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Collaborative Foresight in the Age of AI: A Framework for Evolving Human-AI Dynamics in Strategic Decision-Making and Futures Research

by
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Abstract

This study explores the transformative potential of AI in futures research and strategic decision-making. Addressing the challenge of decision myopia in the innovation economy, it proposes the Foresight-Driven Innovation Framework as a novel theoretical contribution for enhancing strategic planning through human-AI collaboration. This exploratory research investigates the central question: "To what extent can a multi-agent AI system, operating within the proposed FDI framework, augment human capabilities in the process of strategic foresight and long-term planning?" The study provides an overview of current futures research practices, delves into relevant methodologies, and examines the evolution of human decision-making in this context. It introduces a collaborative foresight system based on the FDI Framework, outlining a technical architecture for data processing, scenario exploration, and knowledge management, while considering agentic AI and multimodal engagement to address information overload. Ethical considerations crucial for human-AI collaboration, such as transparency, explainability, and maintaining human agency, are thoroughly addressed. The study concludes by exploring future directions and suggesting a pilot implementation for the proposed FDI framework to empirically validate its potential in shaping more sustainable and desirable futures. This study contributes to the growing field of AI-enhanced strategic foresight, offering insights into the synergies between human expertise and artificial intelligence in navigating complex, long-term challenges through a newly proposed framework and a pathway for future empirical investigation.

Keywords: Artificial Intelligence, futures research, strategic decision-Making, collaborative foresight, scenario planning, decision myopia, long-term planning, AI ethics, multimodal engagement

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Introduction

The rapid advancements in artificial intelligence (AI) are poised to revolutionize a wide range of sectors, including strategic decision-making and futures research. Organizations and policymakers today face unprecedented levels of uncertainty and complexity when making long-term decisions in a fast-paced and interconnected world. These challenges are further compounded by the pressures of the innovation economy which, characterized by intense competition and a focus on immediate results, can lead to *decision myopia* and a disconnect between strategic planning and long-term impact. This short-term thinking can result in suboptimal outcomes and missed opportunities for addressing complex, long-term societal challenges. This study examines the transformative potential of AI in augmenting human abilities within futures research and strategic decision-making.

This exploratory study investigates the central question: To what extent can a multi-agent AI system, operating within the proposed FDI framework, augment human capabilities in the process of strategic foresight and long-term planning? To this end, the study analyzes the prevailing challenges within the innovation economy, including decision myopia, and the inherent limitations of human decision-making. A Foresight-Driven Innovation Framework is proposed, with the purpose of aligning long-term value and societal resilience to innovation efforts. This AI-augmented framework uses collaborative foresight to enhance strategic planning processes in innovation. Its key component is the Foresight Scope, which is a visual tool for exploring future scenarios that is conceptually based on Voros' Futures Cone. The framework expands on the Voros Cone with more specific contextual layers in terms of trajectories between future scenarios.

This study seeks to examine the foundational principles and methodologies of futures research, investigating the potential for AI to augment techniques such as scenario planning and the creation of futures artifacts. It explores the shift in human decision-making towards collaborative approaches, paving the way for a collaborative human-AI foresight system, AI bias mitigation and the establishment of transparency and explainability for AI-generated results while maintaining human control over strategic decisions. It presents a vision for future research directions emphasizing the role of AI-augmented foresight through the FDI framework to create sustainable and desirable outcomes and propose a pilot study as the essential next step for empirical validation of the framework's potential.

The Transformative Impact of AI on Futures Research

Advancements in artificial intelligence technologies hold transformative potential across diverse sectors such as marketing (Davenport et al., 2019), the future of work (Howard, 2019), and strategic decision-making processes (Van Rooy, 2024). The ability of AI to process huge data sets, detect patterns and create novel solutions has captured the interest of business executives and policymakers along with academic researchers. The sophistication of modern AI systems has enabled their widespread application for strategic planning support and automation of futures research processes (Korhonen et al., 2024; Mandarano, 2023). Integrating AI into essential processes initiates crucial debates about human-AI teamwork dynamics as well as maintaining human decision-making power alongside necessary ethical standards.

Decision Myopia and the Problem with the Innovation Economy

The innovation economy, characterized by rapid technological change and intense competition, has given rise to a culture of short-term decision-making and a focus on immediate results. This "decision myopia" has led to a disconnect between strategic planning and long-term impact, often resulting in suboptimal outcomes and missed opportunities (Korhonen et al., 2024). The 2024 Startup Genome Ecosystems Report reveals that successful startups funded by venture capital achieve exits within a global average timeframe of six to eight years. The Global Startup Ecosystem Report 2024 shows that successful VC-funded startups reach exit in 5-7 years in top North American ecosystems compared to 8-12 years in European systems. The emphasis on quick time-to-exit and short-term financial performance fails to account for essential innovation measures like long-term social impact alongside sustainability (Davenport et al., 2019; Mariani et al., 2022; Soeiro de Carvalho, 2024).

The emphasis on quick financial returns hinders efforts to build solutions that can transform long-term societal problems. Venture capitalists focus on high company valuations and profitable exits instead of building sustainable long-term value which results in downstream broken systems:

1. Myopic incentives: Venture success is often evaluated on financial metrics such as year-over-year growth, time-to-exit, etc.
2. Lost opportunities: Sustainable venture attempts are stifled due to their lack of short-term returns, and detached from resources.
3. Fractured strategy: Without strategic design and longer-term thinking, post-exit companies often pose solutions for made-up problems.

The rapid advancement of artificial intelligence, particularly in the realm of generative AI and large language models, has opened up new possibilities for enhancing strategic foresight and scenario-planning processes. In today's fast-paced and interconnected world, organizations and policymakers face unprecedented levels of uncertainty and complexity when making long-term decisions (J. Chen, 2024; W. Chen et al., 2024).

The Need for Collective Strategic Foresight

Collaborative foresight, which combines the rationality and creativity of diverse stakeholders, is crucial for addressing the biases and limitations inherent in individual and group decision-making. Any valid line of inquiry must consider the following:

- Discounted Present Value: A framework that quantifies the long-term value of future scenarios can provide decision-makers with a meaningful representation of the present-day worth of each phase of innovation. This can be modelled as an extended market valuation approach that encompasses the anticipated future scenarios.

- Co-Creative Futures: By integrating AI systems into foresight processes, researchers and practitioners can tap into the collective intelligence of diverse stakeholders, including experts, thought leaders, and grassroots communities, actualizing a common future with compounding returns.
- Societal Carrying Capacity: Innovations should be evaluated not merely on financial performance metrics, but rather on their capacity to enhance the overall sustainability, resilience, and societal well-being of broader socio-ecological systems.
    - The Societal Carrying Capacity framework applies the ecological carrying capacity concept to measure a system's resilience and its ability to recover from disruptions (Goswami, 2020). Within human societies, this framework describes how community resilience and adaptability are demonstrated through strong infrastructure systems that support vital resources like food and energy. The idea of "centres" utilizes concepts from Christopher Alexander's "A Pattern Language" to show how decentralized systems promote societal resilience through interconnected structures (Alexander et al., 1977).
    - The "societal return on investment" (SocROI) method evaluates long-term innovation outcomes in environmental preservation, social equity, public health and community well-being while moving past short-term profit interests to measure comprehensive societal value creation.
- Evolutionary Scenario Planning: Futures researchers can create and evaluate various plausible future scenarios by integrating historical data with expert knowledge and AI-powered simulations.
- Collaborative Sense-Making: To tackle complex 21st-century challenges, strategic foresight approach that involves multiple stakeholders working together must be used. Human decision-making processes benefit from an AI-augmented expert panel because it synthesizes multiple perspectives and identifies limitations and blind spots.
    - The focus on "sense-making" instead of "decision-making" demonstrates how AI agents support information processing and mental model development to enhance human decision-making without taking full control of the decision-making workflow.
    - An AI-augmented "council of experts" holds promise for improving strategic foresight even though current AI systems present notable limitations. The training data may contain biases, complex information could be misinterpreted and human oversight needs to validate AI-generated findings. The trustworthiness and reliability of AI inputs in the foresight process depend on thorough validation processes combined with human oversight.
- Human-AI Collaboration: The notion of a virtual council of subject-matter experts mirrors historical decision-making approaches, positioning humans at the centre and leveraging AI as a supportive tool. Agentic AI refers to artificial intelligence systems that exhibit autonomous decision-making capabilities, allowing them to dynamically adapt to changing environments and make informed choices without

direct human intervention. As noted, these agents can be trained in specialized domains to autonomously assist in tasks such as scenario exploration and signal categorization (Djock, 2023; Silva et al., 2023).

- Manage Information Overload: The sheer volume of data available today makes it difficult for human analysts to process and synthesize information effectively. AI-augmented systems can help categorize and interpret large-scale data sets, ensuring that critical signals and drivers are not overlooked, thus enhancing strategic foresight (Korhonen et al., 2024).
- Enhance Responsiveness**:** AI-augmented foresight systems, with continuously trained agents, can provide the necessary agility to adapt foresight tools and scenarios to new information and evolving contexts, meeting the demands imposed by the rapid pace of technological and social change (Silva et al., 2023).
- Democratize Foresight Tools: Democratizing access to foresight methodologies is an increasing necessity, allowing a wider range of stakeholders such as businesses, policymakers, and civil society organizations to leverage these tools. AI-enhanced systems can facilitate greater accessibility to foresight capabilities, fostering more informed and collaborative decision-making processes (Korhonen et al., 2024).
- Promote Inclusivity and Reducing Bias: Conventional foresight approaches may be constrained by individual or institutional biases. However, AI-powered systems, designed to emulate a virtual council of subject-matter experts, can integrate diverse viewpoints and data sources, thereby enhancing inclusivity within decision-making processes (Korhonen et al., 2024).

The author proposes a Foresight-Driven Innovation framework (FDI) which systematically ensures alignment with long-term values. The framework uses collaborative foresight driven by AI capabilities to promote innovative solutions that strengthen both social welfare and environmental durability.

Futures Research

As a multidisciplinary field, futures research explores potential future scenarios alongside their subsequent effects according to Voros (2017). The analysis of current trends and technological changes alongside societal developments allows it to predict outcomes and create strategies for upcoming challenges. Through scenario planning and trend analysis methods futures researchers develop insights that guide decision-making in multiple sectors. This field enables organizations, governments and societies to prepare for future uncertainties while identifying opportunities to shape their preferred futures.

Futures research requires consistent investigation of potential future conditions and their various elements to develop a pathway towards achieving preferred future states. According to Galla et al. (2022), the primary goal of futures research is to develop foresight capabilities rather than predict future events. According to Dator (2019), effective futures research should avoid predicting future events and instead prioritize the processes of envisioning future possibilities alongside their creation and monitoring. Dator stated that people should actively work to create the future instead of just trying to predict it because the future can be shaped through joint efforts aimed at realizing preferred outcomes. Futures researchers need to eschew claims of authority over future predictions and instead act as facilitators who assist people and organizations in broadening their viewpoints while preparing for potential future scenarios.

Signals and Drivers

Futures research relies heavily on signals and drivers to establish the foundation for scenario development and future outcome prediction. Signals represent early signs of upcoming trends or changes that could become important in the future. Drivers function as powerful forces that significantly direct the development of future trends according to Gorbis (2019). Signals that indicate future societal changes or technological progress can be seen in various emerging trends and developments.

- the increasing adoption of plant-based diets,
- the rise of decentralized finance, and
- the growing interest in space tourism.

Drivers that may shape future developments include demographic trends alongside technological innovations together with environmental challenges and geopolitical shifts. The aging population represents an important driver which affects multiple societal dimensions such as healthcare systems and workforce composition (Wang, 2024). Futures researchers need to analyze these signals and drivers to fully comprehend the future's complex interconnections and develop realistic scenarios based on dynamic factor interactions (McGonigal, 2019). This work establishes the groundwork needed to create diverse future simulation scenarios.

Futures Scenarios

Futures scenarios serve as stories that illustrate credible potential future situations by using recognized signals and drivers. They deliver an extensive world depiction that includes social, economic, technological, environmental, and political dimensions as suggested by the signals and drivers. The future scenarios include a dedicated timeframe and path of development that demonstrates the potential interactions and evolution of various factors including social, economic, technological, environmental, and political elements to visualize what the future might become.

Futures scenarios function as a form of thought experiment which examines potential outcomes from varying decisions and uncertainties instead of predicting the future.

Preferred Futures

A preferred futures scenario demonstrates greater advantages compared to an alternative scenario through superior performance in key areas including sustainability quality of life social equity and technological progress. The scenarios function as aspirational benchmarks for joint decision-making processes and strategic planning which pursue the achievement of future goals.

Scenario Trajectory

The trajectory of a futures scenario represents the progression of events that create a specific future condition. Futures research typically uses several standard trajectories to model possible future development, these include:

- Crisis/Collapse, a trajectory characterized by a rapid decline in societal structures.
- Growth, a trajectory where societal development and progress continue.
- Transform, a trajectory involving a radical shift in the underlying values and structures of society.
- Discipline/Order, a trajectory where a centralized government orchestrates a transition to a new, more controlled system.

These trajectories help researchers frame and explore diverse possibilities, considering factors that may drive a future in each of these directions, notably used in Sayah's Thing From the Future workshops (Sayah, 2019).

Trajectory + Scenarios

Current Situation

Global trends point toward a brewing **Energy Crisis**, from extreme weather events caused by climate change, to increasing energy demands from population and technological vectors (blockchain, generative AI, etc.)

Crisis

Collapse of the energy infrastructure, a brittle power grid, leads to access inequity to energy and technology. Only few privileged elites maintains disconnected microgrids, failure of global supply chains inhibit resolutions.

Growth

Research and development towards **micro-nuclear and fusion generators** to co-locate with (power-wise) city-scale data centers maintain grid stability and carbon neutrality.

Transform

A shift in grid planning to create minimally resilient neighborhood (MRNs), which are **mixed-use, interconnected microgrids** at every scale (neighborhood, town, city, state, country).

Discipline

Strict regulation of energy usage implemented for merit-based energy distribution. **Energy no longer be considered a basic human right**, but rather a privilege allocated based on productivity, conservation efforts, and societal contribution.

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An example of a current situation is "Global trends point toward a brewing Energy Crisis, from extreme weather events caused by climate change, to increasing energy demands from population and technological vectors" such as blockchain, generative AI, etc. (Wang, 2024). A scenario envisions a world where advancements in micro-nuclear power generation resolve an energy crisis driven by population growth and data centre construction. This contrasts with a "collapse" alternative, where a failed power grid leads to persistent outages and limited electricity access for privileged groups (Wang, 2024).

World Building and Microfiction

The rapid advancements in artificial intelligence have profoundly impacted various domains, including strategic foresight and futures research. These transformative technologies hold immense potential to augment and enhance collaborative decision-making processes, enabling us to navigate the complex and uncertain landscapes of the future (Duin & Pedersen, 2021).

This process is similar to science fiction writing, where researchers use their imagination and creativity to develop vivid narratives that explore potential future developments. By selecting provocative deltas for technological innovations, geopolitical shifts, sociocultural transformations, and scenario trajectories, researchers can craft thought-provoking futures scenarios (Wang, 2024). This design fiction approach, enables researchers to construct futures artifacts that vividly channel the impact of these scenarios, aiming to inspire audiences and promote actualization toward preferred futures.

Futures Artifacts

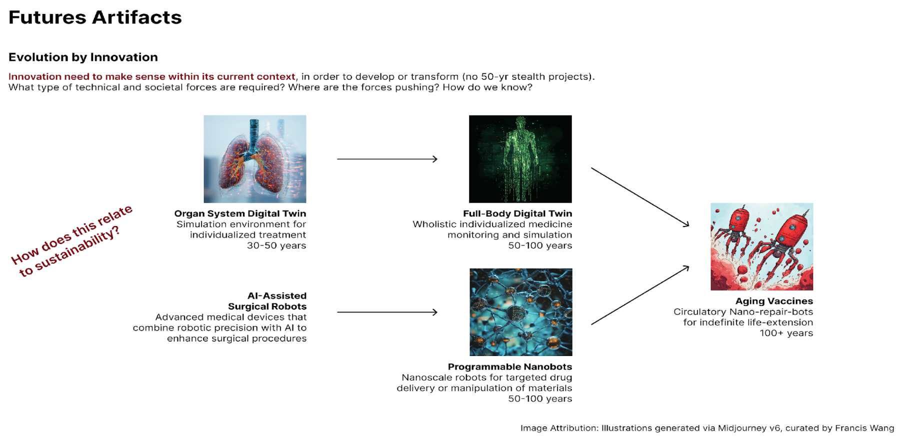
Crafting futures artifacts is an interactive approach for conveying potential future scenarios and promoting discourse on thought-provoking subjects (Tham, 2021). Futures artifacts are physical or digital representations of potential future scenarios, built using current technologies. Some examples of futures artifacts are:

- A collection of treetop community housing with flood-adapted vertical farming practices, exploring a future where climate change causes frequent, permanent floods in coastal regions (Wang, 2024).
- A mock healthcare experience showcasing a nanobot-based aging vaccine delivered annually. These nanobots monitor and repair all aspects of the human body, effectively enabling biological immortality (Wang, 2024).
- A mock AI-enabled mobility and climate control robot for a tomato plant, where people must "pay" the plant for its fruits. This explores a future where anthropic rights are extended to plant life (Tham, 2021).

By immersing audiences in these vivid futures artifacts, researchers can elicit emotional responses, stimulate imagination, and inspire critical thinking about the implications of various technological and societal developments (Soeiro de Carvalho, 2024).

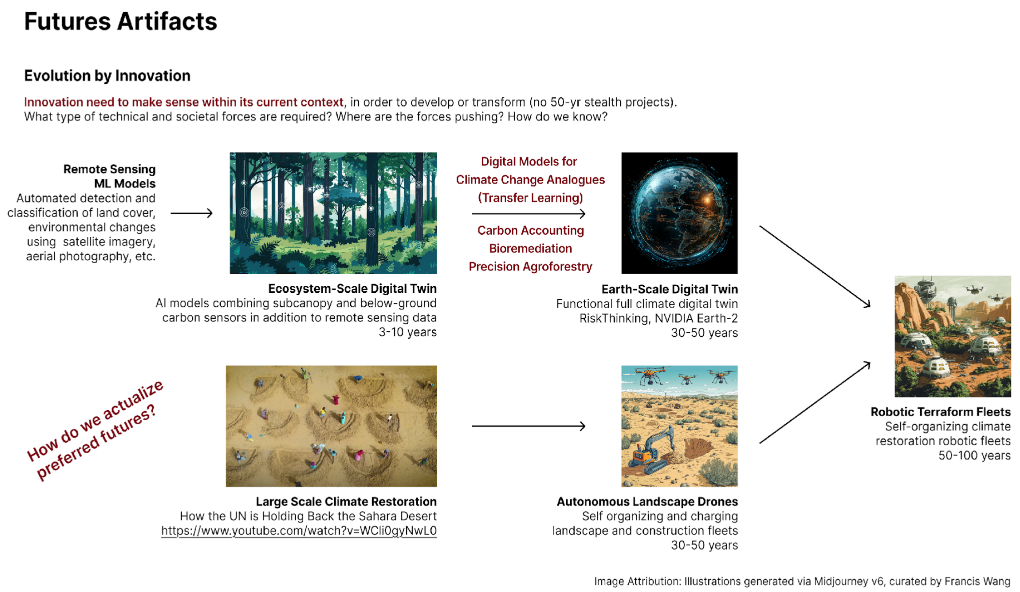
Futures Artifacts as Innovation Milestones

Futures artifacts do not remain static, but rather evolve over time, reflecting the ongoing advancements in technology and societal changes. These artifacts serve as visual markers, depicting the roadmap of innovations and their potential societal impacts and implications.



As the earlier example mentioned, an aging vaccine delivered by nanobots necessarily depend on considerable progress in nanotechnology, biotechnology, and healthcare infrastructure. Specifically digital twin technology, next-gen biosensors, and

automated drug delivery systems would all need to advance in conjunction with nanotechnology in order for this artifact to become a reality.
However, similar patterns of innovation evolution may apply to alternative scenarios. An example is applying concept to a planetary scale, deriving a similar roadmap for terraformation technologies to transform the environment of an entire planet.



Both roadmap require robust digitization of the underlying context to understand *what to do*, and development in delivery mechanism to answer *how to implement* the insights generated from digital twins. These innovation milestones are back cast from the future scenario to the present day, with signals, drivers, and patterns in the current context suggesting their possibility. Analyzing these scenarios and artifacts can help decision-makers make more informed choices about directing societal, technological, and environmental progress. The use of futures artifacts in scenario planning and foresight exercises enhances stakeholder engagement and improves the communication of complex ideas. These tangible representations of abstract concepts bridge the gap between present realities and future possibilities, enabling a more inclusive and participatory approach to shaping our collective future.

Futures Methodologies

Foresight integrates rational analysis with creative thinking by drawing on collective intelligence from diverse stakeholders and utilizing participatory methods (Soeiro de Carvalho, 2024). Jane McGonigal, who is recognized as an expert in futures thinking, teaches about different analytical techniques that researchers use to develop scenarios and foresee futures artifacts during her instructorship at the Institute for the Future.

Futures Wheel

The futures wheel represents a systematic approach to brainstorming that diagrams the first-order effects as well as the second and third-order outcomes following a specific change or occurrence (McGonigal & Lyn, 2019). Primary consequences emerge directly from the change and secondary and tertiary consequences manifest as indirect and cascading effects. This tool allows participants to systematically examine future complexities and to pinpoint possible ripple effects and unintended consequences according to Finlev et al. (2019).

The expanding futures wheel lets researchers spatially align each corner to show consequences that stem from specific scenario trajectories. This method serves two functions as it enables researchers to visualize and categorize their findings while making certain that all exploration paths have been investigated.

Futures Cone

The futures cone serves as a popular visual method to organize future possibilities exploration. The Voros Cone stands out as a primary method among several related approaches. In this representation, futures scenarios within each time horizon are arranged into a series of concentric disks, with each disk representing a different level of likelihood: probable, possible, plausible, and preposterous. The concentric disks representing various probabilities of future scenarios take on a conical shape to visualize how these possibilities evolve through time (Galla et al., 2022; Voros, 2017).

The cone grows in size as time moves forward to show how possibilities become more diverse. The Foresight Scope represents an integrated extension developed by our team over the futures cone with further details provided later in this text.

Backcasting

Backcasting starts from a preferred future outcome to work in reverse order to determine essential steps and policies for reaching that outcome. It operates through two primary approaches :

- Features-centric: The features-centric approach begins with analyzing the required characteristics of the future artifact before identifying the components and features needed to create that future state.
- Purpose-centric: The purpose-centric approach focuses on ensuring that the functional goal of the artifact becomes achievable while this goal evolves alongside progressing timelines.

Research about future developments often demands the combined application of features-centric and purpose-centric backcasting approaches (Tham, 2021). A frequent error occurs when developers assemble a futures artifact based only on its features instead of establishing a guiding purpose for feature coordination.

Predicting the Past

Through predictive retrospection, researchers gain new perspectives which are beneficial for future-oriented studies. This method demonstrates the profound influence past decisions exert on today's circumstances by considering alternative historical choices and their potential impacts (McGonigal, 2019). This demonstrates that present decisions have the potential to create significant impacts on future outcomes. A widely applied method in depression treatment helps patients confront their belief about the ineffectiveness of their actions.

Remembering the Future

Remembering the Future provides a novel method to access fresh perspectives. Utilizing a systematic approach like the **XYZ** method helps people create visions of unique experiences. This method involves identifying:

- X: an activity or interest that captures someone's deep attention and engagement.
- Y: a personal friend who is not involved in public life.
- Z: a remote or unfamiliar location.

By visualizing a future situation where X happens with Y in Z over the next year and treating it as a past memory enables this exercise to build a more concrete mental image of what lies ahead.

This approach works on the concept that vivid mental visualization and logical justification of potential scenarios lead to easier brain reprocessing and reimagination. People tend to believe scenarios they can easily imagine will happen makes this strategy beneficial for future research and strategic planning (McGonigal, 2019).

Hard Empathy

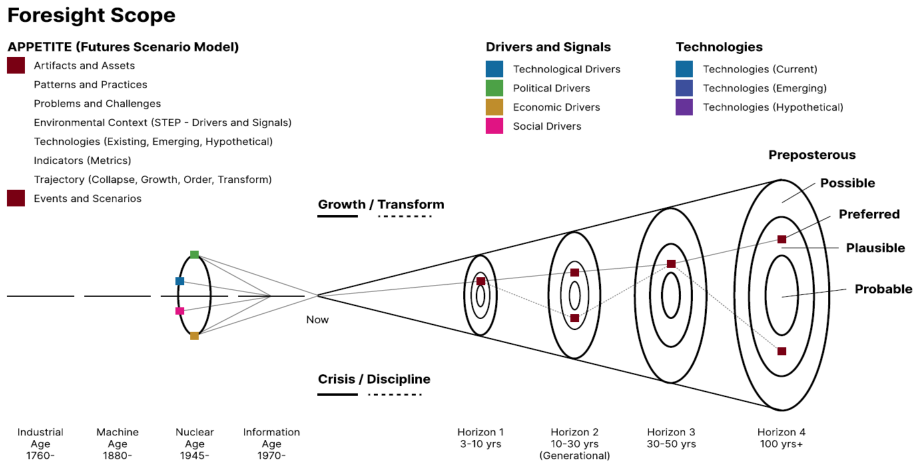
A third technique involves placing oneself at the center of a distant situation and integrating that scenario into one's personal environment. Through the hard empathy approach individuals must explore their reactions to an immediate establishment of a completely new norm within their current environment. Empathy research has distinguished two different forms of empathetic response.

- Emotional empathy: Emotional empathy lets people directly connect with another person's experiences without needing to imagine beyond their own understanding.
- Cognitive empathy: The absence of direct experience makes cognitive empathy dependent on both intuition and rational thinking.

Human beings typically display limited emotional connection when considering their future selves according to the "your future self as a stranger" principle. Research findings indicate that when people imagine their lives a decade from now their brains react similarly to when they observe a person they don't know. The majority of people lose connection with their future selves within a period of one to three years according to research by McGonigal (2019) and McGonigal & Lyn (2019).

Foresight Scope

The Foresight Scope is a visual component of the author’s Foresight-Driven Innovation (FDI) Framework, developed to help researchers and decision-makers systematically explore the dynamics and complexity of possible future scenarios.



This framework builds upon the futures cone, but provides more specificity in the context between futures scenarios within each time horizon. Futures scenarios are positioned by their source trajectory inside their probability ring, and are described using the APPETITE Futures Scenario Model. (Wang, 2024), which includes the following components:

- Artifacts - Futures artifacts that mark points of interest along a futures trajectory;
- Patterns and Practices - Emergent sociotechnical patterns and human/organizational practices that shape futures;
- Problems and Challenges - Specific to a futures scenario based on surrounding context;
- Environmental Context - Drivers and Signals, can be Social, Technical, Economic or, Political (STEP);
- Technologies - Existing, Emerging, and Hypothetical;
- Indicators - Metrics for monitoring trends and triggers that signify the unfolding of futures;
- Trajectories - Transition hypothesis between scenarios and describe a changeset in the underlying context. One of four types: Collapse, Growth, Order, or Transform; and
- Events and Scenarios - Rich potential futures descriptions and story narratives.

This approach involves documenting the historical environmental context and how it has shaped the current scenario. Critically, describing the "delta" or changes in environmental context factors from one time period to the next is essential for capturing the transition between futures scenarios. The Foresight Scope framework empowers researchers and decision-makers to explore the complexity of possible futures through a structured, multi-dimensional lens.

How People Make Strategic Decisions

Understanding how people naturally engage in the strategic decision-making process is crucial for comprehending the role of AI in supporting this endeavour.
Throughout history, humans have often turned to figures of authority, whether experts or those in positions of power, to help guide decisions that affected the collective. This

council of elders model has endured for centuries. As societies have grown more complex, our strategic decision-making process has evolved to involve a broader group of stakeholders with increased need for analytical techniques.

Asking Experts: The Delphi Technique

The Delphi technique serves as a common approach to harness expert knowledge, experience, and insights from a diverse group for consensus-building on complex topics. The Delphi technique utilizes a systematic iterative process which anonymously surveys expert panels then aggregates their responses before providing feedback through successive rounds until consensus is reached. (Störmer et al., 2020)

The Delphi technique operates on fundamental principles which consist of three main components:

- Anonymity: In this process participants submit their responses without being affected by the influences of group dynamics or peer pressure.
- Iteration: The process cycles through iterative feedback phases which enable experts to modify their perspectives based on new insights.
- Controlled feedback: Participants receive feedback summaries from prior rounds which helps them to refine their responses.

The approach demonstrates particular effectiveness when dealing with complex problems that contain elements of uncertainty and ambiguity through the inclusion of diverse perspectives. However, the Delphi technique has limitations. Expert judgments can be distorted by their biases, incomplete data and their vested interests.

Limitations of Human Decision-Making

The Influence of Cognitive Biases and Heuristics on Forecasting

Cognitive biases and heuristics shape the process of making forecasts. The use of mental shortcuts known as heuristics combined with cognitive biases creates substantial effects on both decision-making processes and forecasting activities. Understanding the ways biases create systematic errors and distort judgments remains essential for strategic decision-making and futures research (Mccarley et al., 2015) (Todd, 2001).

Forecasting accuracy is often compromised by several common cognitive biases which include:

- Availability bias: Reflects the common mistake of assigning greater probability to events which people can easily remember or imagine.
- Anchoring bias: Occurs when people depend excessively on a single piece of information known as the "anchor" during their decision-making process.
- Confirmation bias: People tend to seek out and give more weight to evidence that supports their pre-existing beliefs and theories.
- Overconfidence bias: Manifests when individuals wrongly assess their abilities and knowledge as superior or their predictions as more accurate than they truly are.
- Framing effect: The presentation method of a decision problem influencing how decision-makers choose their preferred option.

According to Tversky & Kahneman (1975), mental shortcuts known as heuristics can create systematic errors in people's judgment. The representativeness heuristic creates misinterpretations of patterns and exaggerated assessments of rare event probabilities.

Bounded Rationality and Information Overload

Herbert Simon introduced the concept of bounded rationality to demonstrate how human decision-making operates within certain limitations. Human decision-making exhibits bounded rationality because our cognitive resources and available information combined with time limitations shape our rational choices (Simon, 1955).
Decision-makers face substantial difficulties when they must operate within intricate information-dense settings. The vast quantity and complicated nature of data can inundate people leading to reduced capacity for effective processing and synthesis of information.

A Framework for Human-AI Collaboration in Futures Research

The goal is to utilize AI technology for creating a collaborative foresight system which will work alongside human decision-making processes and futures research to improve them. The collaborative foresight system combines advanced artificial intelligence models with expert-curated data which allows for the effective collection and synthesis of information from multiple sources to identify emerging trends and future possibilities (Culver et al., 2019; Solaiman, 2023; Stucki & Sandal, 2025).

The primary goals of this system include:

1. Analyzing future scenarios that hold potential viability to reduce risks and establish enduring value;
2. Establishing a strategic planning and decision-making framework that uses foresight principles to maintain organizational alignment with sustainable value goals; and
3. Engaging human-AI partnership models to boost foresight procedures while expanding human potential for thorough future investigations.

AI capabilities help overcome cognitive biases and information overload limitations as well as bounded rationality, opening new pathways for strategic foresight and decision-making processes (Ganapini et al., 2023).

Agentic AI in Futures Research

Agentic AI systems represent a type of artificial intelligence which makes decisions independently by adapting to new circumstances while selecting appropriate actions without requiring human input (Jin, 2024). Futures research utilizes Agentic AI agents to study intricate scenarios while simulating possible results and verifying the durability of suggested strategies. Their primary features include environmental perception capabilities alongside their ability to reason through complex scenarios and execute autonomous actions for goal achievement. This includes:

- Autonomous decision-making and learning: Agentic AI systems develop and refine their decision-making capabilities through experience-based learning to achieve better results beyond the limitations of fixed programming rules.
- Real-time data processing and analysis: These AI agents quickly analyze massive datasets that contain real-time information for decision-making and strategic planning.
- AI-driven scenario modelling: Agentic AI develops sophisticated models and uses scenario simulation to find strategic solutions for complicated problems. The models enable assessment of multiple possible futures while analyzing their potential outcomes.
- Self-organization and coordination: Agentic AI systems work together with other agents to self-organize for handling complex dynamic challenges through the coordination of decision-making across multiple stakeholders.

Through collaborative foresight interfaces AI agents help human experts assess and improve upon the insights and scenarios generated by AI systems. The human-in-the-loop approach ensures AI outputs remain unbiased through human intervention while providing strategic decisions that respect human values and domain expertise by utilizing AI-augmented processes that surpass human cognitive boundaries.

Scenario Exploration and World Building

The field of world-building and microfiction has become a particularly successful application for AI through generative models like Small Language Models (SLMs), which produce detailed speculative narratives while maintaining a smaller carbon footprint. Stakeholders find AI-generated narratives powerful because they engage participants and facilitate detailed examinations of potential futures. The application of AI technology enables quick creation of numerous future possibilities that serve as bases for discussions and decision-making processes (Oomen et al., 2021).

The collaborative aspect of foresight work can be strengthened through AI tools which produce a range of feasible future scenarios for consideration while ensuring that reliance on AI predictions remains limited. (Cox, 2021; Stucki & Sandal, 2025).

Unlock Multimodal Means of Engagement

AI-driven multimodal reporting and communication systems enhance published content quality and researcher accessibility and engagement while managing information overload. Researchers achieve more effective communication of complex future scenarios and their environmental context through the use of various output formats including narratives, visualizations, and audio-based media (Durante et al., 2024). A multimedia strategy supports enhanced knowledge comprehension while creating better interactions and enabling smarter strategic choices.

Addressing Information Overload

The AI system for collaborative foresight automates the collection and analysis of media information from news sources. The system classifies and marks these inputs as signals to reduce information overload and facilitate strategic decision-making that is more effective:

1. Automated data collection from diverse sources;
2. AI-powered signal detection, categorization, and scenario planning; and
3. Human experts use a collaborative interface to verify AI-generated insights and provide context which promotes human-in-the-loop learning and content curation.

The automated data collection and processing capabilities of the system enable human experts to dedicate their efforts to advanced analysis and strategic decision-making functions (Korhonen et al., 2024). Through visualizations and natural language processing along with interactive tools human experts receive the power to explore AI-generated data and insights. Human-AI collaboration works without interruption to help experts identify important signals fast and explore future possibilities so they can make better strategic choices which enhances the foresight process.

Technical Architecture for a Collaborative Human-AI Foresight System

The proposed human-AI foresight system will utilize a scalable modular architecture which allows seamless combination of AI models with various data sources and expert human inputs. Practical implementation of a multi-agent AI foresight system requires addressing computational needs as well as financial expenditures for infrastructure development together with scalability considerations for different organizational demands. Future studies need to examine these areas in greater depth.

System Architecture

The AI-assisted collaborative foresight system consists of the following key components:

1. Data Ingestion and Processing Layer: This component functions to collect data from numerous media outlets and news sources before processing and storing it.
2. Signals Analysis Layer: Fine-tuned Large Language Models (LLMs) perform detection, categorization, and analysis of emerging signals and trends in relation to drivers of change using a knowledge base.
3. Scenario Exploration Layer: Utilizes Small Language Models (SLMs) to generate future scenario-based prompts for plausible trajectories in futures research by analyzing insights from the Signals Analysis Layer.
4. Foresight Knowledge Base: This resource provides a complete database filled with curated data and expert analysis to develop scenario plans for strategic decision-making.
5. Governance and Ethics Layer: Maintains responsible AI use through validation guidelines and bias reduction measures that incorporate human supervision.
6. Collaborative Foresight Interface: Web-based tool to enable human experts to assess and enhance AI-provided insights and scenarios while supporting collaborative foresight activities.

Knowledge Base

Human-AI collaboration manages the knowledge base through AI model analysis of vast external data to identify signals and trends and domain experts review and enhance these AI-generated insights. The knowledge base operates as a dynamic collection of future scenarios and strategic insights alongside chartered paths and artifacts to empower continuous foresight activities. The architecture supports ongoing system enhancement via repeated human feedback and model optimization to keep AI functions in line with strategic foresight objectives (Sherson et al., 2023; Soeiro de Carvalho, 2024).

Model Details

Model and data cards are used as a standardized framework to thoroughly record the specifics of the proposed model (Mitchell et al., 2019).

Futures Scenario Explorer

Appropriate use of more specialized Language Models can effectively reduce both the carbon footprint and total cost of the collaborative AI system. Specialized models demonstrate higher efficiency and require fewer resources compared to larger general models. The AI system prompts Small Language Models to generate futures scenarios based on the four common trajectories used in futures research: The collaborative AI system utilizes four established future research trajectories of growth, collapse, order, and transformation as defined by Galla et al. (2022). Specialized SLM agents have the responsibility to creatively write scenarios dedicated to specific trajectories which are based on key contextual data from the knowledge base including relevant signals alongside trends and drivers.

- Model Architecture: A DistilBERT based model with a custom output layer with multiple heads for different aspects of the scenario generation: 1. main narrative generation; 2. key events, actors, and timeline; 3. deltas or changeset over the base scenario; 4. impact assessment. As well as:
    - Additional cross-attention layers to facilitate information exchange between trajectory-specific models.
    - Specialized embedding layer for encoding structured prompts containing context from the knowledge base.
- Inputs: Structured prompt including base scenario context, trajectory specification (e.g. growth, collapse, transformation). Categorized signals and drivers from the knowledge base.
- Outputs: Futures scenarios in a structured format, including the microfiction narrative, key events, timelines, deltas, and impact assessments. Where key elements are linked to sources in the knowledge base.
- By combining the power of Large Language Models for broad knowledge acquisition and the efficiency of Smaller Language Models for specialized tasks, the proposed collaborative foresight system aims to deliver high-quality, flexible, and cost-effective futures research capabilities (Jain et al., 2023; Li et al., 2024).

Intended Uses

- Primary Intended Use: Assist human researchers in exploring futures scenarios to support strategic foresight, policy planning, and risk assessment. Create compelling stories to help communicate potential futures, ideas, and artifacts.
- Domain and Users: Futures research, strategic planning, risk analysis for government, NGOs, and private organizations. For users at all levels to explore futures scenarios and contribute to collaborative foresight.
- Out of Scope Uses: Automated high-stakes decision making, generation of misleading or harmful content.

Factors

- Groups: The model is designed to generate futures scenarios for a wide range of social, economic, technological, and geopolitical contexts. Exploration are done on having specialized agent per cultural context.
    - i.e., North America, Western Europe, Eastern Europe, East Asia, ASEAN, Africa, etc.
- Instrumentation: The data ingestion and processing layer may introduce biases from the original data sources, and have limitation in accessible data.
- Environment: The model is integrated into a collaborative web-based foresight platform with multi-modal interactions including text, audio, visuals, and interactive timeline exploration.
- Metrics and Evaluation

- Diversity of generated scenarios: Ratio of unique generated scenarios per context/trajectory, measured by semantic similarity.
- Relevance of identified signals and drivers: Comparison of generated scenarios to expert-curated reference scenarios, with human experts rating each generated scenario on a 1-5 scale.
- Consistency of outputs across different runs: Measuring variance in key elements like events, timelines, and impact assessments.
- Adaptability to new data and emerging trends: Ability to generate novel scenarios when new data is added to the knowledge base.
- User satisfaction and perceived usefulness of insights: Qualitative feedback from subject matter experts and decision-makers.
- Bias detection scores: Evaluating the relative difference in key scenario elements (e.g., events, impacts, timelines) when generating futures for different demographic, geographic, or socioeconomic groups to ensure equitable representation and avoid perpetuating harmful biases.
- Explainability and interpretability scores: Report LIME (Locally Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) values for key output components (Gramegna & Guidici, 2021; Mane, 2024; Salih et al., 2024).

Training and Evaluation Data

The model is fine-tuned on a corpus of academic publications, industry reports, and media articles related to strategic foresight, scenario planning, and futures studies. In-domain evaluation is done on a held-out dataset of futures scenarios from reputable foresight organizations.

- Data sources: Preprint servers, academic journals, market research reports, technology blogs, government reports, and news media.
- Data collection methods: Web crawling, manual curation, API integration from databases and publications.
- Data composition: Predominately (> 80%) text, with tabular and multimedia (images, charts, interactive visualizations) data.
- Data preprocessing: Cleaning, normalization, and feature extraction.
    - Named Entity Recognition (NER): to identify key actors, organizations, and concepts (Hu & Downie, 2024).
    - Sentiment analysis: using RoBERTa-base to assess emotional tone of content (Xian et al., 2024).
    - Topic modelling: using BERTopic to identify emerging themes and trends (Xian et al., 2024).
- Usage rights: Exclude data with licenses that do not allow for AI training.

Quantitative Analysis and Validation Strategies

To ensure the reliability and rigour of the collaborative foresight system, a range of quantitative analysis and validation strategies will be employed:

- Cross-Validation: K-fold cross-validation to assess model performance across different subsets of data. Stratified K-fold cross-validation for imbalanced datasets (Raschka, 2018).
- Domain-Specific Validation: Involving subject matter experts to validate model outputs in the context of strategic foresight.
- Bias Detection: Using probing tasks and template-based evaluation to detect biases. Correlations of weighted cultural context to severity of scenarios generated under each trajectory type.
    - e.g., North America labelled more optimistic under growth trajectory, while Eastern Europe labelled more dystopian under order trajectory.
- Adversarial Testing: Evaluate the model's robustness by subjecting it to carefully designed input scenarios.
- Coherence: The internal coherence between narratives, events and their impacts within a future scenario must remain consistent.
- Diversity: Generated scenarios display distinct new features that set them apart from earlier outputs and established futures research.

Together with human supervision and feedback these approaches will safeguard the collaborative foresight system's quality in terms of reliability transparency and accountability.

Ethical Considerations and Challenges

The ethical challenges facing the collaborative foresight system need thorough examination and proper mitigation methods. The collaborative foresight system faces ethical challenges which include potential system failures along with the necessity for transparency and explainability while preserving human decision-making agency and considering workforce implications. Maintaining appropriate safeguards during system deployment will be essential to ensure responsible operation.

Potential System Failures

Human experts working alongside AI in a council setting represents an appealing vision yet current AI systems are unable to achieve the level of strategic foresight required from experts because of their inherent limitations. The collaborative foresight system encounters several potential risks and challenges. Malfunctions of the system may trigger various adverse effects including:

- Misinterpretation of signals caused by contextual nuances and biases present within the training data (Aqua, 2023). The creation of skewed or unrepresentative scenarios can worsen existing biases and social inequalities.
- News sources and data sources will show stronger existing biases (Lawton, 2024).
- Unauthorized access and privacy breaches pose significant threats to the protection of sensitive strategic information (Lawton, 2024).
- The system faces risks when AI-generated insights are reused without validation from human experts (Kidd & Birhane, 2023; Lloyd, 2018).
- The AI-generated scenarios demonstrate a poor alignment with human values and societal requirements (LaCroix & Mohseni, 2020).

The system will use strong failure detection methods along with human supervision and established AI governance protocols to reduce these risks.

Ensuring Transparency and Explainability

The integration of AI into decision-making systems will likely cause conflicts when human expertise opposes AI-generated data which can result in decreased trust and malfunctioning decision-making processes. (Van Rooy, 2024).

Interpretable AI Models

The collaborative foresight system will emphasize deploying AI models which deliver clear and understandable explanations of their outcomes to build user trust and acceptance. The presence of biases and possible misinterpretations in AI results highlights the essential requirement for AI models that are transparent and explainable within the collaborative foresight system. Human experts need these models to build trust while identifying and rectifying errors within AI-generated future scenarios.

Transparency and explainability stand out as fundamental concerns in AI-driven strategic foresight according to Korhonen et al. (2024). Collaborative foresight platforms must develop AI models that generate results which stakeholders can interpret and audit because demand for accountability in AI decision-making is increasing. AI-generated futures scenarios become more transparent when we apply techniques such as Shapley Additive Explanations and Local Interpretable Model-Agnostic Explanations (Mane, 2024).

Communication of AI-Generated Insights

The formation of AI-generated futures scenarios should be comprehensible to stakeholders through transparent visibility of data sources, algorithms and assumptions (Díaz-Rodríguez et al., 2023). Successful integration of the collaborative foresight system depends on effectively communicating AI-generated insights. The system needs to deliver transparent details about its reasoning processes while identifying the assumptions it makes and its operational limitations for human users (Ahmad et al., 2023; Petković, 2023). Within futures research the generation of outputs that emphasize key signals and drivers alongside environmental context narrative generation factors and APPETITE parameters helps establish trust and supports shared decision-making instead of depending on unclear "black box" predictions (Hamon et al., 2020; Korhonen et al., 2024; Soeiro de Carvalho, 2024).

Maintaining Human Agency in Decision-Making

The collaborative foresight system requires ethical attention to ensure decision-making remains under suitable human control and supervision. The capacity of AI models to generate valuable insights and predictive scenarios demands that human experts preserve their control over strategic decisions (Floridi et al., 2018). The system requires a "human-in-the-loop" design to ensure human stakeholders can review AI-generated recommendations while applying their own expertise and contextual knowledge before making final decisions (So, 2020). A proper equilibrium between artificial intelligence systems and human decision-making capabilities must be established to ensure accountability and ethical standards while maintaining human dominance over future developments (Maas, 2023).

Practical Implementation Feasibility

Previous sections have focused on the ethical issues surrounding AI integration into collaborative foresight practices. The practical challenges that may emerge during system implementation must be given equal consideration. Substantial computational resources are necessary to implement the proposed collaborative foresight system. Real-time data processing and fine-tuning of large-scale language models for signal analysis together with the deployment of various smaller models for scenario exploration must be supported by the system. Processing large data sets with complex AI models requires substantial computing power because these operations are very computationally demanding. It requires evaluating the environmental impact and carbon footprint from AI model training and fine-tuning while embedding carbon-aware computing strategies into system development and implementation. Furthermore, the financial costs associated are significant. Expenses extend past the basic hardware and software costs to cover data acquisition along with AI model training and refinement and the development and maintenance of collaborative interfaces together with system management personnel costs.

Larger organizations and think-tanks that possess sufficient resources might find the proposed system appropriate for their needs. The principles of collaborative foresight and AI assistance have the potential to benefit smaller businesses as well as non-profits and public sector organizations that operate with restricted technology budgets. Achieving system adaptation and scalability to address different organizational needs and limitations demands methodical preparation alongside customized resolutions.

Workforce Considerations

Automated scenario generation will take over certain labour-intensive foresight processes yet aims to strengthen human expert capabilities rather than substitute them.

- Misuse Prevention: Ensure appropriate guardrails and contractual policies are in place to prevent the system from being used for harmful or deceptive purposes, or used without human validation.
- Upskilling: Implement a reskilling and upskilling program to enable employees affected by signal classification and scenario writing automation to perform more strategic work.
- Augmentation over Automation: Design the system as a collaborative tool that enhances human decision-making, not a fully autonomous system that replaces human expertise.

These ethical considerations must be addressed throughout the design, deployment, and ongoing operation of the collaborative foresight system in order to ensure its responsible and trustworthy use.

Future Directions and Conclusion

The development of a collaborative foresight platform that integrates AI-driven futures research and human decision-making represents a promising frontier in strategic planning and organizational adaptation. Opportunities to expand the collaborative foresight approach to other domains beyond the organizational context, such as urban planning, healthcare, and sustainable development, where anticipatory governance informed by AI-enhanced scenarios could yield significant societal benefits. (Howard, 2019)

Compounding Economic Impact

Strategic alignment of research agendas, product roadmaps, and business models across multiple organizational units and ecosystem partners offers the potential for compounding economic impact. Unlocking innovation scenarios beyond the capabilities of any single unit or corporation. Take the example of Tesla’s open patent strategy, where the automaker chose to share its electric vehicle technology broadly across the industry. This helped catalyze greater innovation and investment in electric mobility, ultimately accelerating the transition away from internal combustion engines (Hu et al., 2018; Ingram, 2018).

Such a macro-level innovation strategy enabled by foresight can unleash self-reinforcing positive feedback loops - where new technological capabilities, industry and market shifts, and regulatory frameworks co-evolve in mutually reinforcing ways. The long-term innovators and investors are able to coordinate such a patent strategy, informed by the insights of a robust foresight program, stand to gain disproportionately as the ecosystem is reshaped around their core technology offering (Djock, 2023; Ruff, 2006). This potential brings short-term financial valuation to long-term innovation, in the form of a comprehensive patent strategy.

Think about the market capitalization of hypothetical technologies, such as aging vaccines, artificial neurons, autonomous terraforming fleets; each requiring a sequence of emerging technologies to actualize. In the case for terraform fleets, both earth-scale digital twinning technology and autonomous drone swarms become critical building blocks, which in turn require ecosystem-scale digital twins and robotization of large-scale climate restoration processes.

Strategic foresight combined with technological innovation can create these compounding effects, where each layer of foundational technology compounds the potential of the layer above. Hence is it vital to research futures scenarios, trajectories, and socio-techno-economic conditions to guide strategic innovation towards preferred futures scenarios.

Prospects for Future Research

This study has proposed a comprehensive framework and outlined technical considerations for a collaborative foresight system leveraging human-AI dynamics. Future research should prioritize the design and execution of a pilot implementation of the proposed framework. This pilot can serve as a crucial initial validation of the conceptual model and the feasibility of the technical architecture in a real-world setting.

After the pilot implementation, researchers must perform an empirical analysis to assess how well the collaborative foresight system works and its overall impact. This analysis should encompass these dimensions:

- Effectiveness of Human-AI Collaboration: The evaluation of Human-AI collaboration should focus on foresight tasks such as signal detection and strategic decision-making. This involves evaluating generated insight quality and diversity while also assessing collaborative process efficiency and system user satisfaction.
- Mitigation of Cognitive Biases: The AI-augmented system's capability to reduce established human cognitive biases enables stronger foresight outcomes by minimizing short-sighted thinking.

- Accuracy and Reliability of AI Models: The precision and reliability of fine-tuned LLMs and specialized SLMs should be examined using quantitative measurements and qualitative validation by experts for their designated tasks.

The pilot implementation will deliver critical data essential to assessment of system feasibility which includes cost analysis and scalability assessment. Detailed information about the financial expenses should be collected for developing and running the pilot system which included computational resources, software, data acquisition and personnel costs. This information will establish a definitive understanding of the required financial investment for broader implementation. The system's ability to manage larger datasets, higher user load ,and diverse organizational requirements will be assessed with focus on potential bottlenecks and architectural design adaptability. Quantitative findings from the pilot evaluation concerning cost and scalability will serve as essential inputs for refining the framework, optimizing technical architecture and directing future research efforts toward wider application and impact of AI-enabled collaborative foresight in strategic decision-making and futures studies.

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