (Hines & Bishop, 2013), foresight seeks to convert uncertainty into strategic learning and adaptive choice. It provides a rigorous method to find emerging signals, constructing alternative futures, and crafting robust strategies that can execute multiple futures.

It owes its intellectual roots to the early post-war futures research of the 1950s and 1960s. Bertrand de Jouvenel (1967), Gaston Berger (1957), and Herman Kahn (1962) were the first to argue that the future needed to be addressed as an area of rigorous research, and not as fanciful dreaming. Berger's foresight put into sharp relief the idea of "seeing far, wide, and deep" (regarder loin, large et profond), establishing a philosophical foundation for systematic forecasting. Later, Jouvenel (1967) emphasized that futures thinking must be made room for human values and ethical thinking. On these early premises, Godet (1991 ; 2001) formalized La Prospective as a methodological science grounded in systems thinking, stakeholder participation, and strategic scenario planning.

During the 1980s and 1990s, foresight evolved from being essentially a technological preoccupation—e.g., technology forecasting and Delphi methods—to a more socio-political and organizational use. These authors such as Slaughter (1990 ; 1996), Masini (1993), and Glenn (1994 ; 2009) took the discipline a step forward by outlining participatory and normative dimensions, accepting that futures thinking must account for values, power relations, and cultural environments. Voros (2017) later formalized this evolution in his Generic Foresight Process Framework (GFPF) by conceptualizing foresight as a cyclical process of environmental scanning, sense-making, visioning, and strategy formulation.

Strategic foresight, in its modern incarnation, has become not only a research paradigm but also a professional practice for anticipatory governance and innovation. It is being applied in a variety of contexts such as sustainability transitions (Miller, 2018), urban resilience (Eriksson & Weber, 2008), corporate innovation (Rohrbeck & Kum, 2018), and policy design (Cuhls, 2020). Its fundamental purpose is to increase the capacity of decision systems to anticipate, learn, and adapt within more complex and faster-changing environments.

Strategic foresight has also been recognized as an institutional capability underpinning anticipatory governance—described as the systematic use of foresight to advise public policy and collective action (Boyd et al., 2015 ; Poli, 2019). Anticipatory governance is a forward-looking style that integrates foresight, collaboration, and learning into governance practices, allowing institutions to prepare for many contingencies ahead of time instead of reacting to crises after they have developed. This paradigm change—toward preventive over responsive policy-making—is a drastic change in the handling of complexity and uncertainty by governments, companies, and global institutions.

Despite intellectual maturation and practical applicability, foresight remains methodologically constrained to restrict its use in evidence-based policy-making. Its most common criticisms are on the grounds of subjectivity, low reproducibility, and empirical invalidation challenges (van der Heijden, 2005 ; Börjeson et al., 2006). Few foresight exercises remain dependent on expert judgment and facilitation skill and thus hard to replicate or compare. It is this requirement that demands new methodological innovation, which combines foresight's participation and creativity with more open analytical procedures and systematic testing. That transformation involves initiating computation and system methods aligned with bridging qualitative understanding and quantitative modeling—a move the present study has set out to conceptualize.

B. Methodological Limitations of Traditional Foresight

Historical approaches to foresight—such as scenario planning, Delphi analysis, and horizon scanning—rely on qualitative interpretation and subjective opinion. Even though these techniques promote group thought and innovation, they are typically criticized for lack of scientific rigor, replicability, and transparency (van der Heijden, 2005 ; Börjeson et al., 2006). Since they are founded in subjective opinion, they may introduce variation between exercises, depending on facilitator skill and attendee diversity.

As decision environments become more data-rich and interdependent, such qualitative approaches struggle to cope with complex and dynamic information. By way of reaction, recent research has sought to develop foresight through concepts from complexity science and systems theory. Sytnik and Proskuryakova (2024) argue that foresight should evolve into models capable of understanding "hard-to-predict" phenomena based on chaos theory and principles of self-organization. This echoes the growing realization of the importance of futures research moving beyond narrative logic in order to address dynamic, multi-level systems.

However, these efforts are fragmented and largely technical. The majority of foresight studies adopt computational or data-heavy tools at discrete stages—e.g., horizon scanning or impact analysis—at the cost of their incorporation into an overarching theoretical framework. Foresight's cognitive foundation thus remains resoundingly qualitative and interpretive (Rohrbeck & Kum, 2018).

C. Rise of Computational Approaches to Foresight

Foresight studies have, in recent years, been increasingly attracted to computational and quantitative approaches to transcend these methodological limitations. System dynamics has been used to model causal feedback loops and test policy interventions (Sterman, 2000 ; Börjeson et al., 2006). Agent-based modeling (ABM) allows simulation of complex interactions and emergent behavior in socio-technical systems (Epstein, 2006). Moreover, data analytics and machine learning have been applied in trend detection and scenario quantification (Könnölä & Haegeman, 2012 ; Rohrbeck et al., 2015).

Recent contributions extend these computational approaches by drawing on artificial intelligence and big data analytics. Cheng and Sul (2023) built future scenarios for smart home services from social media data, demonstrating how evidence of the digital at scale can support horizon scanning.Barbosa et al. (2024) used AI-driven event extraction to identify emerging themes in foresight research, demonstrating how computerized systems can perform aspects of the scenario-building process. Similarly, Schühly et al. (2023) explored scenario-based foresight during the age of AI, noting digital technologies can augment but not replace the interpretive and participatory nature of foresight.

These studies collectively confirm computation's role in enhancing foresight's analytic potential and scalability. They also reveal a basic limitation : the majority of computational integrations remain tool-oriented and do not yet reflect an overarching cognitive framework for combining human and machine reasoning. The issue is therefore not merely technological but epistemological—how to conceptualize foresight itself as a computationally supported learning process rather than as a sequence of discrete tools.

D. Computational Thinking as a Conceptual Bridge

Computational Thinking (CT), originally introduced by Wing (2006), provides a cognitive integrating basis for the integration of computation into human thought processes. CT involves four principles that are interrelated: decomposition (breaking up difficult problems into components), abstraction (identifying relevant structure and patterns), algorithmic design (designing logical procedures), and iterative simulation (testing and refining solutions) (Grover & Pea, 2013 ; Shute et al., 2017).

Applied to foresight, CT can reframe it as a systematic and reflexive process of decomposition, modeling, and learning. CT enables the formal representation of complex systems with interpretive flexibility for human agents. In this sense, it transcends the qualitative–quantitative divide that has long polarized foresight methods.

The complementarity of computational and human-centered approaches is also stressed in recent publications. Marshall, Wilkins, and Bennett (2023) have suggested Story Thinking as a narrative methodology that coexists with data-driven foresight, attesting to the need for a synergy between creativity and computation. Similarly, Sytnik and Proskuryakova (2024) and Schühly et al. (2023) promote hybrid foresight systems that couple analytical modeling with participatory engagement to ensure rigor as well as inclusivity. Collectively, these advances suggest that computational thinking is perhaps the conceptual bridge for this hybridization.

E. Comparative Analysis of Foresight Approaches

To put the proposed Hybrid Foresight–CT Framework into the perspective of existing methods, Table 1 summarizes the defining characteristics, limitations, and the specific contributions made by CT integration.

Table I

Comparative Overview of Foresight Approaches and the Added Value of Computational Thinking

APPROACH	KEY FEATURES	MAIN LIMITATIONS	ADDED VALUE OF CT INTEGRATION
SCENARIO PLANNING	Exploratory narratives and participatory visioning (Hines & Bishop, 2013).	Subjective interpretation, lack of validation.	Enables formal modeling, consistency checks, and feedback loops.
SYSTEM DYNAMICS	Quantitative modeling of causal feedbacks (Sterman, 2000)	Limited stakeholder engagement, data dependency	Enhances abstraction and decomposition of complex systems
AGENT-BASED MODELING	Simulation of agent interactions and emergent behaviors (Epstein, 2006)	Complex calibration and parameterization	Supports iterative testing and multi-scenario experimentation
HORIZON SCANNING	Identification of weak signals and emerging trends (Voros, 2017)	Fragmented data interpretation	Enables automated data classification and pattern recognition through AI
HYBRID FORESIGHT–CT FRAMEWORK (PROPOSED)	Integration of CT principles across foresight phases	Conceptual validation stage (requires empirical testing)	Combines qualitative creativity with computational rigor and adaptive learning.

F. Synthesis and Identified Gap

The literature demonstrates an increasing convergence of computational and foresight sciences, particularly in their shared quest to understand and cope with complexity. For all this progress, however, there remains a conceptual gap regarding how computation is to be embedded in the cognitive architecture of foresight. Existing research largely focuses on using computational tools for improved efficiency but seldom explores the epistemological implications of computational reasoning for foresight practice.

This conceptual gulf argues the need for an integrative framework that positions computational thinking not merely as a toolkit, but as the actual logic of foresight design. The Hybrid Foresight–CT Framework presented in this paper responds to this challenge by embedding CT principles throughout the foresight process, from horizon scanning to strategy testing. It aims at closing the gap between creativity by humans and formalization by computers, thereby contributing to a more systematic, explicit, and reactive foresight paradigm.

III. PROPOSED HYBRID FRAMEWORK

A. Introduction to the Hybrid Foresight–CT Framework

The Hybrid Foresight–CT Framework presented herein integrates computational thinking (CT) as both an intellectual and operational foundation of the strategic foresight process in its entirety. Rather than treating computational tools as autonomous appliances, the framework integrates the logic of computation—decomposition, abstraction, algorithmic design, and iterative simulation—into the foresight cycle itself. The result is a systemic and adaptive architecture with which to address complex, data-rich, and uncertain environments.

This hybridization aims to transcend the dichotomy between the qualitative nature of foresight creativity and the analytical strength of computational modeling. Foresight is cast as a feedback-informed, iterative, and purifying learning process. The framework follows an input–process–output logic: environmental signals (inputs) are deconstructed and computationally modeled based on CT principles (process) to lead to adaptive strategies and tested intelligence (outputs).

Grounded in systems thinking (Senge, 1990 ; Meadows, 2008) and design science research (Hevner & Gregor, 2013), the framework proposes an iterative, reflexive design that combines participatory sense-making with computational formalization. It thus addresses the emerging discourse on computational foresight (Liu et al., 2023 ; Kim et al., 2024) with a methodological pathway to more open, replicable, and data-driven futures work.

Table II

Key Computational Thinking Principles Embedded in the Framework

PRINCIPLE	DEFINITION IN CT CONTEXT	APPLICATION TO FORESIGHT
DECOMPOSITION	Breaking down complex systems into manageable subcomponents.	Segmenting the foresight domain into key drivers, variables, and actors.
ABSTRACTION	Focusing on essential patterns and relationships while ignoring noise.	Simplifying complex interactions to identify key system archetypes and feedbacks.
ALGORITHMIC DESIGN	Developing structured procedures for problem-solving.	Formalizing scenario construction and causal modeling logic.
ITERATIVE SIMULATION	Model testing and refinement repeatedly to enhance precision.	Using computational models for simulating alternative futures and testing strategic alternatives.

These principles collectively ensure that foresight evolves from an interpretive and narrative process to a computationally enabled system of strategic learning.

B. Structure and Phases of the Framework

The framework consists of five mutually dependent phases, representing a comprehensive cycle of foresight with computational thinking principles. Each phase incorporates qualitative and quantitative reasoning to support iterative feedback between exploration and validation.

Phase 1 : Environmental Decomposition and Horizon Scanning

This first step focuses on scanning, decomposing, and structuring the subsequent environment of foresight. It leverages CT's rule of decomposition and involves the following: delimiting key system boundaries, variables, and interactions defining the foresight domain. Horizon scanning routines (Cuhls, 2020 ; Voros, 2017) are complemented with computational techniques like text mining, network mapping, and trend clustering to detect weak signals and nascent patterns.

Output : A framework system map defining the key drivers, uncertainties, and interdependencies that influence the future environment.

Phase 2 : Abstraction and Scenario Structuring

At this stage, CT's abstraction principle directs the reduction of complex information to higher-order conceptual models. It seeks to identify major system dynamics without over-simplifying the actual world. Phase 1 driver identified drivers are categorized into thematic areas, and their relationships are traced with influence matrices or causal loop diagrams (Godet, 2001).

Output : A set of abstracted system models and scenario architectures representing substitute future configurations.

Phase 3 : Algorithmic Design of Foresight Models

Here, the algorithmic design principle makes foresight reasoning an explicit function of formal rules and logical sequences. Every scenario is translated into an algorithmic process specifying relationships between variables, actors, and events. This translation allows the use of computational modeling tools—like system dynamics or agent-based simulations—to play out the internal consistency of scenarios (Sterman, 2000 ; Epstein, 2006).

Output : Algorithmic foresight models that are testable and can be simulated for consistency.

Phase 4 : Iterative Simulation and Learning

Within this phase is contained CT's iterative simulation principle. Models developed in Phase 3 are executed to simulate various futures, stress-test strategic options, and track emergent patterns. Tuning is enabled through iteration: parameters and assumptions are adjusted on the basis of results seen and the views of experts (Ramos, 2012). This computer-based experimentation supports evidence-based foresight while enabling interpretive freedom to stakeholders.

Output : A validated set of simulated scenarios and strategic knowledge with uncertainty ranges measured.

Phase 5 : Integration, Strategy Design, and Feedback

The final stage connects computational results back to participatory foresight practice. Shared interpretation of simulation outcomes is utilized to develop resilient and adaptive strategies. This incorporation aligns with the feedback principle of anticipatory systems (Rosen, 1985 ; Poli, 2019), ensuring learning through simulation is fed back to subsequent foresight cycles. The approach is recursive in nature—each step increases model precision as well as anticipatory ability among participants.

Outcome: Combine strategic guidance and an ongoing learning feedback loop for continuous improvement of foresight.

C. Framework Visualization and Conceptual Logic

The Hybrid Foresight–CT Framework can be visualized as a circular and adaptive system integrating human and computational reasoning within the same iterative process. Each stage of the framework is constructed upon the outputs of the preceding stage, but also exists in dynamic feedback loops repeatedly addressing the previous steps. The process is representative of the ideals of learning organizations (Senge, 1990) and anticipatory systems (Rosen, 1985), where knowledge evolves through recursive feedback and reflexive adaptation.

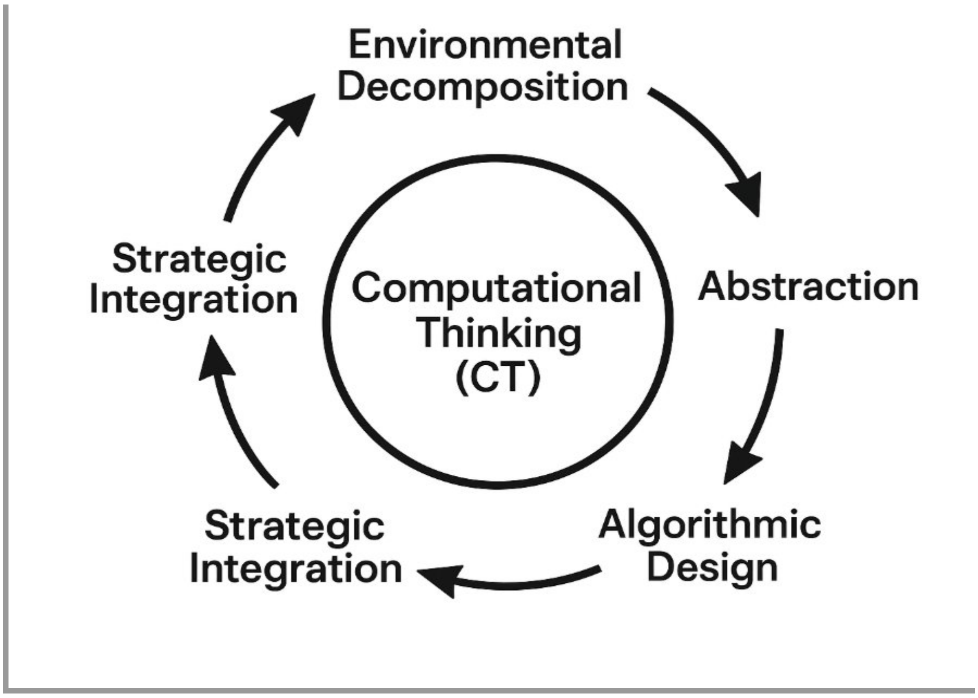

Fig 1. Framework Visualization And Conceptual Logic

This configuration illustrates that foresight in this case is neither static nor linear but a cycle of exploration, modeling, validation, and learning with no terminus. Feedback during the Strategic Integration phase is cycled back to the Environmental Decomposition stage so adaptive scanning and model updating are performed when new data, trends, or strategic viewpoints become present.

Conceptual thinking in this visualization illustrates three characteristics of systems:

1. **Recursivity and Learning** – As the iteration proceeds, model accuracy and the foresight team's conceptualization of the system increase, building cumulative knowledge rather than one-result solutions.
2. **Interoperability between Qualitative and Quantitative Dimensions** – The approach represents the merging of narrative scenario construction and computational modeling, showing how human interpretation and algorithmic reasoning interact throughout the cycle.
3. **Dynamic Adaptability** – By using feedback mechanisms, the model captures the dynamics of complex adaptive systems (Holland, 1995 ; Meadows, 2008), allowing foresight processes to adjust as conditions in the outside world evolve.

The Hybrid Foresight–CT Framework thus redeployes foresight practice from linear planning activity to computational-based forward-looking system—capable of simulating, testing, and optimizing strategic trajectories in real time.

D. Theoretical and Practical Implications

Conceptually discussed, this design contributes to foresight studies by positioning computational thinking as a meta-methodology—a mental framework that introduces analytic rigor without sacrificing participatory creativity. It follows recent calls for the practical application of artificial intelligence, systems modeling, and participatory methods in foresight (Sytnik & Proskuryakova, 2024 ; Liu et al., 2023).

In actuality, the framework offers practitioners of foresight and policymakers a methodical approach to addressing the complexities of the future. It enables scenario developers to incorporate formal testing in addition to intuition, increasing the validity, openness, and transferability of foresight results.

IV. RESEARCH METHODOLOGY

A. Research Design and Rationale

This study adopts a conceptual design research approach (Gregor & Hevner, 2013 ; Hevner & Chatterjee, 2010) aiming to design and theoretically defend a hybrid foresight method with the addition of the principles of Computational Thinking (CT) to strategic foresight practice. Conceptual design research is suitable in the instance of underdeveloped or emerging phenomena where theory building by developing an artifact and rational argumentation rather than empirical hypothesis testing is the goal (March & Smith, 1995).

The research process was constructive in character, following the steps: (1) mapping methodological deficits in foresight literature; (2) conceptualizing CT principles as cognitive benefactors of foresight; (3) integration into a general framework; and (4) theoretical appraisal by coherence, internal consistency, and analytical generalization.

This conceptual-oriented approach is in line with the exploratory–illustrative school of foresight studies (Slaughter, 1990 ; Ramos, 2012), where conceptual models are developed as working prototypes for methodological innovation before being used empirically. The research in this case thus does not aim to empirical generalization but seeks to provide a systematic and transferable conceptual foundation.

B. Framework Operationalization: Integrating Foresight Tools and CT Contributions

Operationalization of the Hybrid Foresight–CT Framework involves mapping traditional foresight process to corresponding CT principles and contributions. Figure 2 below illustrates such integration as a two-layer effort : the upper layer is made up of classic foresight tools, while the lower layer indicates how every stage is complemented by CT principles through formalization, decomposition, and iterative simulation.

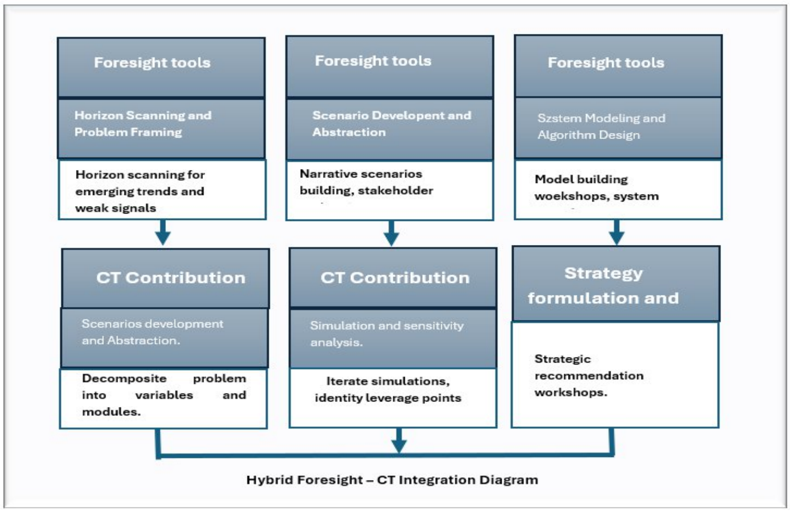

Fig 1. Foresight–CT Integration Diagram

The diagram shows the functional relationship of traditional foresight tools with computational thinking (CT) inputs along the foresight process. The corresponding CT principles of decomposition, abstraction, algorithmic design, and iterative simulation support each of the foresight stages : Horizon Scanning and Problem Framing ; Scenario Development and Abstraction ; System Modeling and Algorithm Design ; and Strategic Formulation and Adaptive Planning. The combined illustration demonstrates how CT serves as a cognitive link that improves the analytical precision, model openness, and adaptability of foresight.

C. Data and Validation Approach

Because of its conceptual nature, analytical and theoretical validation rather than empirical testing was applied in the research. Validation was accomplished through three complementary criteria characteristic for design science and conceptual modeling (Gregor & Hevner, 2013 ; Venable et al., 2016) :

1. **Construct Validity** – Conceptual consistency was provided by aligning the framework structure and definitions with existing foresight and CT theory.
2. **Internal Coherence** – Logical relations between foresight phases and CT principles were verified to ensure each CT contribution facilitates the intended foresight function.
3. **Analytical Generalization** – The hybrid model was tested for possible use in a variety of foresight contexts (public policy, innovation, sustainability transitions).

To add conceptual rigour, the model was also tested against contemporary computational foresight applications (Cheng & Sul, 2023 ; Barbosa et al., 2024 ; Sytnik & Proskuryakova, 2024), confirming its relevance to emerging AI-supported foresight methods.

D. Summary of Methodological Approach

The Hybrid Foresight–CT Framework is thus a conceptually verified methodological contribution crafted through iterative synthesis and theoretical alignment. Figure 2 operationalizes this hybridization visually, showing how foresight and computation can co-evolve as complementary processes.

This methodological design paves the way for empirical testing in real-world strategic contexts—in public policy foresight, energy transition planning, and innovation ecosystems, for instance—where the framework proposed herein can be applied, simulated, and further optimized.

E. Illustrative Case Study and Conceptual Modeling

To demonstrate the possible operational use of the proposed Hybrid Foresight–CT Framework, an illustrative conceptual model was developed in the energy transition and sustainability policy area. This was selected because it is a complex adaptive system with multi-actor interdependencies, high uncertainty, and competing strategic goals—conditions best suited to applying foresight methods supported by computational reasoning (Berkhout, 2006 ; Miller, 2018).

In this thought diagram, the foresight process begins with horizon scanning for weak signals on renewable technology, regulatory transformation, and behavioral change. By employing CT's decomposition principle, the signals were decomposed into clusters of drivers (technological, economic, social, and policy) to set the stage for a systemic influence map. The abstraction phase then translated this complex network of variables into condensed-to-essential-facets scenario types that represent potential paths of energy transition (e.g., centralized vs. decentralized innovation regimes).

Subsequently, algorithmic design was called upon to translate the causal relationships between the key drivers into a formal causal model to facilitate preliminary simulation and sensitivity analysis. Despite there being no empirical implementation, this conceptual modeling exercise shows how computational foresight can bridge the gap between qualitative scenario narration and quantitative system investigation. The process also demonstrates foresight's transition from a deliberative process to a dynamic learning model capable of testing assumptions and visualizing systemic implications.

This outstanding case confirms that the hybrid model can convince researchers and practitioners to create foresight activities that are openly analytical, participatory, and responsive. Potential future empirical applications may involve multi-stakeholder workshops or simulation policy platforms, affirming the model's practical usability.

F. Shortcomings and Limitations of the Approach

Although the Hybrid Foresight–CT Framework is a promising conceptual innovation, there are certain shortcomings that have to be identified.

To begin with, the current validation of the framework is conceptual rather than empirical. Its applicability in different sectors or governance areas has yet to be systematically tried. Its future studies should therefore perform pilot applications under participatory foresight workshops coupled with computational simulations to validate its operational resilience.

Second, the effectiveness of CT principles relies on technical expertise and cognitive literacy that may not always be accessible to foresight practitioners. This could present barriers to adoption, particularly for organizations without in-house modeling expertise. Capacity development and interdisciplinary collaboration will be essential to enable effective implementation.

Third, as computation enhances analysis, it may unintentionally harbor over-formalization risks—flattens social and behavioral complexity's nuances in a way reducing participatory richness (Poli, 2019). It remains a methodological challenge to strike a balance between computational precision and human interpretation.

Finally, the hybrid approach depends on being able to access quality data and appropriate modeling tools that may be restricted in policy environments or developing regions. Future studies should explore lower complexity or open-source model forms to further promote openness and equity in computer-aided foresight use.

Lastly, the study limitations are not defects in the framework per se, but opportunities for coming of age methodologically. As foresight scholarship evolves further towards further integration with data science and systems modeling, the Hybrid Foresight–CT Framework can serve as a first scaffold to be iteratively refined by empirical means.

V. ILLUSTRATIVE CASE STUDY : THE ENERGY TRANSITION

To illustrate the practical application of our hybrid framework, we propose a conceptual case study of energy transition. It is currently the most urgent challenge facing decarbonization in the energy sector, characterized by systemic complexity, high-tech uncertainty, and rising geopolitical tensions (Barnabè et al. 2022). The challenge provides, therefore, an optimal setting to test the robustness and usability of a framework that combines computational thinking with strategic foresight.

A. Scenario Development

Initially, various possible futures were created via participatory workshops involving industry players, policymakers, and energy policy analysts. Some of these include an "Accelerated Decarbonization" future based on a mass uptake of renewable sources of energy and technological advancement at a rapid rate ; a "Fragmented Transition" future, which is linked to asymmetrical uptake of green technologies and extensive regional heterogeneity; and a "Technological Stagnation" future, whose technological progress is hindered by economic and political constraints.

B. Computational Modeling

After creating the narratives, the circumstances were translated into computer models, according to the third step of the approach. We utilized a combination of agent-based modeling and dynamic system modeling, so that we could include both global energy flows and adaptive behaviors by the stakeholders (governments, consumers, investors). Computational reasoning required breaking the systems into modular sub-models (e.g., generation of electricity, final consumption, subsidies, technology spillover effects) and then abstracting key interactions to build a solid formal model.

C. Simulation and Results

The simulations revealed several points of criticality. For instance, in the "Fragmented Transition" case, key vulnerabilities emerged, including over-reliance on certain technologies and increased stranded asset risks. Sensitivity analysis highlighted the significance of financial incentive policies and flexibility infrastructure (smart grids, energy storage) as system drivers.

In addition, new and unexpected behaviors were found in some cases, excessive subsidies had the counterintuitive impact of slowing down private investments through the creation of a long delay before additional subsidies were received. This type of knowledge, difficult to access through conventional narrative analysis, is made available because of the simulation and iteration capacities provided by CT.

D. Strategic Implications

These results have allowed one to design adaptive strategies, opting for a combination of sequential incentives and technology innovation support directly, in addition to mechanisms for constant monitoring. Recommendations proposed are well-defined trigger levels, which allow readjusting actions in relation to fluctuations in key indicators (technology adoption, carbon prices, geopolitical dependence).

By the hybrid method, the transition of energy is thus not perceived as a linear trend, but as a process in development requiring ongoing adaptability in the face of uncertainty and change, based on foresight as well as computation for exploration.

VI. DISCUSSION AND AMPLICATIONS

The findings of conceptual application of the Hybrid Foresight–CT Framework indicate the growing potential for integrating computational reasoning with strategic foresight in confronting challenging and uncertain policy spaces. This section sets out the theory, practice, and governance implications of the findings for theory, placing the framework within broader academic controversies surrounding anticipatory systems and methodological novelty.

A. Theoretical Implications

In theory, the hybrid method contributes to improving foresight further towards a constantly changing computational epistemology of anticipation from a qualitative focus. Traditional foresight methods—though rooted in participatory and interpretive knowledge—are typically criticized for their low reproducibility and testability empirically (Börjeson et al., 2006 ; van der Heijden, 2005).

By embedding Computational Thinking (CT) ideas such as decomposition, abstraction, and algorithmic design in the process of foresight, the new framework creates a meta-methodological connection between narrative exploration and quantitative modeling. This is aligned with recent literature on computational foresight (Sytnik & Proskuryakova, 2024 ; Cheng & Sul, 2023) and supports the idea of foresight as an adaptive learning system (Ramos, 2012).

Besides, the hybrid methodology extends the epistemological foundation of foresight by introducing a dual-cognition framework: human foresight provides interpretative imagination and sense-making and computational reasoning adds formal structure and analytical discipline. The complementarity increases the validity of foresight as both science and strategy with the capacity for closing the exploration-validation gap.

B. Methodological Contributions

Methodologically, the Hybrid Foresight–CT Framework is a systematic innovation in foresight design. It offers a step-by-step procedure integrating CT principles into all steps of foresight, from environmental scanning until scenario testing, thus turning the foresight cycle into a recursive data process.

Such a design responds to the demands for increased methodological transparency, replicability, and analytical consistency in foresight studies (Rohrbeck & Kum, 2018 ; Cuhls, 2020). Computational modeling—especially agent-based and system dynamics models—shows how foresight outputs can be tested, compared, and iteratively optimized.

At a practical level, the method provides a methodological roadmap for researchers and practitioners seeking to integrate qualitative foresight with quantitative testing. The application of CT as an intellectual framework ensures that foresight is human-scale but technically adequate—capable of holding uncertainty without simplifying complexity to reductionist games.

C. Practical and Governance Implications

The hybrid method also has significant practical consequences for policy decision-making and governance. With computation and foresight, it becomes possible to create adaptive strategies that continuously update themselves in response to changing environments—beyond single-instance planning exercises to anticipatory systems of governance (Boyd et al., 2015 ; Poli, 2019).

In the case of the energy transition, the hybrid model demonstrated how computational foresight was applied in designing trigger-based adaptive policies that can adjust incentives and rules based on real-time indicators. These types of strategies are becoming increasingly significant in domains where uncertainty, feedback loops, and nonlinear dynamics dominate policy effects.

Furthermore, the model encourages a shift in organizational foresight culture—away from passive watching toward active experimentation—where testing scenarios and simulation are part of strategic design. For governments and companies, the application of computational foresight would most probably enhance transparency, accountability, and evidence-based policy-making.

D. Reflexive Insights and Future Directions

While the study provides an intriguing conceptual breakthrough, it also invites greater reflection on the philosophical and practical paradoxes of hybrid foresight. Formalization in terms of computation risks limiting interpretative variation unless the researcher is mindful of a balance being maintained between analytical form and imaginative vision so that algorithmic calculation is kept subordinate to human judgment and ethical reflection (Poli, 2019).

Future research must focus on empirical testing of the framework using its implementation within real-world policy situations, leveraging participatory modeling and policy labs as labs. Comparative studies can explore how the hybrid approach operates across different policy domains (e.g., urban planning, climate adaptation, digital governance). Incorporating AI-driven pattern recognition or machine learning into the cycle of foresight can potentially enhance horizon scanning and scenario development capabilities even further.

Finally, this hybrid approach repositions foresight as a computationally enabled anticipatory science—a discipline that can not only envision futures but experimentally enter into them.

VII. CONCLUSIONS

This article has developed and conceptually tested a Hybrid Foresight–CT Framework that integrates principles of Computational Thinking (CT) into the strategic foresight process. By integrating qualitative anticipation with computational reasoning, the research contributes to the ongoing evolution of foresight as narratively and participatory-oriented exercise towards a computationally enabled anticipatory science.

The framework advances foresight research in the following three areas : Theoretically, it positions CT as a meta-methodology that bridges the epistemological gap between exploratory scenario work and analytical modeling. Methodologically, it offers a structured, iterative process wherein each foresight phase is informed by CT principles—decomposition, abstraction, algorithmic design, and iterative simulation—thus strengthening analytical rigor, transparency, and reproducibility. Practically, it illustrates through an exemplary case study in the energy transition sector how hybrid foresight can inform adaptive policy making, build strategic resilience, and unveil systemic feedbacks normally hidden in qualitative analysis.

In addition to its explicit contribution, the research also emphasizes the importance of empirical testing and participatory validation of computational foresight models. Its application in real practice—i.e., sustainability transitions, innovation policy, or digitalization—will enable researchers to test its performance, flexibility, and usability in different fields.

In short, the Hybrid Foresight–CT Framework redefines foresight as a learning system, which can be optimally enhanced through the fusion of human creativities and computational intelligence. It demands a new research and practice wave according to which thinking about the future is no longer only a question of imagining it, but also of simulating, experimenting, and adapting to it in real time.

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