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Addressing the Limitations of the Futures Cone: Introducing the Adaptive Futures Mesh

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Abstract

This paper aims to address the limitations of traditional strategic foresight methodologies, specifically the Futures Cone (FC), by introducing and evaluating a novel framework called the Adaptive Futures Mesh (AFM). The study employs a conceptual analysis, drawing on systems thinking, complexity science, and participatory design principles to develop the AFM. The AFM is structured around key components including a dynamic mesh network, uncertainty gradients, adaptive feedback loops, and an emergence engine. The analysis finds that the AFM offers a more robust approach to navigating uncertainty by explicitly incorporating unknown unknowns (dark matter nodes). It visualizes cascading impacts, emphasizing human agency, and enables continuous adaptation through feedback loops. Research limitations include the lack of empirical validation and potential challenges in implementing the AFM across diverse contexts. However, the AFM offers significant practical implications for strategic planning. It enables organizations to move beyond prediction and cultivate futures-readiness. Socially, the AFM promotes more inclusive and equitable futures by democratizing foresight and empowering stakeholders to shape their own destinies. The originality and value of this paper lie in its articulation of a novel, adaptive framework that enhances strategic resilience in facing complexity and multiple crises.

Keywords: Adaptive Futures Mesh (AFM), Futures Cone (FC), strategy development; resilience, strategic foresight; uncertainty; philosophy; cognitive psychology; quantum physics; history and philosophy of science; complex adaptive systems (CAS)

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Introduction

The Futures Cone (FC) has long been a conceptual framework in the field of Futures Studies (FS) (Gall et al., 2022). It provides a visual representation of various potential futures that can emerge from the present. It has helped individuals and organizations think about the future and explore different scenarios. However, as foresight practitioners continue to evolve in their understanding of time, complexity, and uncertainty, it is essential to gently re-evaluate this framework to ensure it remains relevant and effective in addressing emergent challenges.

This analysis acknowledges that the FC is a simple visual and adjusts desired expectations accordingly. It is not intended to undervalue or downplay the significant contributions that previous studies based on the FC have made. Many practitioners have utilized this model to stimulate discussions about future possibilities and guide strategic planning (Mao, Liu, 2023; Migone, Howlett, 2024; Park, Shin, 2024). Instead, the study aims to facilitate a constructive dialogue about how to enhance contemporary approaches to FS. This analysis recognizes the limitations of the FC, such as its linear assumptions and susceptibility to cognitive biases. It opens up new perspectives that may better capture the complexities of time and future developments.

Considering the changes and uncertainties organizations encounter today, it feels timely to think about alternative frameworks that embrace a more interconnected and dynamic understanding of time and future possibilities. In this way, the study builds upon the foundation laid by previous work and adapts to new insights from philosophy, quantum physics, and cognitive psychology.

Based on that premise, this study analyzes the FC as a two-dimensional or three-dimensional shape expanding in one direction to visually represent a range of alternative potential futures (Migone, Howlett, 2024). Characterized by its cone-like shape, this framework illustrates how various futures branch out from the present. It originated from the work of Henchey (1977) who proposed four categories of future scenarios: possible (any future that could happen), plausible (a future that makes logical sense), probable (a highly likely future based on current trends), and preferable (the best possible future). These categories were later visualized by Hancock and Bezold (1994), and reinterpreted by Voros (2003) to illustrate the expanding range of potential futures as one moves forward in time. As demonstrated by Figure 1, this model encourages the exploration of alternative scenarios. It stimulates thinking about complex problems and dynamics.

However, the FC is not without limitations. While useful for visualizing potential futures, it is essential to examine its underlying assumptions and potential shortcomings. This analysis will evaluate the FC from philosophical, scientific, and cognitive perspectives to identify areas where the framework may oversimplify or misrepresent the nature of time and future possibilities. This examination will consider challenges to the cone's assumed linear progression of time, its handling of uncertainty, and its susceptibility to cognitive biases. It offers recommendations for improving the process of envisioning future possibilities.

In light of the comprehensive critique, this analysis will propose an alternative framework. It is a groundbreaking framework that addresses the limitations inherent in the FC. The Adaptive Futures Mesh (AFM) integrates dynamic systems thinking, participatory agency, and uncertainty absorption to model futures more effectively and responsively. Figure 2 represents an overview of the AFM in which its core components—emergence engine, adaptive feedback loops, and uncertainty gradients—are highlighted. Thus, this analysis aims to provide a more reliable and robust framework for understanding potential futures.

The current study sets the stage for a thorough evaluation of the FC and the proposition of an alternative framework that addresses its limitations. This exploration will contribute to the ongoing dialogue in FS. It enhances the tools and approaches used to envision and prepare for the future. This critical review also serves as an invitation for reflection and growth within the field of FS. As practitioners continue to learn from one another, it will be critically important to remain open-minded and supportive in joint efforts to envision futures that are not only possible but also preferable for all.

The subsequent sections outline the methodology, theoretical framework, problems with the FC framework, an interdisciplinary analysis, and the alternative framework. Finally, the need for adopting the proposed framework to better conduct foresight studies will be noted in light of acknowledging the study's limits and recommending further research.

Method

The methodology utilized in this study involves a structured and interdisciplinary approach (Hvidtfeldt, 2018). It integrates insights from philosophy, quantum physics, and cognitive psychology. A key question drove this study: How can foresight practitioners develop more adaptive frameworks for envisioning the future? This question was raised by acknowledging the complexities of uncertainty and the interconnectedness of potential outcomes. It was aimed at going beyond the limitations of traditional models like the FC. It encouraged the exploration of innovative approaches for FS.

This study examines the philosophical, scientific, and cognitive foundations of the FC to determine if an alternative framework is warranted. Then, the study develops a methodology for an alternative framework. It also assesses its feasibility and utility in supporting strategic decision-making within complex domains such as AI-driven and climate-related strategies.

The study is both epistemological and ontological in its approach. It is epistemological as it focuses on how future possibilities are considered through the FC. It questions how knowledge about potential futures is constructed and validated. It investigates the assumptions underlying the FC and how these assumptions affect the epistemological stance toward envisioning futures. It also explores how different disciplines like philosophy, quantum physics, and cognitive psychology contribute to practitioners' understanding of future possibilities.

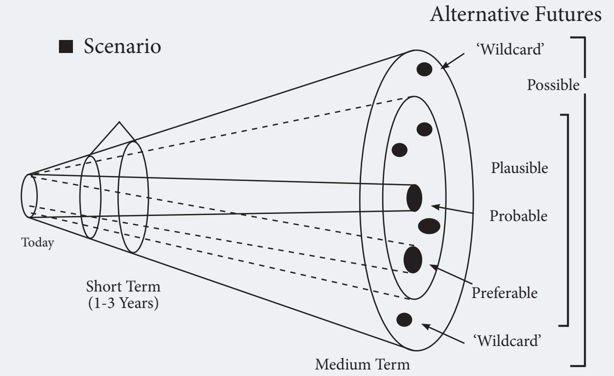
It is ontological as it deals with the nature of time and reality. The study explores what can exist in terms of future possibilities. It considers whether the FC reliably represents the potential realities that could emerge. It examines whether the concept of "possible" futures in the FC aligns with the current understanding of physical laws and cognitive limitations. Ontologically, it proposes an alternative framework concerned with how a different model may better capture the essence of future realities. This involves exploring how quantum physics offers insights into the nature of reality that could inform new ways of conceptualizing future possibilities and how cognitive psychology reveals biases in the perception of future scenarios.

The analysis process began with a review of the literature that created a foundational understanding of the FC and its application. The review involved examining primary sources on the FC, including its origins and adaptations over time, as well as exploring philosophical theories of time. Key works by Hancock and Bezold (1994) provided essential insights into the framework's development, while philosophical texts by Eliade (2018) and Hawking (2011) offered critical perspectives on the nature of time as they challenged the linear assumptions that underpin the cone.

Figure 3 represents the research flow briefly. Following the literature review, a philosophical analysis was conducted to scrutinize the underlying assumptions about time within the FC framework. The analysis highlighted how the assumption of linear time fails to account for cyclical and complex views that emphasize the interconnectedness of past, present, and future. Insights from Eastern philosophies, which view time as a repeating cycle, alongside modern physics concepts such as loop quantum gravity (Rovelli, 2007) revealed that the FC's linear model is limited in its ability to reflect the intricate relationships that shape future possibilities.

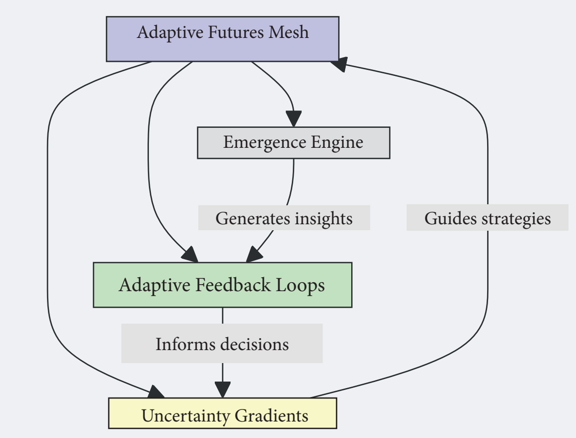
The next phase involved a scientific critique of the FC's treatment of uncertainty and predictability. This critique drew on principles from quantum physics and complex systems theory to illustrate how these fields introduce concepts of uncertainty that challenge traditional models. Quantum mechanics reveals that outcomes are probabilistic rather than predetermined (Bohr, 2011; Heisenberg, 2013), while complex systems theory emphasizes emergent phenomena and non-linear dynamics (Érdi, 2008; Sterman, 2000). The analysis underscored how the FC's static categorization of futures into "probable," "plausible," "possible," and "preferable" oversimplifies the complexities inherent in anticipating future developments.

Figure 1. **The Futures Cone**



Source: (Hancock, Bezold, 1994).

Figure 2. **An Overview of Adaptive Futures Framework**

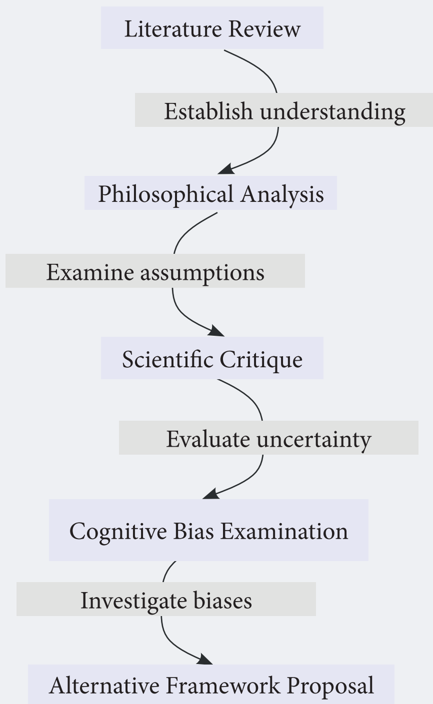


Source: author.

In addition to philosophical and scientific perspectives, cognitive biases were examined to understand their influence on how individuals interpret and apply the cone. The analysis identified common biases such as confirmation bias and anchoring bias that can distort futures thinking. The recognition of these biases revealed that decision-makers might prioritize specific outcomes while neglecting alternative scenarios (Ramos, 2019). This insight led to a discussion of strategies for mitigating these biases through diverse perspectives and inclusive decision-making processes.

Building upon these critiques, an alternative framework was proposed. This approach emphasizes the interconnectedness of past, present, and future while acknowledging uncertainty and complexity. It advocates for incorporating multiple perspectives to mitigate cognitive biases and recognizes the dynamic nature of time and potential futures. Adopting an interdisciplinary approach offers a more reliable model for understanding uncertainty and complexity.

Figure 3. **The Research Flow**



Source: author.

Theoretical Framework

The networked perception of the future aligns with several theories and approaches, including networked foresight, systems thinking, and concepts related to social-ecological systems. These theories emphasize interconnectedness, dynamic interactions, and the importance of multiple perspectives, which are central to the networked perception framework.

Systems Thinking

Systems thinking is a holistic approach that focuses on understanding the relationships among parts of a system rather than analyzing the individual components in isolation. It emphasizes that the interactions and feedback loops between its elements determine the behavior of a system (Meadows, Wright, 2008). In the context of FS, systems thinking encourages practitioners to consider the broader social, technological, economic, environmental, and political factors that shape future outcomes (Hynes et al., 2020). Systems thinking analyzes these interdependencies and helps to reveal potential leverage points and unintended consequences that linear approaches likely overlook.

Interdisciplinary Approach

Including multiple perspectives is an essential component of a networked or complex perception. Taking such an approach requires practitioners to go beyond the conventional borders of the foresight field and embrace views from other disciplines, including cognitive psychology. For instance, cognitive biases can significantly distort human understanding of the future, leading to narrow and inaccurate predictions.

Similarly, modern physics has introduced theories such as loop quantum gravity, which imply that spacetime itself may be fundamentally non-linear (Rovelli, 2007). These insights highlight the limitations of viewing time through a linear lens and underscore the need for a wider understanding of how time operates. For example, quantum physics challenges the FC's assumptions by introducing concepts of uncertainty and non-linearity. At the quantum level, particles exist in superpositions of states until they are measured. This indicates that outcomes are not predetermined but probabilistic (Heisenberg, 2013). The inherent uncertainty suggests that the future cannot be envisioned or anticipated based solely on present conditions.

Practitioners may seek out diverse viewpoints and challenging assumptions to mitigate the impact of these biases and gain a more comprehensive understanding of the range of possible futures. This approach also aligns with creating environments where all voices are heard and collective intelligence is harnessed (van den Ende et al., 2022). Perceived societal anomie, as a negative perception of the present, can shape imagined futures. Again, this further emphasizes the need for diverse perspectives.

Dynamic Perspective

A networked perception emphasizes the dynamic and evolving nature of the future. Unlike the FC, which presents a static view of potential outcomes, this approach recognizes that a multitude of interacting factors shape the future constantly. If decision-makers embrace such a dynamic perspective, they can remain agile and responsive to changing conditions and adapt their strategies as new information emerges. This approach aligns with networked thinking. It encourages unbounded exploration and embraces the chaotic nature of the journey (Stechert, 2006). Network analysis can reveal structural linkages between trends and emerging issues, and thereby enrich foresight analysis.

Social-Ecological Outlook

The concept of social-ecological systems (SES) recognizes that human societies and natural ecosystems are intertwined and co-evolve (Walker et al., 2004). Understanding SES dynamics is critical for sustainable futures. It highlights the reciprocal relationships between human actions and environmental impacts (Partelow, 2018). In FS, an SES perspective encourages practitioners to consider how social and ecological systems interact and influence each other over time (Drees et al., 2022).

This approach often involves engaging diverse stakeholders, including scientists, business owners, government officials, landowners, and nonprofit representatives, to develop integrated plans for managing resources and building resilience in the face of uncertainty. The SES concept also highlights the importance of considering outcomes where advanced technologies or large-scale systems result in immense suffering. Addressing these risks involves ethical foresight and robust frameworks to prevent scenarios where suffering could persist or multiply across vast scales.

Futures Literacy

Futures literacy involves the ability to imagine and shape the future, i.e., how the future influences perception and actions, and learning to apply strategies to build resilience and opportunities for the futures (Miller, 2018). This capacity has been recognized as an important skill for education today. It can enhance the exploration of new ways of engaging with what is happening in the world. From the perspective of educational technology, it provides learners with a method to anticipate the ethical, social, and economic challenges that may arise in the new educational landscape and to design policies and practices that promote equity and inclusion in an increasingly digital world (Mangnus et al., 2021). Futures literacy aligns with the network perception of the future.

The networked perception framework integrates these concepts, theories, and approaches to provide a more holistic and adaptive approach to FS. It aligns with the interdisciplinary and systematic study of technological and social advancement. This theoretical foundation makes the exploration of potential futures possible and facilitates the development of robust strategies for navigating complexities and interconnections.

Main Problems with the FC

The FC framework, while a valuable tool in strategic planning, presents significant limitations when confronted with the complexities of real-world scenarios. Its primary deficiency lies in its inability to adequately account for unknown unknowns, those unpredictable and unforeseen events that can drastically alter the course of future outcomes, as well as the inherent dynamic, non-linear nature of reality (Heisenberg, 2013). These shortcomings can lead to strategic plans that are ultimately rigid and ill-prepared for the challenges of uncertain futures. An overview of the main problems with the FC framework is offered below.

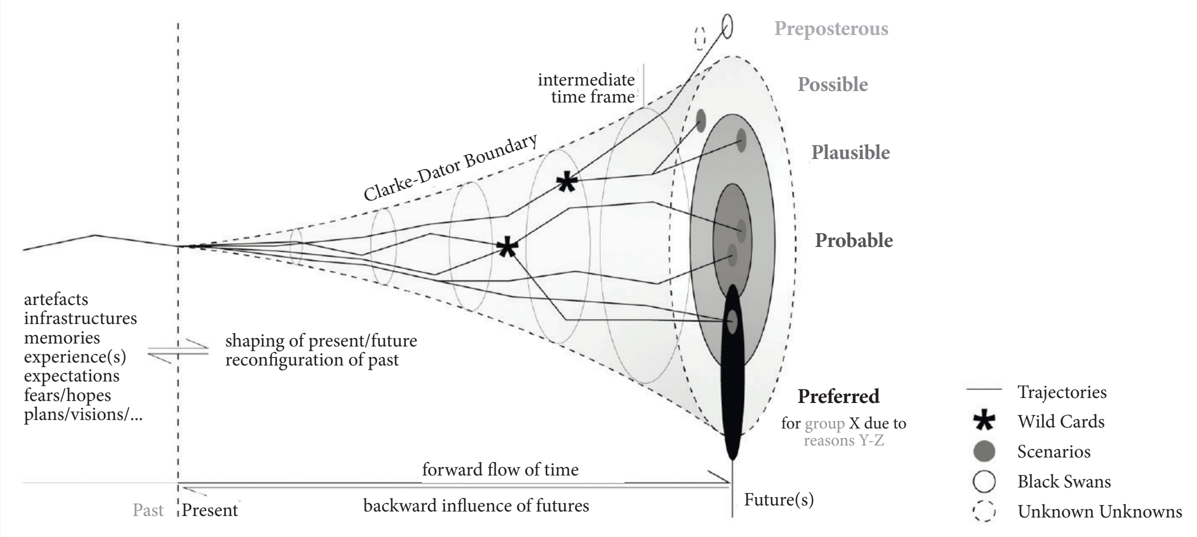
Linear Conception

The FC inherently presumes a linear progression of time. It is an assumption that faces considerable scrutiny from philosophical and physical science perspectives. This linear model suggests that the future unfolds sequentially from the present and branches out into a range of possibilities. The FC operates under static and linear assumptions that do not reflect the intricate dynamics of reality (Migone, Howlett, 2024). The framework implies a linear progression from the present to various potential futures. It neglects the complex interdependencies, feedback loops, and emergent phenomena that constantly reshape the world.

Furthermore, it cannot often dynamically adapt as new information emerges. It offers strategies that can quickly become outdated and irrelevant. Constant change and interconnectedness characterize the world. Thus, a linear and static model can prove inadequate. As depicted by Figure 4, even later representations of the FC framework that attempted to optimize its structure amplified that concept of linearity (Gall et al., 2022).

However, a significant body of philosophical thought challenges this notion. They argue that time is not necessarily a straight line but may exhibit cyclical patterns (Overton, 1994), complex interdependencies (Hawking, Penrose, 2015), or

Figure 4. **The Revised FC**



Source: (Gall et al., 2022).

even be an illusion altogether (Jaffe, 2018). This issue will be discussed further in the upcoming section.

Illusion of Comprehensiveness

One of the most significant drawbacks of the FC is the false sense of comprehensiveness it can engender. The framework categorizes potential futures into discrete segments such as "probable," "plausible," "possible," and "preferable." It creates an illusion that all critical scenarios have been accounted for. However, practitioners' current knowledge base inherently limits this categorization. The FC struggles to address blind spots or so-called black swan events, unpredictable, high-impact developments that fall outside existing frameworks of understanding (Taleb, 2010). Because it relies on what is already known or anticipated, it inherently fails to account for what decision-makers cannot know.

Overlooking Human Agency and Interaction

Another key limitation of the FC is that it overlooks the critical role of human agency and interaction in shaping future outcomes. The cone tends to treat futures as passive results rather than recognizing the influence of proactive decisions, innovation, and the complex interplay between different scenarios and stakeholder actions. The framework is merely a simplified representation of an assumption that does not adequately model the multifaceted interactions that can significantly alter the course of events. Thus, it diminishes the impact of human actors.

Underestimating Uncertainty

The FC runs the risk of underestimating the true extent of uncertainty as it structures the future into distinct categories. This categorization can create a sense of overconfidence in strategic plans. It may lead organizations to prioritize "probable" or "plausible" paths and neglect the potential for radical disruption. This can leave them vulnerable to unanticipated challenges and ill-prepared to navigate the complexities of a changing environment. When uncertainty is downplayed, resilience is compromised.

There is a growing need for adaptability and agility in making future-focused decisions. Strategic plans that rely solely on the FC framework may prove rigid, incomplete, and ultimately ineffective. To develop truly resilient strategies, decision-makers must embrace adaptability, scenario agility, and a sense of humility in the face of the unknown. Effective strategy requires acknowledging the limitations of anticipatory models and cultivating the capacity to respond effectively to unforeseen events—elements that the FC does not inherently address.

Analysis

To propose an alternative framework to the FC, it was necessary to integrate insights from several disciplines, including philosophy, quantum physics, and cognitive psychology. In this way, a comprehensive understanding of how humans envision potential futures could be achieved. Therefore, the limitations of the FC were examined through an interdisciplinary lens. This analytical framework aims to highlight the complexities of time, uncertainty, and human cognition in shaping perceptions of future possibilities.

Philosophical Perspective

Philosophical viewpoints on time vary widely. Some, like Aristotle, define it as a "measure of movement" and inextricably linked to change (Hutton, 1977). Others, such as Newton, posited the existence of "absolute time," flowing uniformly and independently of external events (Schliesser, 2013). In contrast, relationists like Leibniz argued that time is not independent of events but rather a series of moments defined by the relations of "earlier-than" and "simultaneous-with" among co-existing events (Futch, 2008). These contrasting views highlight a fundamental debate about whether time is an objective reality or a construct dependent on perception and the events that unfold within it.

The concept of cyclical time (Oosterling, Tiemersma, 1996), prevalent in many early cultures and religions like Hinduism, Buddhism, and Jainism, further undermines the linear assumption of the FC. These traditions perceive time as consisting of repeating ages and periods. They suggest that the future may echo patterns from the past (Bendor et al., 2021). This cyclical view contrasts sharply with the FC's unidirectional projection, where the future is seen as a divergence from the present rather than a recurrence of past trends.

Modern philosophical perspectives also challenge the traditional understanding of time. Some philosophers propose that time might be an illusion, with everything happening simultaneously, and that the perception of sequential events is merely a construct of mind (Merleau-Ponty, 2004). Others focus on subjective time. They emphasize how consciousness and changing perceptions shape the human experience of time (Varela, Depraz, 2005). Kant suggested that time and space are forms that the mind projects (Copenhaver, 2019). They influence how humans perceive the external world. These ideas suggest that human's understanding of time is not a direct reflection of an objective reality but is filtered through cognitive processes (Nozick, 2001).

Consequently, the FC's depiction of the future as a set of possibilities branching out from the present may be an oversimplification. Influenced by past patterns, present conditions, and the subjective experiences of individuals, a more reliable approach might envision the future as a complex web of interconnected events. This perspective aligns with complex systems theory (Estrada, 2024), where small changes can lead to significant and unpredictable outcomes. This view emphasizes the interconnectedness and emergent properties of the future.

Scientific Perspective

Quantum physics fundamentally alters the assumption of determinism. At the quantum level, particles do not have definite states until they are observed. Instead, they exist in a superposition of states (Colosi, Rovelli, 2009). This principle suggests that the future is not merely a linear extension of the present but is influenced by probabilistic outcomes that are not predetermined. As a physicist, Niels Bohr famously stated, "We must be clear that when it comes to atoms, language can be used only as in poetry" (Anderson, 1971). This highlights the limitations of classical deterministic models in anticipating future events. The FC's reliance on probability overlooks this quantum uncertainty and presents a misleadingly simplistic view of how future events may unfold.

Moreover, complex systems theory further complicates the linear notion of time. In complex systems, small changes can lead to disproportionately large effects—a phenomenon known as the butterfly effect. This unpredictability means that while certain trends may appear probable based on current data, they can be disrupted by unforeseen variables or interactions within the system. As noted by physicist Edward Lorenz, "The flapping of a butterfly's wings in Brazil can set off a tornado in Texas" (Érdi, 2008). Thus, the structure of the FC may imply a false sense of security regarding the ability to predict future outcomes based solely on present conditions.

On the other hand, deterministic assumptions in complex systems often hold only within specific spacetime scales. For instance, while short-term anticipations may yield reasonable accuracy due to more stable conditions, long-term forecasts become increasingly unreliable as more variables and uncertainties come into play. This limitation is crucial for understanding how the FC might misrepresent the fluidity and complexity of future scenarios. As noted by researchers like Sterman (2000), neglecting these dynamics can lead to oversimplified models that fail to capture the intricate interdependencies present in real-world situations.

In light of these scientific insights, it becomes evident that the FC framework requires re-evaluation. Rather than viewing the future as a series of branching paths emerging from a fixed present moment, it may be more productive to conceptualize it as a dynamic network of interconnected possibilities influenced by a myriad of factors, both predictable and unpredictable, namely, a mesh. If practitioners embrace the inherent complexity and uncertainty of the future as described by quantum mechanics and complex systems theory, they may develop more robust models that reflect the true nature of time and future outcomes.

Cognitive Perspective

The FC is inherently susceptible to cognitive biases that can significantly distort foresight and anticipatory thinking. Cognitive biases are systematic patterns of deviation from the norm or rationality in judgment. They arise from the way the human brain processes information (Muntwiler, 2023). These biases can affect how individuals perceive the present, interpret signals, and imagine future possibilities. They may lead to errors in judgment and decision-making.

One of the primary cognitive pitfalls of the FC is the tendency for individuals to focus on a particular image of the future and neglect alternative scenarios. This often results from confirmation bias, where people selectively seek out and interpret information that confirms their pre-existing beliefs or hypotheses (Nickerson, 1998). For instance, if someone believes that renewable energy will dominate the future, they might overemphasize trends supporting this view and dismiss evidence that suggests otherwise. This narrow focus can lead to a skewed and incomplete understanding of the range of possible futures. It can limit the effectiveness of strategic planning and risk assessment (Cristofaro et al., 2021).

The structure of the FC itself can inadvertently reinforce confirmation bias. By categorizing futures into "possible," "plausible," "probable," and "preferable," the cone may create a cognitive framework that encourages individuals to prioritize scenarios that align with their current expectations or desires. This can result in a self-fulfilling prophecy and drive efforts that are concentrated on realizing a specific future while neglecting the exploration of alternative paths that may be more beneficial or resilient in the face of unanticipated events.

Anchoring bias also poses a significant challenge when using the FC. This bias refers to the tendency to rely too heavily on the first piece of information encountered when making decisions (Chapman, Johnson, 1994). In the context of futures thinking, the initial assumptions or trends considered can disproportionately influence the subsequent analysis and scenario development. This can limit the ability to see beyond the probable spectrum. It may eliminate chances of finding plausible or possible alternatives.

To mitigate the impact of cognitive biases, decision-makers must be aware of these tendencies and actively employ strategies to overcome them (Winkler, Moser, 2016). This includes seeking diverse perspectives, challenging assumptions, and using structured decision-making processes to ensure that a wide range of possibilities is considered. Additionally, scanning the environment for weak signals and emerging trends can help to identify potential disruptions that might be overlooked due to cognitive biases (Tabatabaei, 2011).

Recognizing that worldviews are tacit, with practitioners participating in future exercises unaware of their biases, it becomes essential to expand the FC (Kunseler et al., 2015). This requires considering the past and present to ensure a more effective and inclusive supervisory style of foresight. Consideration of likelihood, interdependence, and power dynamics can enrich future scenario planning and ensure that the range of possible futures is captured.

Adaptive Futures Mesh

Instead of the FC's linear approach, an alternative perspective, particularly a networked one can offer a more robust and adaptable framework for understanding the nature of time and the future. The Adaptive Futures Mesh framework, AFM, is designed to handle unexpected events through several key components. Its components work together to provide a more comprehensive and reliable understanding of the future. This approach recognizes the intricate interconnectedness of the past, present, and future. It acknowledges the inherent uncertainty and complexity that characterizes future outcomes. This approach integrates multiple perspectives and actively mitigates cognitive biases. It emphasizes the dynamic and evolving nature of the future and leads practitioners toward a better foresight practice.

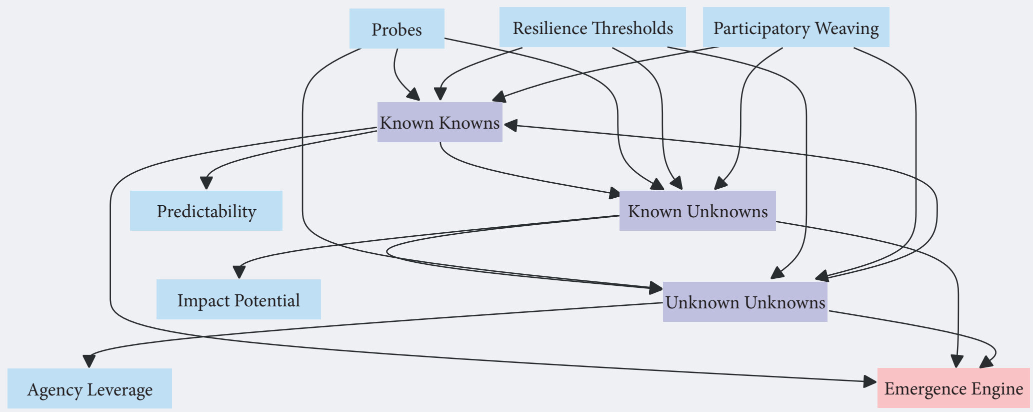
Principles

At the heart of the AFM are several core principles that redefine how it conceptualizes futures. Firstly, it emphasizes the 'non-linear interconnectedness' of futures. It replaces the linearity of cones with a dynamic network that reflects the complexity of real-world interactions. Secondly, it treats uncertainty as a core variable rather than an afterthought. This creates a more realistic representation of future scenarios. Thirdly, the concept of participatory emergence is introduced. In this sense, futures are co-created by both human and non-human actors. Lastly, the framework promotes continuous adaptation. It utilizes feedback loops that replace static scenarios with evolving strategies.

Components

One of the fundamental aspects of the AFM is its mesh structure. Instead of visualizing futures as a simple cone, this framework models them as a three-dimensional network composed of interconnected nodes. These nodes represent various categories: known knowns, which include established

Figure 5. **The Key Components of Adaptive Futures Mesh**



Source: author.

trends and data; known unknowns, encompassing identified risks; and unknown unknowns. Inspired by astrophysics, the AFM represents them as "dark matter nodes" that absorb ambiguity (Choudhury, 2023).

In the fields of space science and astrophysics, dark matter is believed to make up more than 80 percent of the universe's matter, but it remains invisible to scientists. Since it emits neither light nor energy, it cannot be detected using traditional methods. Dark matter appears to be dispersed throughout the universe in a web-like structure, with galaxy clusters forming at the intersections of these cosmic fibers (Garrett, Duda, 2011). Likewise, the nodes within the AFM dynamically adjust in size and position based on real-time data, stakeholder actions, and external shocks. Figure 5 represents the key components of this mesh.

Drawing from cognitive science, another significant element is the concept of "uncertainty gradients" (Skov, Nadal, 2023). Each node is evaluated based on three distinct gradients: "predictability," which assesses how well we understand it; "impact potential," which gauges the magnitude of potential disruption; and "agency leverage," which measures how much influence stakeholders can exert over it. Together, these gradients create a heat map that guides strategic resource allocation as represented by Figure 6.

The AFM also incorporates adaptive feedback loops (Zavala Rodríguez et al., 2019). This involves small-scale experiments known as probes, which test assumptions and generate signals to update the mesh accordingly. Resilience thresholds are established to define critical tipping points where strategies must pivot in response to significant changes. Moreover, participatory weaving allows stakeholders to collaboratively add or remove nodes, ensuring that emerging risks are flagged by those closest to them. Figure 7 shows how feedback loops contribute to updating the mesh.

Lastly, an "emergence engine" serves as a layer for emergent futures that arise from interactions between nodes (Maltarich, Havrylyshyn, 2023). For instance, debates on artificial intelligence (AI) ethics combined with climate migration can lead to new governance models. This engine leverages generative AI or crowdsourcing techniques to simulate various combinatorial possibilities. Figure 8 models these components and flows.

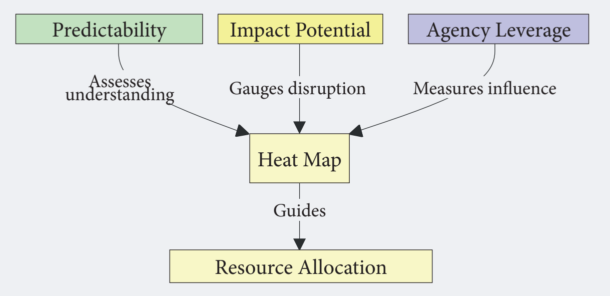
Dealing with the FC's Problems

The AFM effectively addresses several shortcomings of the traditional FC. It incorporates the "dark matter nodes" metaphor and acknowledges the existence of unknown unknowns. In this way, it encourages humility in foresight by explicitly reserving space for unimaginable scenarios. The non-linear structure visualizes cascading impacts. For example, if a supply chain node collapses, it may significantly alter geopolitical dynamics. Furthermore, human agency is emphasized. Stakeholders have the power to rewire the mesh through their decisions and actions. Finally, adaptive feedback loops ensure that strategies evolve more swiftly than disruptions can occur.

Superiority

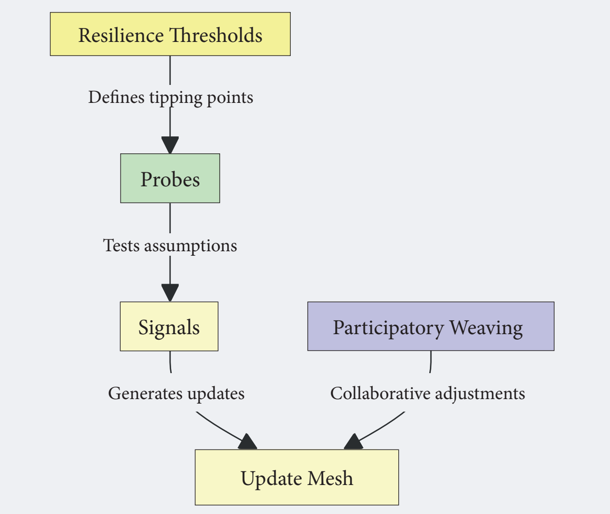
The AFM promotes an resilient approach that thrives on volatility by viewing uncertainty as a catalyst for innovation rather than an obstacle. It democratizes foresight by involving diverse voices in shaping future trajectories through collaborative weaving. Most importantly, it shapes a living strat-

Figure 6. **Uncertainty Gradients**



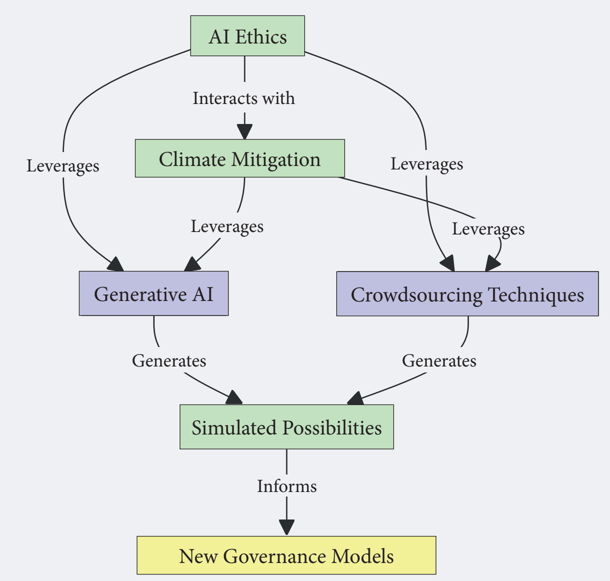
Source: author.

Figure 7. **Adaptive Feedback Loops**



Source: author.

Figure 8. **An Emergence Engine Model**



Source: author.

egy where plans are never final but evolve organically in response to changing circumstances. This framework represents a crucial shift from merely anticipating futures to actively cultivating futures-readiness. This is an essential capability in today's era characterized by poly-crisis challenges (Raczkowski, Komorowski, 2025). Organizations interested in operationalizing this approach can explore tailored applications specific to their industries.

Example

Consider a company that strategizes for climate-related initiatives by 2030. A traditional FC approach might focus narrowly on plausible carbon taxes. However, applying the AFM allows for a broader perspective. The company could map nodes such as "geoengineering start-ups," "water conflicts," and "unknown climate feedback loops." Through this comprehensive modeling, they might identify a dark matter node—like permafrost methane release—that poses significant risks to other elements within their strategy. If they invest in innovative methane-capture prototypes while continuously monitoring Arctic conditions, they can adapt their strategy as new nodes emerge — such as youth-led climate litigation.

Conclusion

This analysis has critically examined the FC, a prominent framework in futures studies that categorizes potential futures into probable, plausible, possible, and preferable types. While the FC serves as a useful tool for visualizing alternative futures and stimulating strategic thinking, it is not without limitations. The reliance upon a linear progression of time oversimplifies the complexities and uncertainties inherent in forecasting future developments. Philosophical critiques challenge the notion of linear time, suggesting instead that time may be cyclical or complex, where past, present, and future are interconnected. Furthermore, scientific insights from quantum physics and complex systems theory highlight the unpredictability of future outcomes, emphasizing that they are influenced by chance and new conditions rather than deterministic pathways.

Additionally, cognitive biases play a crucial role in shaping how individuals interpret and engage with the FC. Confirmation bias and anchoring bias can lead to a narrow focus on specific futures while neglecting alternative scenarios. This underscores the importance of incorporating diverse perspectives and challenging assumptions to mitigate these biases. If decision-makers recognize these limitations, they can avoid complacency and develop a more comprehensive understanding of potential futures.

To address the shortcomings of the FC, this analysis proposed the AFM alternative framework. This approach emphasizes the interconnectedness of past, present, and future while acknowledging uncertainty and complexity. This framework incorporates multiple perspectives and recognizes the dynamic nature of future developments. It offers a more reliable understanding that can better inform strategic planning and decision-making. Embracing this complexity allows organizations to remain agile in the face of uncertainty and adapt their strategies as new information emerges.

The exploration of alternative frameworks like networked perception is essential for enhancing practitioners' ability to envision and prepare for the future. As organizations navigate an increasingly complex world characterized by change and uncertainty, adopting comprehensive approaches to futures thinking will be crucial for empowering resilience and adaptability. The AFM moves beyond the limitations of the FC. It embraces a more holistic view of potential futures that better equip decision-makers to respond effectively to emerging challenges and opportunities.

While this study introduces and details the AFM as a novel framework for strategic foresight, it is inherently limited by its primarily theoretical and conceptual nature. The proposed framework requires extensive empirical validation across diverse real-world scenarios and organizational contexts. Furthermore, the effectiveness of specific components, such as the dark matter nodes and the emergence engine, requires rigorous testing to determine their practical contribution to improved decision-making. The study also acknowledges the potential challenges in implementing the AFM, including the need for cross-functional collaboration, data availability, and stakeholder engagement, which may vary significantly depending on the specific context.

Future research should focus on empirically validating the AFM framework through case studies and experimental designs. This includes developing quantifiable metrics to assess the performance of the AFM in comparison to traditional strategic foresight methods like the FC. Investigating the optimal methods for identifying and managing dark matter nodes, as well as exploring the ethical implications of using AI and crowdsourcing in the emergence engine, are critical areas for future research. Furthermore, studies should address the practical challenges of implementing the AFM in various organizational settings, including developing best practices for team composition, data governance, and stakeholder engagement to maximize the framework's effectiveness and impact.

References

Anderson E.E. (1971) *Modern physics and quantum mechanics*, Philadelphia, PA: Saunders.

Bendor R., Eriksson E., Pargman D. (2021) Looking backward to the future: On past-facing approaches to futuring. *Futures*, 125, 102666. https://doi.org/10.1016/j.futures.2020.102666

Bohr N. (2011) *Atomic theory and the description of nature: Four essays with an introductory survey*, Cambridge: Cambridge University Press.

Chapman G.B., Johnson E.J. (1994) The limits of anchoring. *Journal of Behavioral Decision Making*, 7(4), 223–242. https://doi.org/10.1002/bdm.3960070402

Choudhury P.P. (2023) Formation of multiphase plasma in galactic haloes and an analogy to solar plasma. *Frontiers in Astronomy and Space Sciences*, 10, 1155865. https://doi.org/10.3389/fspas.2023.1155865

Colosi D., Rovelli C. (2009) What is a particle? *Classical and Quantum Gravity*, 26(2), 025002. https://doi.org/10.1088/0264-9381/26/2/025002

Copenhaver R. (2019) *Philosophy of mind in the early modern and modern ages*, New York: Routledge.

Cristofaro M., Sousa M.J., Sánchez-García J.C., Larsson A. (eds.) (2021) *Managerial and entrepreneurial decision making: Emerging issues*, Basel: MDPI.

Drees L., Liehr S., Batbuyan B., Marg O., Mehring M. (2022) In search of a nomadic pastoralism for the 21st century. A transdisciplinary development of future scenarios to foster a social-ecological transformation in Mongolia. *Innovation: The European Journal of Social Science Research*, 35(3), 481–505. https://doi.org/10.1080/13511610.2022.2100744

Eliade M., Trask W.R., Smith J.Z. (2018) *The myth of the eternal return: Cosmos and history* (1st ed.), Princeton, NJ: Princeton University Press.

Érdi P. (2008) *Complexity explained*, Cham: Springer.

Estrada E. (2024) What is a complex system, after all? *Foundations of Science*, 29(4), 1143–1170. https://doi.org/10.1007/s10699-023-09917-w

Futch M.J. (2008) *Leibniz's metaphysics of time and space*, Cham: Springer.

Gall T., Vallet F., Yannou B. (2022) How to visualise futures studies concepts: Revision of the futures cone. *Futures*, 143, 103024. https://doi.org/10.1016/j.futures.2022.103024

Garrett K., Duda G. (2011) Dark Matter: A Primer. *Advances in Astronomy*, 2011, 968283. https://doi.org/10.1155/2011/968283

Hancock T., Bezold C. (1994) Possible futures, preferable futures. *Healthcare Forum Journal*, 37(2), 23–29.

Hawking S.W. (2011) *A brief history of time: From the big bang to black holes*, New York: Bantam.

Hawking S.W., Penrose R. (2015) *The nature of space and time* (2nd ed.), Princeton, NJ: Princeton University Press. https://doi.org/10.1515/9781400834747

Heisenberg W. (2013) *Physical principles of the quantum theory* (first published in 1930), New York: Dover Publications.

Henchey N. (1977) The future of Quebec: Alternative scenarios. *McGill Journal of Education*, 12(1), 17–27.

Hutton S. (1977) Some renaissance critiques of Aristotle's theory of time. *Annals of Science*, 34(4), 345–363. https://doi.org/10.1080/00033797700200271

Hvidtfeldt R. (2018) *The structure of interdisciplinary science*, Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-90872-4

Hynes W., Lees M., Müller J.M. (eds.) (2020) *Systemic thinking for policy making: The potential of systems analysis for addressing global policy challenges in the 21st century*, Paris: OECD Publishing. https://doi.org/10.1787/879c4f7a-en

Jaffe A. (2018) The illusion of time. *Nature*, 556(7701), 304–305. https://doi.org/10.1038/d41586-018-04558-7

Kunseler E.-M., Tuinstra W., Vasileiadou E., Petersen A.C. (2015) The reflective futures practitioner: Balancing salience, credibility and legitimacy in generating foresight knowledge with stakeholders. *Futures*, 66, 1–12. https://doi.org/10.1016/j.futures.2014.10.006

Maltarich M., Havrylyshyn A. (2023) The emergence engine: Socially mediated individual change. *Academy of Management Proceedings*, 2023(1), 13126. https://doi.org/10.5465/AMPROC.2023.84bp

Mangnus A.C., Oomen J., Vervoort J.M., Hajer M.A. (2021) Futures literacy and the diversity of the future. *Futures*, 132, 102793. https://doi.org/10.1016/j.futures.2021.102793

Mao H., Liu S. (2023) Research on the influence of innovative design based on the futures cone In: *Proceedings of the 2022 2nd International Conference on Computer Technology and Media Convergence Design* (CTMCD 2022) (eds. K. Subramanian, J. Ouyang, W. Wei.), New York: Atlantis Press International BV, vol. 99, pp. 403–410. https://doi.org/10.2991/978-94-6463-046-6_48

Meadows D.H., Wright D. (2008) *Thinking in systems: A primer*, London: Chelsea Green Pub.

Merleau-Ponty M. (2004) *World of perception*, New York: Routledge.

Migone A., Howlett M. (2024) Multiple streams and plausibility cones: Using concepts from future studies to depict policy dynamics. *International Journal of Public Administration*, 48(5–6), 368–380. https://doi.org/10.1080/01900692.2024.2381769

Miller R. (2018) *Transforming the future: Anticipation in the 21st century*, New York: Routledge.

Muntwiler C. (2023) *Cognitive biases and debiasing in strategic decision making* (PhD thesis), St. Gallen: University of St. Gallen.

Nickerson R.S. (1998) Confirmation bias: A ubiquitous phenomenon in many guises. *Review of General Psychology*, 2(2), 175–220. https://doi.org/10.1037/1089-2680.2.2.175

Nozick R. (2001) *Invariances: The structure of the objective world*, Cambridge, MA: Belknap Press of Harvard University Press.

Oosterling H.A.F., Tiemersma D. (eds.) (1996) *Time and temporality in intercultural perspective*, Leiden (Netherlands): Brill.

Overton W.F. (1994) The arrow of time and the cycle of time: Concepts of change, cognition, and embodiment. *Psychological Inquiry*, 5(3), 215–237. https://doi.org/10.1207/s15327965pli0503_9

Partelow S. (2018) A review of the social-ecological systems framework. *Ecology and Society*, 23(4), 26796887. JSTOR. https://www.jstor.org/stable/26796887

Raczkowski K., Komorowski P. (eds.) (2025) *International economic policy for the polycrisis*, New York: Routledge. https://doi.org/10.4324/9781003487913

Ramos V.J. (2019) *Analyzing the role of cognitive biases in the decision making process*, Hershey, PA: IGI Global.

Rovelli C. (2007) *Quantum gravity*, Cambridge: Cambridge University Press.

Schliesser E. (2013) Newton's philosophy of time. In: *A companion to the philosophy of time* (eds. H. Dyke, A. Bardon), New York: Wiley, pp. 87–101. https://doi.org/10.1002/9781118522097.ch6

Skov M., Nadal M. (eds.) (2023) *The Routledge international handbook of neuroaesthetics*, New York: Routledge.

Stechert P. (2006) Informatics system comprehension: A learner-centred cognitive approach to networked thinking. *Education and Information Technologies*, 11(3–4), 305–318. https://doi.org/10.1007/s10639-006-9014-4

Sterman J.D. (2000) *Business dynamics: Systems thinking and modeling for a complex world* (International student edition), New York: McGraw-Hill.

Park E., Shin H. (2024) *Contextualizing comedy techniques for speculative design: Unraveling futures cone from sketch comedy series, '2032/2033 futures'*. Paper presented at the DRS2024 Conference, 23–28 June, Boston, USA. https://doi.org/10.21606/drs.2024.433

Tabatabaei N. (2011) *Detecting weak signals by internet-based environmental scanning* (Master's Thesis), Waterloo: University of Waterloo.

Taleb N.N. (2010) *The black swan: The impact of the highly improbable* (2nd ed.), New York: Random House.

Taleb N.N. (2012) *Antifragile: Things That Gain From Disorder,* New York: Random House.

Van den Ende M.A., Wardekker A., Hegger D.L.T., Mees H.L.P., Vervoort J.M. (2022) Reflection: Applying participatory foresight methods in practice. In: *Towards a climate-resilient future together* (eds. M.A. van den Ende, A. Wardekker, D.L.T. Hegger, H.L.P. Mees, J.M. Vervoort), Cham: Springer International Publishing, pp. 61–70. https://doi.org/10.1007/978-3-031-07682-4_4

Varela F.J., Depraz N. (2005) At the source of time: Valence and the constitutional dynamics of affect. *Journal of Consciousness Studies*, 12(8–10), 61–81.

Voros J. (2003) A generic foresight process framework. *Foresight*, 5(3), 10–21. https://doi.org/10.1108/14636680310698379

Walker B., Holling C.S., Carpenter S.R., Kinzig A.P. (2004) Resilience, adaptability and transformability in social-ecological systems. *Ecology and Society*, 9(2), 5. https://doi.org/10.5751/ES-00650-090205

Winkler J., Moser R. (2016) Biases in future-oriented Delphi studies: A cognitive perspective. *Technological Forecasting and Social Change*, 105, 63–76. https://doi.org/10.1016/j.techfore.2016.01.021

Zavala Rodríguez E.B., Marco Gómez J., Franch Gutiérrez J. (2019) *Towards adaptative monitoring for self-adaptative systems*, Barcelona: Universitat Politècnica de Catalunya.

AI amid the US-China Rivalry: Scenarios and Policies for Small States

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Abstract

Emerging disruptive technologies such as artificial intelligence (AI) are fueling global rivalry by changing the power dynamics among countries. This article examines the implications of AI for the prospects of defense competition between major powers such as the United States and China. It presents possible scenarios of such competition through 2050 and their implications for smaller countries with limited geopolitical influence as they adapt to the increasingly complex context these processes create. The scenarios provide not only structured pictures of possible futures but also a strategic canvas for developing proactive national security policies in the changing international landscape. In the context of rapid technological advances and strategic competition, smaller countries face both challenges and opportunities as they navigate their own paths. The proposed recommendations aim to "level the playing field" and help such states not only address the challenges posed by AI in the military sphere but also seize the opportunities arising from technological shifts. The findings presented can serve as a basis for developing national security strategies even in the context of institutional and infrastructural limitations. Decision makers will be able to navigate and effectively act in a complex, changing arena, the dynamism of which is largely determined by AI technologies.

Keywords: US-China rivalry; innovation in the defense sector; artificial intelligence (AI); technological competition; national strategies; foresight; small states; global security; international cooperation

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Introduction

The dynamic development of new technologies is radically transforming a wide range of activities in both the civilian and military spheres. This is especially true for dual-use technologies, including artificial intelligence (AI). The increased integration of AI into military strategies is reformatting the sphere of global security, changing the nature of strategic planning, and data collection. (Johnson, 2019; Mori, 2018). Qualitatively different approaches to decision-making are emerging, it becomes possible to more accurately predict the tactics and strategies of opponents, and the arsenal of means for retaliatory steps is expanding. The dynamics of the balance of power in international relations are closely related to economic and technological development. According to some estimates, by 2030, thanks to the spread of AI technology, global GDP may increase by $15.7 trillion, with 70% of this increase coming from the two most influential powers, the United States and China (PWC, 2017). The rivalry between these countries, including in the creation of technologies for the military sector, is increasing global tensions. The Center for a New American Security (CNAS) compares this kind of technological competition to the space race of past decades (Horowitz et al., 2018). The critical role of this technology in shaping the future geopolitical landscape is emphasized not only for world-leading states but also for other players (Fernández-Montesinos, 2019). For smaller countries, this means a widening technological gap that will make them critically vulnerable to a wide range of complex challenges. Unlike major powers, such entities do not have sufficient technological and military resources to compete directly. As a result, the risks of destabilization for them increase. However, if they engage in multilateral international cooperation and form strategic alliances that promote the ethical governance of AI, they have greater opportunities to strengthen their security and sovereignty.

This study fills a critical gap in the existing literature: researchers have rarely considered the long-term impact of AI on global power dynamics and its implications for different states. We analyze the transformative effect of AI on future conflicts between the United States and China, focusing on the military and geopolitical domains. We develop a set of possible scenarios up to 2050. We offer practical recommendations to help small states navigate the rapidly changing international system based on flexibility, adaptability, and proactivity. The analysis of risks and opportunities presented in this paper can provide a solid foundation for future research and policy development in the era of AI-influenced geopolitics.

Literature Review

General Trends in the Development of AI in the Military Sphere[1]

As AI technologies advance, their potential to alter the global balance of power and strategic stability is increasingly being revealed (Boulanin et al., 2020). Most of these breakthroughs, which have resulted from the combined efforts of the commercial and academic spheres, have already led to significant changes in the dynamics of weapons.[2] The formation of a critical mass of publicly available basic research and tools has allowed for significantly reducing the cost of development and accelerating their adaptation to military applications (Morgan et al., 2020). States are beginning to recognize the potential of such innovations and are changing their defense strategies accordingly (Horowitz et al., 2020). Many researchers agree that AI is pushing the limits of technology per se, creating uncertainty in terms of strategic stability (Larson, 2021). There is growing concern about the ethical implications associated with this process (Johnson, 2020). The literature provides numerous assessments of the changing nature of warfare, with emerging political, social, and technological trends leading to conceptual shifts in approaches to resolving military conflicts.

Another view is that AI can improve the effectiveness of all types of military operations by working through established systems and interacting with other, more established forms of military power.[3] This technology is seen as an important complementary resource to traditional military operations. The introduction of an AI system can add some level of creativity to certain routine tasks. However, there are limits when it comes to adapting to new contexts and developing transformational strategies. Emerging unprecedented contexts require creating new rules and capabilities. Strategy remains an "essential human competence" (Payne, Warbot, 2021). Like any advanced technology, AI eliminates some existing problems, but at the same time new "black boxes" (Gardner, 2021) and issues of trust in information sources arise. One potential side effect of the introduction of more powerful

[1] The section is prepared on the basis of (Horowitz et al., 2020).

[2] https://www.chathamhouse.org/2017/01/artificial-intelligence-and-future-warfare, accessed 18.01.2025.

[3] https://samf.substack.com/p/does-artificial-intelligence-change?utm_source=+substack%26utm_medium=email, accessed 07.02.2025.

computing resources and data analytics is the increased risk of miscalculation by decision-makers when they rely on unreliable sources of information.[4] AI systems and their databases may contain vulnerabilities, with opportunities for adversaries to deliberately distort content, creating uncertainty. New challenges will arise from mechanical failures, algorithmic degradation, biased data, and adversarial or counter-technologies. In other words, the use of AI in military operations requires a fine-grained trade-off between opportunities and risks across a wide range of options.

The Potential of the USA and China

As the geopolitical landscape shifts toward a more multipolar world, the US and China are banking on the development of AI technologies to maintain their strategic advantages.

In **the United States,** research and development (R&D) into military AI has been underway since the 1950s. For example, Defense Advanced Research Projects Agency (DARPA) has been implementing projects related to natural language processing, facial recognition, and predictive analytics (Morgan et al., 2020). Since 2016, a special strategic R&D program in the field of AI has been implemented (the National Artificial Intelligence Research and Development Strategic Plan) aimed at strengthening national defense and security (Johnson, 2021). When introducing new technologies, a key focus is on cooperation between the state and technology companies. An example is the Maven project, carried out jointly by Google and the US Department of Defense. Within its framework, computer vision algorithms are being developed to recognize and identify classes of objects in video footage from reconnaissance drones. Based on this information, decisions are made on potential targets for destruction (Malmio, 2023). Another program, Sea Hunter, aims to create an autonomous vessel to counter submarines.[5] Despite significant investments in AI development by the government, technology companies, and universities in the United States, their volumes remain lower than expected. As a result, a number of experts question the ability of the United States to maintain its leadership position in the long term (Hunter et al., 2023), predicting that China will take over the lead in the next 10 years (NSCAI, 2023). However, other experts, while acknowledging certain challenges, still believe that the United States will retain its lead in military AI development, and do so by a large margin.

As in the US, **China** sees AI as a key competitive tool in its bilateral geopolitical rivalry. It is predicted that by 2030, the country's GDP could be increased by $600 billion annually as a result of AI technology implementation (for comparison: Shanghai's GDP in 2021 was $680 billion).[6] The growth will occur mainly due to such sectors as the automotive industry, transportation and logistics services, manufacturing, manufacturing software, healthcare, and life sciences.[7]

China's first-mover strategy in AI development involves a broad conceptualization that the defense sector synthesizes into a holistic framework for future "intelligent" military operations and strategic superiority (Johnson, 2019). A three-stage strategy has been developed to achieve global leadership in AI by 2030 (He, Ji, 2023). The creation of an AI system is considered key as a tool for military modernization. The R&D spectrum ranges from a drone program[8] to the widespread integration of advanced cloud computing, surveillance, and facial recognition technologies.[9] These initiatives are seen as an entry point into the AI race with other powers.

China has been actively responding to the US restrictions on access to chip manufacturing technology. Even before the deterioration of bilateral relations, China believed that rapid technological transformation would turn into a zero-sum race between major powers and recognized the need to reorganize the national innovation system (Cheung, 2022). China officially designated AI development as a national priority in 2017. Specific areas include algorithms, advanced semiconductors, high-performance computer chips, quantum computing, big data, brainmatics, brain-computer interfaces, computational neuroscience, brain-cognition, among other fields. A wide range of national players are involved in new AI developments. Military applications of AI are seen as a fast and effective way to modernize the defense sector. Key areas of AI application in military operations include: unmanned combat platforms for pinpoint destruction of enemy targets; operational collec-

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[4] https://securityintelligence.com/articles/data-poisoning-big-threat/, accessed 19.01.2025.

[5] https://www.nationaldefensemagazine.org/articles/2020/6/19/navy-industry-eager-to-develop-bigger-robo-ships, accessed 19.01.2025.

[6] https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-next-frontier-for-ai-in-china-could-add-600-billion-to-its-economy, date 01/16/2025.

[7] Since the turn of the millennium, China has overtaken Germany and Japan to become the world's second-largest R&D funder after the United States. Notably, the gap in R&D funding between the United States and China is rapidly narrowing, as the United States, although increasing its own investments, has done so at a significantly slower pace since 2000 (https://www.nature.com/articles/d41586-020-00084-7, accessed 15.02.2025) .

[8] https://www.businessinsider.com/chinas-underwater-drone-allies-in-pacific-2019-10, accessed 02.03.2025.

[9] https://www.wired.co.uk/article/china-social-credit-system-explained, accessed 02.03.2025.

tion, processing, and analysis of data; defensive and strike cyber systems.

China has been heavily investing in UAV development since the late 1990s, building the world's largest UAV manufacturing capacity to produce a full range of military drones (He, Ji, 2023). Next-generation technologies are being developed, including directed energy systems and human-machine systems (Hunter et al., 2023). Development has been accelerated significantly by the government's close cooperation with technology giants Huawei and Tencent (Johnson, 2021; Lu, 2021).

Conceptual Basis of the Study

Our analysis is based on two basic concepts that are critical to understanding the dynamics of the balance of power and constructing future scenarios: realism in international relations and strategic foresight. In the course of our research, based on expert opinions, four scenarios were developed that describe the impact of AI on military and geopolitical strategies. Specialized foresight tools were used, including expert surveys, PESTEL analysis, and the Régnier Abacus[10] and Schwartz Axes (Schwartz, 1997). The presented results can be useful for developing national strategies to prepare for global shifts caused by the introduction of AI.

Since the 1930s, the behavior of countries in the system of international relations has been viewed primarily through the prism of "political realism." According to this paradigm, states as rational actors prioritize maximizing their influence to ensure security and development (Velázquez, González, 2016). Historically, the dynamics of the balance of power have manifested themselves through conflicts, often driven by territorial and economic interests. In light of the geopolitical confrontations of recent decades, realism has evolved into a structural paradigm (or neorealism), acquiring a systemic perspective. Distinctions are made between the hierarchical nature of domestic politics and the unstructured framework of international relations, based on the assumption that the balance of power arises from the interaction of systemic processes, rather than the actions of individual states (Waltz, 1979). According to this approach, major powers play a central role, and global competition is determined by the distribution of power and systemic constraints.

The international system is currently largely determined by the geopolitical competition between the United States and China and their desire for dominance. The processes taking place within it inevitably have a large-scale impact on other states. Looking through the prism of the realist paradigm helps to better understand the broader implications of the influence of these processes (including the introduction of AI) on the prospects for global security and national strategies. Given that the countries in question seek to dominate in the field of AI, their actions are consistent with the principles of realist theory, since they are determined by the desire to maximize their strategic advantages in a competitive international system. In this scenario, technological innovation, military potential, and strategic alliances play a central role as key components of national security (Morgenthau, 2005; Mearsheimer, 2014).

Alfred Whitehead defines foresight as "the ability to see through apparent confusion to notice developments before they become trends, to see patterns before they are fully manifested, and to understand the particular social currents that will determine the direction of future events" (Whitehead, 1967; Tsoukas, Shepherd, 2004). In contrast to deterministic approaches, foresight starts from the multiplicity and uncertainty of potential scenarios for the development of events (futuribles) and emphasizes the role of man in their formation (de Jouvenel, 1964). This concept is based on the understanding that decisions made today significantly affect future developments (Godet, 1994; Godet, Durance, 2011; Mojica, 2005). In other words, Foresight complements political realism by offering the prospect of working with alternative futures to restructure actions in the present to ensure the implementation of the most preferred options.

Methodology

From a methodological point of view, the study was carried out in several stages. First, an in-depth analysis of the military use of AI in the United States and China was conducted. In particular, a bibliometric review of scientific publications, reports from various organizations, and government documents was carried out to identify trends and drivers of change. An analysis of political, economic, social, technological, environmental, and legal aspects (Politics – Economy – Social – Technology – Environment – Legal, PESTEL) allowed us to comprehensively assess the factors determining the development of military AI for use in a potential conflict between the United States and China (Table 1). We also studied expert opinions on the development of AI and the geopolitical consequences of this process.[11] Then, the variables determining geopolitical competition in the field

[10] https://www.colorinsight.fr/?lang=2, accessed 03.03.2025.

[11] A non-probability sampling method was used to select experts in military AI, geopolitics, and international relations. Participants were selected based on their research experience, professional reputation, and contributions to debates on relevant topics. This provided qualified expert assessments of potential future scenarios.

Table 1. **Results of PESTEL Analysis**

Dimensions	Variables
Politics	• Geopolitical competition • Governmental policies • International alliances
Economy	• Investment in AI • Industrial competitiveness • Global economic power
Social Field	• Ethical challenges • Privacy • Human rights • Unequal access to technology
Technology	• Advancement in AI • Autonomous systems • Changes in war
Environment	Indirect environmental impact of military technology
Legal Issues	• Regulation of autonomous weapons • Ethical rules enforcement

Source: author.

of AI were identified and evaluated. The variables were ranked using the Rainier mosaic panel method, which consisted of marking expert assessments of the degree of significance of a particular factor using a color scale. Two key drivers acted as axes of the scenario matrix, namely: "Cybersecurity and Digital Manipulation" and "Militarization and Space Race." Based on the matrix, four internally consistent scenarios were constructed (Figure 1) with a horizon up to 2050. Let us consider them in more detail.

AI Use Scenarios to 2050

Scenario 1: Masters of Cyberspace, Peace in the Stars

This scenario depicts a future where the geopolitical competition between the United States and China moves forward to cyberspace, leaving the physical space virtually demilitarized. In this scenario, high-tech data manipulation and digital control become the central hub in the conflict, and the global powers use artificial intelligence to affect the public discourse and destabilize their opponents without the need for direct military confrontation. Advanced surveillance systems and cyber espionage will then lead all the national security strategies, while cyberwar will virtually replace traditional conflicts.

In the meantime, in outer space, a cooperative approach is applied, and both the United States and China have agreed to preserve this as a weapon-free environment. The aforementioned is expressed through their collaboration in scientific missions and the joint development of technologies for space exploration, instead of an armed race. This scenario reflects a delicate balance between the digital war on Earth and peace in space, with an emphasis on the growing relevance of cyberspace as the new geopolitical battlefield.

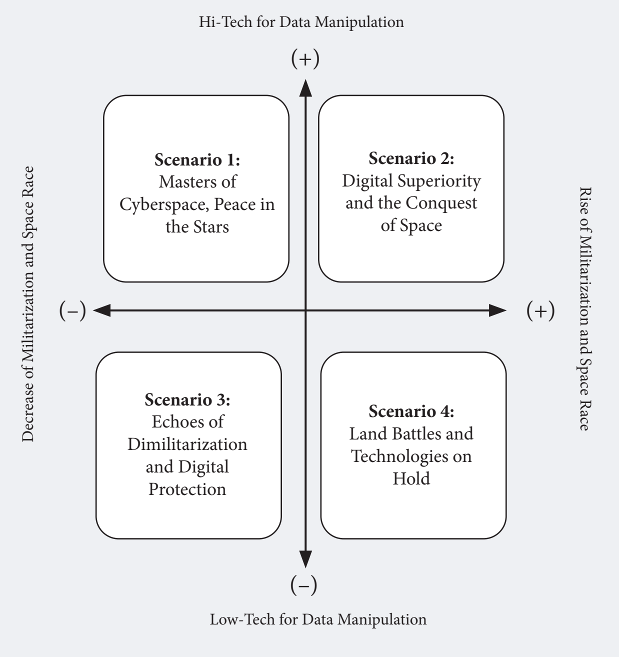
Implications: For small countries, this scenario highlights the need to strengthen their cybersecurity capacities and to develop policies to regulate the use of AI for data manipulation. Likewise, it implies active commitment in the field of international diplomacy to ensure that outer space continues to be a space for scientific cooperation and does not become a theater of operations.

Scenario 2: Digital Supremacy and the Conquest of Space

In this scenario, both cyberspace and physical space are the main battlefields in the competition between the United States and China. Artificial Intelligence, with the support of advancements in quantum computing, has boosted the development of surveillance, espionage, and social control technology, while the militarization of space has occurred due to the construction of armed satellites, combat stations, and military bases on the Moon and Mars. The conquest of space is assumed not only as a national prestige affair but also as a survival and geopolitical supremacy issue.

Artificial intelligence plays a key role in military logistics, as it optimizes the deployment of forces and allows rival powers to efficiently reply to threats, in real-time. This scenario depicts a future where the

Figure 1. **Scenario Matrix**



Source: author.

war in cyberspace and physical space are intrinsically intertwined and lead to an unprecedented military escalation.

Implications: For small states, this scenario highlights the need to participate in international fora on space governance and the regulation of artificial intelligence for military purposes. Additionally, it shows the relevance of developing a strategy for the protection of critical infrastructure facing potential cyberattacks, as well as the preparation for a potential environment where space becomes increasingly militarized.

Scenario 3: Echoes of Demilitarization and Digital Protection

In this scenario, the military tensions between the United States and China are reduced and open the gates for an era of progressive demilitarization and international cooperation. In this case, artificial intelligence, while still present, has not advanced as fast as projected, due to ethical concerns and the high costs linked to its development. Cybersecurity and data manipulation are ruled by international standards aimed at protecting digital rights and ensuring privacy.

In this scenario, outer space becomes a field for scientific collaboration. The space powers have dismantled their arsenals and shifted their efforts toward research and peaceful exploration. In this world, global stability is a priority over conflict and the nations choose diplomacy and cooperation instead of the arms race.

Implications: This scenario provides smaller nations with the chance to play a significant role in space diplomacy and the protection of digital privacy. Simultaneously, it underscores the importance of adapting technological innovation policies to ensure that emerging technologies evolve ethically, allowing less powerful states to thrive in a more cooperative and less militarized global landscape.

Scenario 4: Land Battles and Technology on Hold

In this last scenario, space militarization reaches an alarming level, while the development of digital technologies, particularly those linked to artificial intelligence, has stagnated. The United States and China are focused on competing for the control of strategic resources in outer space and set innovation in cybersecurity and data manipulation aside. Space, once perceived as the last border of pacific exploration, becomes a highly militarized battlefield, with bases and satellites orbiting around the Earth.

Tensions intensify on Earth, and the capacities for digital surveillance and cybersecurity have not progressed at the required pace to face the new threats. This scenario depicts a future where the war is fought both on Earth and in space, and where the absence of technological progress in cybersecurity leaves most nations vulnerable to face attacks and destabilization.

Implications: In this scenario, small states must focus on strengthening their traditional and digital defenses, in preparation for a world where military tensions and space conflict have intensified. Additionally, countries will have to invest in improving the resilience of their technological and energy infrastructures aimed at mitigating the impact of potential destabilization caused by the competition between the superpowers.

General Comments and Policy Recommendations for Small States

An analysis of the prospects for the development of AI and geopolitics in the period up to 2050 has shown that AI is becoming a major factor in the dynamics of the balance of power in the world. The scenarios presented in this article illustrate the different paths that the United States and China could take: from cyberwarfare and the militarization of space to cooperation and active demilitarization. For smaller countries, all scenarios emphasize the need for active policies on cybersecurity, AI governance, and space diplomacy. Strategic foresight and flexibility will be key to countering new challenges and seizing emerging opportunities. Policy recommendations are summarized in Table 3.

Conclusions

This study analyzed the impact of AI on future conflicts between the United States and China, successfully addressing the research objectives. A prospective approach facilitated the exploration of various scenarios through 2050, highlighting how AI could reshape geopolitical dynamics and military strategies for both major powers. These insights are crucial for less powerful states, enabling them to begin formulating national security policies despite institutional and infrastructure constraints.

The first stage of this work included a detailed analysis of the development and implementation of AI for military purposes in both countries through a methodology encompassing bibliometric review and Delphi surveys, aimed at identifying key variables and strategic axes that may influence the geopolitical competition. This approach facilitated the understanding of the current capacities in terms of AI while anticipating their evolution and impact regarding deterrence and conflict escalation.

Table 2. **Policy Recommendations for Small Countries**

Key Message	Measures to be Undertaken
Strengthening National Cybersecurity	
Cybersecurity is a priority for facing the increased use of AI in conflicts	• Develop a National Cybersecurity Strategy to protect critical infrastructure. • Collaborate with regional and international scoped cybersecurity initiatives. • Train staff in the fields of cybersecurity and advanced technologies, aimed at mitigating potential attacks.
Regulation and Governance of AI	
AI implies risks for the sovereignty of small states	• Create regulatory frameworks that promote transparency and responsibility regarding the use of AI. • Participate in the preparation of international standards on AI. • Promote research in AI at the local level and through international partnerships aimed at reducing technology dependence.
Preparation for the Scenarios of Space Militarization	
Outer space is a new field for geopolitical competition	• Develop special policies to protect their interests, particularly in the fields of communications and satellite security. • Strengthen international cooperation in space issues to fully take advantage of advanced technology. • Train experts in space rights for participation in international negotiation.
Promotion of Strategic Partnership in the Security and Defense Areas	
Strategic partnerships may improve the defensive capacities of small states.	• Participate in regional military exercises to reinforce their capacities to respond to threats. • Develop an adaptive defense strategy that encompasses new technologies such as drones and AI. • Strengthen relations with key global actors to balance their relations with world powers like the United States and China.
Development of a Multidimensional Approach to National Defense	
Defense should integrate traditional capacities and cybersecurity, together with AI.	• Include cybersecurity in their national defense strategy, through specialized units. • Coordinate the efforts of the governments, private sector, and academic institutions to develop a comprehensive defenses. • Monitor global trends in the fields of technology and security to adapt their defense strategies.
Source: author.	

Subsequently, four prospective scenarios were constructed, outlining potential trajectories in the geopolitics of AI, ranging from digital supremacy to demilitarization and enhanced digital protection. These scenarios not only offer a structured vision of possible futures but also provide a strategic framework through which smaller nations can craft proactive national security policies while adapting to an ever-evolving international landscape.

Given the findings of this study, it is evident that AI will play a pivotal role in shaping future conflicts between the United States and China, as well as in influencing global power dynamics up to 2050. This research contributes to bridging the gap in the existing literature on AI's impact on future conflicts while laying a foundation for further studies in this critical field. By deepening the understanding of how technology might redefine international relations, this work serves as a reference for scholars and policymakers alike.

This context presents significant challenges, particularly for nations with limited geopolitical influence, as they must navigate an increasingly complex environment shaped by technological competition. AI presents not only opportunities but also risks that could threaten national security and stability, making it imperative to adopt forward-looking policy strategies. The recommendations below aim to assist smaller states in strengthening their position within this evolving landscape by fostering resilience and international collaboration in AI governance. The ultimate goal of these proposals is to mitigate the risks associated with AI while maximizing its potential benefits in the realms of security and strategic development.

Within the geopolitical rivalry between the United States and China, smaller nations will encounter both obstacles and opportunities as they navigate the landscape of emerging technologies and strategic competition. By implementing the proposed recommendations, these states can develop a long-term vision that strengthens their position in an evolving global order.

Thus, their approach to AI, particularly in the context of military and geopolitical challenges, must be characterized by resilience, adaptability, and strategic foresight. By proactively anticipating change and preparing accordingly, less powerful states can safeguard their national interests while contributing to global stability in the AI era.

The recommendations outlined in this study seek to level the playing field, enabling smaller nations not only to address the challenges posed by AI and military advancements, but also to seize the opportunities arising from technological shifts. By incorporating these strategies, they can help shape a global landscape that is secure, competitive, and strategically balanced. Furthermore, by navigating the complexities of AI-driven geopolitics with foresight and collaboration, these nations can enhance their influence and ensure their long-term stability in an increasingly technology-driven world.

References

Boulanin V., Saalman L., Topychkanov P., Su F., Carlsson M.P. (2020) *Artificial Intelligence, Strategic Stability, and Nuclear Risk*, Stockholm: Stockholm International Peace Research Institute.

Cheung T.M. (2022) *Innovate to Dominate the Rise of the Chinese Techno-Security State*, Ithaca, NY: Cornell University Press.

De Jouvenel B. (1964) *L'art de la conjecture*, Monaco: Ed du Rocher.

Fernández-Montesinos F. (2019) *La inteligencia artificial como factor geopolítico*, Madrid: Instituto Español de Estudios Estratégicos.

Gardner N. (2021) Clausewitzian Friction and Autonomous Weapon Systems. *Comparative Strategy*, 40(1), 186–198. https://doi.org/10.1080/01495933.2021.1853442

Godet M. (1994) *From Anticipation to Action: A Handbook of Strategic Prospective*, Paris: UNESCO.

Godet M., Durance P. (2011) *Strategic foresight: For corporate and regional development*, Paris: UNESCO.

He T., Ji Y. (2023) China's Techno-Economic Statecraft Amid US-China Strategic Rivalry: AI and the "New Whole-State System". *Orbis*, 67(4), 605–625. https://doi.org/10.1016/j.orbis.2023.08.008

Horowitz M., Kania E.B., Allen G.C., Scharre P. (2018) *Strategic Competition in an Era of Artificial Intelligence*. Washington, D.C: Center for a New American Security (CNAS).

Horowitz M., Kahn L., Mahoney C. (2020) The Future of Military Applications of Artificial Intelligence: A Role for Confidence-Building Measures? *Orbis,* 64(4), 528–543. https://doi.org/10.1016/j.orbis.2020.08.003

Hunter L.Y., Albert C.D., Henningan C., Rutland J. (2023) The military application of artificial intelligence technology in the United States, China, and Russia and the implications for global security. *Defense & Security Analysis*, 39(2), 207–232. https://doi.org/10.1080/14751798.2023.2210367.

Johnson J. (2019) Artificial intelligence and future warfare: Implications for international security. *Defense & Security Analysis*, 35(2), 147–169. https://doi.org/10.1080/14751798.2019.1600800

Johnson J. (2020) Artificial Intelligence in Future Hyper-Warfare: A Perfect Storm of Instability? *The Washington Quarterly*, 43(2), 197–211. https://doi.org/10.1080/0163660X.2020.1770968

Johnson J. (2021) *Artificial intelligence and the future of warfare: The USA, China, and strategic stability*, Manchester: Manchester University Press.

Larson E. (2021) *The Myth of Artificial Intelligence,* Cambridge, MA: Belknap.

Lu S.-M. (2021) The CCP's Development of Artificial Intelligence: Impact on Future Operations. *Journal of Social and Political Sciences*, 4(1), 93–105. https://doi.org/10.31014/aior.1991.04.01.255

Malmio I. (2023) Ethics as an enabler and a constraint – Narratives on technology development and artificial intelligence in military affairs through the case of Project Maven. *Technology in Society*, 72, 102193. https://doi.org/10.1016/j.techsoc.2022.102193

Mearsheimer J. (2014) *The Tragedy of Great Power Politics*, New York: Norton & Company.

Mojica F.J. (2005) *La Construcción del futuro: Concepto y modelo de prospectica estratégica, territorial y tecnológica*, Bogotá: Universidad Externado de Colombia.

Morgan F.E., Boudreaux B., Lohn A.J., Ashby M., Curriden C., Klima K., Grossman D. (2020) *Military Applications of Artificial Intelligence: Ethical Concerns in an Uncertain World*, Santa Monica, CA: RAND Corporation.

Morgenthau H. (2005) Politics Among Nations: The Struggle for Power and Peace (7th ed.), New York: McGraw Hill Education.

Mori S. (2018) US Defense Innovation and Artificial Intelligence. *Asia-Pacific Review*, 25(2), 16–44.

Payne K., Warbot I. (2021) The Dawn of Artificially Intelligent Conflict, New York: Oxford University Press.

PWC (2017) *Sizing the prize: What's the real value of AI for your business and how can you capitalise?*, London: PWC.

Schwartz P. (1997) *The Art of the Long View: Planning For the Future in an Uncertain World*, New York: John Wiley & Sons.

Tsoukas H.T., Shepherd J. (2004) Coping with the future: Developing organizational foresightfulness. *Futures*, 36(2), 137–144. https://doi.org/10.1016/S0016-3287(03)00146-0

Velázquez R., González S. (2016) El realismo clásico. In: *Teorías de las Relaciones Internacionales en el siglo XXI: Interpretaciones criticas desde Mexico* (eds. J.A. Schiavon Uriegas, A.S. Ortega Ramírez, M. López-Vallejo Olvera, R. Velázquez Flores), México: AMEI, pp. 285–295.

Viglione G. (2020) China is closing gap with United States on research spending. *Nature News*, 15.01.2020. https://doi.org/10.1038/d41586-020-00084-7

Waltz K. (1979) *Theory of International Politics, New York: McGraw-Hill*.

Whitehead A. (1967) *Modes of Thought,* New York: MacMillan Company.

Scenarios of Development for Non-Ferrous Metal Markets amid the Spread of Alternative Fuel Vehicles

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Abstract

Advances in technology, growing concern about climate change, and the setting of greenhouse gas emission reduction targets in many countries have contributed to a significant increase in the demand for alternative fuel vehicles globally over the last decade. Electric vehicles, which include all-electric vehicles (BEVs) and plug-in hybrids (PHEVs), are the most promising alternative to conventional hydrocarbon vehicles. It is very likely that in some regions of the world electric vehicles will dominate the market as early as the 2030s. However, compared to internal combustion engine vehicles, the production of electric vehicles requires a wider range of non-ferrous metals, which may become one of the bottlenecks for further electrification of transportation. This paper presents a scenario analysis of the development of the electric vehicle market, and then calculates the key metal requirements for each of the scenarios considered. The results of this analysis reveal that, between now and 2050, the accelerating spread of electric vehicles will have a significant impact on the cobalt market, a moderate impact on the lithium, nickel, and copper markets, and a minor impact on the manganese and aluminum markets. The results of the analysis demonstrate that the increasing use of electric vehicles in the coming decades opens up significant opportunities for countries specializing in the production of non-ferrous metals, including Russia, to increase their supply to global markets.

Keywords: alternative fuels; electric vehicles; all-electric vehicles; plug-in hybrid vehicles; non-ferrous metal market.

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Introduction

Transport is the second largest contributor, after the energy industry, to greenhouse gas emissions, especially carbon dioxide. According to the International Energy Agency (IEA), in 2023 the transport sector accounted for 21.8% of global CO2 emissions, with road transport's share being about 75% of that (IEA, 2024).

Electric vehicles with zero direct greenhouse gas emissions are seen as a key way to reduce the transport sector's carbon footprint (IPCC, 2022). However, compared to internal combustion engine (ICE) vehicles, electric ones have certain design, technological, and operational features limiting their mass adoption. One of the key constraints is the need for parts and components which require materials the automotive industry either did not previously use at all or used in much smaller quantities. This primarily concerns certain non-ferrous metals.

As the world markets' carbon regulation becomes more ubiquitous and stringent, demand for low-carbon vehicles will increase, especially electric vehicles as the segment with the greatest potential. These vehicles' increased adoption, supported by government subsidies, will result in lower production and operating costs due to economies of scale. Such changes will inevitably have a significant impact on metal markets. However, the opposite effect is also possible: the changes in metal prices might affect electric vehicles' global prospects.

The impact of electric vehicles on related industries, including the non-ferrous metals sector, has been widely covered in academic research and industry analytics. The value of such studies largely depends on the relevance of the underlying data (the electric vehicle market only started to emerge in the second half of the 2010s), and on the models applied. Xu et al. (2020) present three most likely scenarios for the development of electric vehicle battery technologies, assess the likelihood of their implementation and future demand for certain non-ferrous metals. To map battery-powered electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) adoption trajectories, the authors relied on the IEA vehicle fleet figures and scenario estimates (IEA, 2020), taking into account various long-term factors (Xu et al., 2020).

The BloombergNEF 2023 report presents two scenarios for the electric vehicle market growth: the Economic Transition Scenario (ETS), dominated by market incentives with no significant regulatory changes, and Net Zero 2050 scenario aimed at making the global vehicle fleet carbon-neutral by 2050. In the less ambitious ETS, the share of electric vehicles in global passenger vehicle sales by 2040 is estimated at 73%. To achieve carbon neutrality by 2050, fossil-fuel vehicle sales must be completely phased out by 2038. Significant growth in demand for lithium, copper, aluminium, and nickel is projected, to ensure sufficient battery production levels. To qualitatively assess demand for non-ferrous metals, the report compares cumulative demand with the available reserves and envisaged production capacity (BloombergNEF, 2023; 2024).

This study examines potential changes in global non-ferrous metals markets based on three scenarios for the electric vehicle segment growth. The scenarios are presented for both the electric vehicle market as such, and the derived demand for metals required to produce vehicle components. To estimate the long-term global electric vehicle market growth (until 2050), the development of disruptive technologies was modeled through scenario analysis based on the most recent available data (for 2024). The cumulative demand for non-ferrous metals was estimated individually by battery types in which these metals are used. Electric vehicles' impact on non-ferrous metal markets was assessed using criteria suggested in various sources.

The objective of this paper is to identify, through scenario analysis, non-ferrous metal markets to be particularly affected by the increased adoption of electric vehicles, and consequently determine the metals, the insufficient supply of which may hinder the development of electric transport. The second section compares the main alternative vehicle fuel types and assesses the prospects for replacing traditional hydrocarbon-powered vehicles with electric ones. The third section models automobile market growth and presents a scenario analysis of the growth of the electric vehicle segment based on the S-curve concept and retrospective data, taking into account a number of long-term factors. The fourth section assesses the cumulative demand for non-ferrous metals needed to produce key electric vehicle components and the effect of consumer reorientation to electric transport for various industry markets. The conclusion summarizes the scenario analysis results and describes compensatory mechanisms on the markets under consideration.

The Potential of Alternative-Fuel Vehicles

The structure of motor vehicles' greenhouse gas emissions is dominated by direct emissions of the products of hydrocarbon fuel combustion. Reducing automobiles' carbon footprint is primarily envisaged by abandoning traditional fuel types such as petrol, diesel, and other oil products. It would hardly be possible to achieve global and national climate goals without decarbonizing the transport industry. Countries with active climate agendas (in particular the European Union (EU) nations, the United Kingdom, and Canada) are already announcing plans to ban non-zero emission cars, while some companies intend to cut the production of ICE vehicles (IEA, 2023; IEA, 2024). This will significantly increase the use of alternative fuels and demand for them.

An analysis of existing alternative fuel types' life cycles reveals a number of major environmental limitations in their use.

Firstly, petrol and diesel can be replaced by natural gas, propane, alcohol and its derivatives, synthetic fuel components and their mixtures with traditional fuels, and so on. However, the combustion of these fuels also produces greenhouse gases such as CO2, CH4 (methane), and N2O (nitrogen oxide), which contradicts the global emission reduction goals, including achieving carbon neutrality and keeping the increase in global average temperature within 1.5-2°C above pre-industrial levels (as stated in the 2015 Paris Agreement).

Secondly, though biofuel cars do exist, many biofuel production technologies are based on processing plant materials (sugar cane, corn, soybeans, etc.) suitable for human and animal nutrition (first-generation biofuels).[1] The use of biofuels in the transport sector reduces the carbon footprint, but in some cases may contradict the social responsibility principle and the objective of eradicating hunger - one of the UN Sustainable Development Goals.[2] The production and broad use of such fuel types as the mainline replacement for traditional fuel potentially may be limited or prohibited.

As to advanced biofuels made of non-food materials (waste fats and oils, wood biomass, organic waste, algae) and carbon-neutral synthetic fuels, high capital intensity and insufficient production capacity reduce their medium-term prospects to facilitate a major reduction in motor vehicles' carbon intensity (IEA, 2024). Until 2050, cars running on such fuels will remain inferior to electric and hydrogen vehicles regarding their potential to reduce the total cost of ownership (TCO) (Khomutov et al., 2021). There are practically no carbon-neutral synthetic fuels on the market and the envisaged capacities for their production remain orders of magnitude below the current needs of the economy (Krajinska, 2021).

Thirdly, despite its potential, the hydrogen electric vehicle segment is developing slowly due to limited hydrogen production and its specific nature as an energy carrier. The production of fuel cell systems is technologically complex and involves the use of expensive platinum group metals, so the costs are comparable to the price of a small ICE car. Also, unlike standard fuel types, hydrogen's chemical and physical properties require the transformation of the entire logistics chain including transportation, storage, and refueling. With low sales, fuel stations' and other infrastructure projects' profit margins will remain insufficient (Khomutov et al., 2021). Hydrogen production also remains inefficient: low demand hinders investment in new capacities and process optimization, leading to higher prices for hydrogen fuel and cars running on it, which undermines their competitiveness. In turn, high TCO and insufficiently developed infrastructure hinder the emergence of mass demand for hydrogen electric vehicles. A vicious circle arises, overcoming which requires the introduction of comprehensive non-market support mechanisms.

Today, BEV and PHEV electric vehicles have the greatest potential among alternative-fuel vehicles. In the former, the electric motor converts stored energy into mechanical energy, while in the latter an electric motor supplements the internal combustion engine, which engages when the battery is exhausted.

Electric vehicles' potential is determined by two key factors. The first is the annual reduction in costs due to the availability of cheaper components, primarily batteries (see Figure 1) and the economy of scale (fixed capital costs are distributed over a larger number of vehicles). When electric vehicles are introduced on national markets, government subsidies to purchase low carbon footprint cars play an important role (as shown in the experience of EU, US, and China). The prices also drop due to vehicle manufacturers' competition as the market grows (IEA, 2023).

The second factor is the fact that the direct carbon footprint of an electric vehicle is minimal, since the conversion of electrical energy into mechanical energy does not involve chemical combustion and CO2 emissions. The indirect carbon footprint of burning fossil fuels to generate electricity still remains significant, but will decrease with the development of low-carbon renewable energy.

In addition to the electric vehicle types mentioned above, various intermediate options are available on the market, such as hybrids (hybrid electric vehicles, HEV), powered primarily by an internal combustion engine, which charges the battery when the car is used thus eliminating the need to connect it to an external power source. Such designs are structurally close to conventional cars and, due to high direct emissions, will not be classified as electric vehicles or taken into account in the further analysis. Long-term IEA and BloombergNEF forecasts predict that the share of BEVs in sales will grow, while that of PHEVs will gradually decline (IEA, 2024; BloombergNEF, 2024).

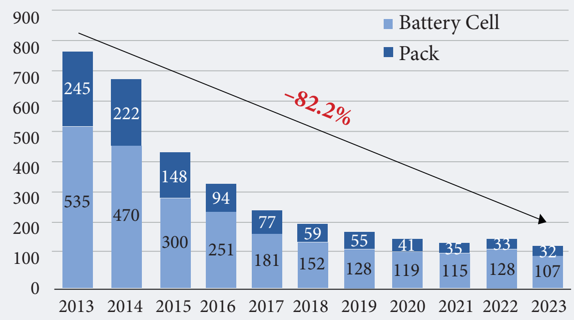
The Current State and Specific Features of the Electric Vehicle Market

The BEV market began to emerge in the 2010s following the development of electricity storage technologies, first of all, rechargeable lithium-ion batteries for home appliances and electronics. Compared to other common types (such as lead and nickel batteries), lithium ones have a higher specific energy capacity by weight and volume, and a longer service life, i.e., it maintains performance characteristics over a greater number of charge-discharge cycles (Liang et al., 2019). Their light weight and small size allowed for using them more widely in the automotive industry, without the need to make significant design changes.

To date, electric vehicles have become the fastest-growing passenger car segment. In 2020 their sales grew by 43% y/y, against a 16% decline in global demand for passenger cars. In 2021 this figure exceeded 120% y/y amid a shortage of components due to the pandemic. In 2022, amid geopolitical instability and the disruption of global supply chains, it decreased to 55% y/y. In 2023, growth slowed to 35% due to a reduction in subsidy programs for the purchase of electric vehicles on a number of major markets and limited penetration into developing markets (IEA, 2024). As a result, this segment's share in global passenger car sales increased from 2.8% in 2019 to over 18% in 2023 (Figure 2).

Direct subsidies and tax deductions for the purchase of electric vehicles remain the key demand drivers on the largest European, North American, and Asian markets, along with economies of scale and high fossil fuel prices (IEA, 2023). There is also a long-term investment flow from the conventional cars segment to the production of new electric vehicles due to the adopted course for decarbonization. The rapid penetration of BEVs is accompanied by the development of relevant infrastructure, such as

Figure 1. **Weighted Average Battery Component Cost (Electrochemical Cell and Case/Container)** (*USD per kWh*)



Source: authors, based on (BloombergNEF, 2023).

charging stations (CS) and specialized service centers. By the beginning of 2024, the number of public CS in the world has reached 3.9 million (IEA, 2024).

The share of BEVs is also growing in the commercial segment, having reached 3.4% of total sales in 2023. However, the requirements for increased range and priority of load capacity limit the use of batteries as an energy source (Figure 3). Increased battery capacity and the greater density of the ultra-high-power charging station network would facilitate the electrification of these segments.

Despite the significant growth of electric vehicles' share in global sales, their geographical distribution remains uneven. China, Europe, and North America account for about 95% of all passenger electric vehicle sales and for more than 85% in the commercial segment (Figure 4). China is the absolute world leader in electric vehicle sales in both segments. In 2023, its share in sales of passenger electric vehicles has reached 60%, and in the commercial segment, about 55%.

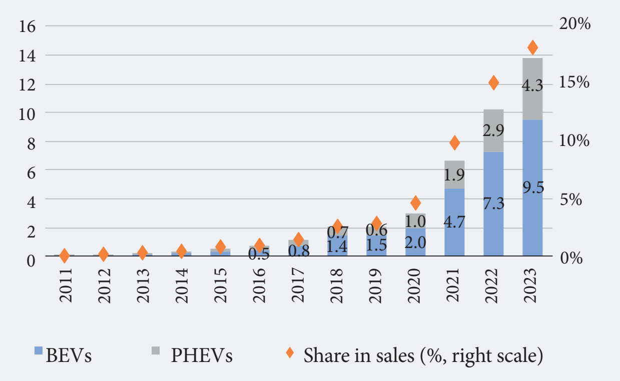
China's leadership remains sustainable due to a combination of several factors including government support programs for buyers and producers offered during the market's early development stage, sufficient control over global supply chains for metals and minerals critical to battery production, and the large-scale domestic production of various classes of electric vehicles.

[1] https://bigenc.ru/technology_and_technique/text/3878201, accessed on 15.03.2025.

[2] https://www.undp.org/sustainable-development-goals, accessed on 15.03.2025.

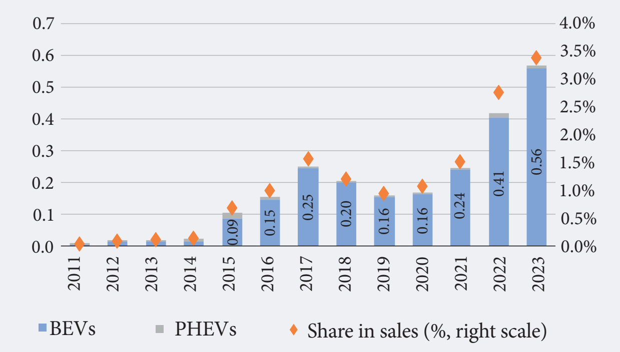
[3] We analysed the passenger car market using OICA data adjusted for North America due to the peculiarities of statistical accounting of large SUVs and pickup trucks. These vehicles are widely used in the region as personal transport, but are not included in the passenger car segment.

Figure 2. **Growth of Global Passenger Electric Vehicle Sales in 2011-2023 (million)**



Source: authors, based on (IEA, 2024; OICA, 2024).

Figure 3. **Growth of Global Commercial Electric Vehicle Sales in 2011–2023 (*million*)**



Note: The commercial segment includes light commercial vehicles, trucks, and buses.
Source: authors, based on (IEA, 2024; OICA, 2024) data.

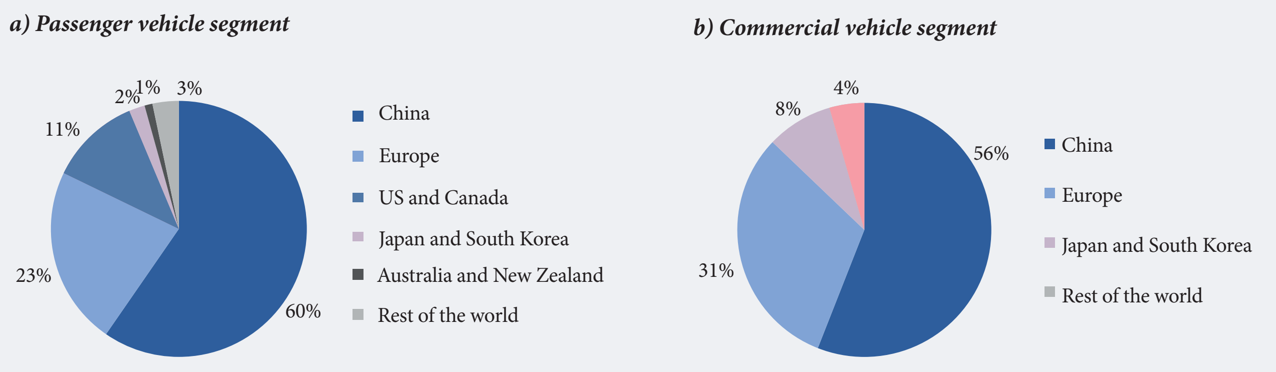
The shares of Europe and the United States and Canada in passenger electric vehicle sales in 2023 amounted to 23% and 11%, respectively. In the commercial segment, in addition to China and Europe, South Korea's share is also worthy of note: the sales of electric light commercial vehicles (LCV) and electric buses made by the national manufacturers Kia and Hyundai are rapidly growing.

Electric Vehicle Market Growth Scenarios

The following key parameters were used to build scenarios for the analysis of non-ferrous metal markets:

1. The target modeling parameter was global new electric vehicle sales (BEV and PHEV).
2. The model was based on the S-curve concept mathematically expressed by the sigmoid function. This approach has demonstrated high accuracy in studies of disruptive technologies, in particular electric vehicles (Foster, 1986; Geroski, 2000; Mahajan, Muller, 1979).
3. The analysis time horizon was the period until 2050. This milestone serves as a benchmark for most long-term greenhouse gas emission reduction targets set by international climate agreements and national decarbonization programs.
4. We have built three scenarios describing the electric vehicle market growth trajectories. Each scenario was determined by factors af-

Figure 4. **Geographical Structure of Passenger and Commercial Electric Vehicle Sales in 2023**



Source: authors, based on (IEA, 2024).

fecting only the rate of electric vehicle adoption; the growth of electric vehicles' share was considered a stable long-term trend. A detailed description of the differences in the scenarios is presented in Table 1.

5. Given the heterogeneity of the electric vehicle market and the differences in transportation models and government policies across countries, global demand was estimated by aggregating the results of regional markets' modeling. The characteristics of the latter are presented in Tables 2 and 3.
6. The distribution of BEV and PHEV market shares is based on historical data and the relevant IEA estimates for 2025, 2030, and 2035 (IEA, 2024)
7. Sales were modeled separately for the passenger and commercial vehicles segments.

The scenario analysis was based on historical data on new electric vehicles sales in 2012-2023 published by the IEA (IEA, 2024), and by the European Automobile Manufacturers' Association (ACEA)[4]; on sales data for all vehicle types in 2005-2023 published by the International Organisation of Motor Vehicle Manufacturers (OICA) (OICA, 2024), and by analytical agencies (S&P Global, 2024). This data was aggregated in line with the methodology described above.

Let us take a step-by-step look at the modeling of new electric vehicle global sales.

At the first stage, the sales of all vehicle types were estimated. Passenger car sales for the period until 2031 were estimated on the basis of S&P Global world light vehicle (up to 6 tons) market forecasts for the regions under consideration (S&P Global, 2024). In 2031-2050, the growth of sales in the passenger car segment was assumed to be equal to the forecasted per capita GDP growth rate. The choice of per capita GDP as a proxy measure was due to the fact that demand for electric vehicles mainly comes from households. Sales in the commercial segment for the entire 2024-2050 period were modeled on the basis of real GDP growth in each region, by equating the

Table 1. **Electric Vehicle Market Growth Scenarios**

Model configuration	Model and scenario characteristics	Examples of application
Scenario 1. Generalised logistic function		
$s(t) = \frac{1}{(1+e^{-bt})^{1/\vartheta}}$ Where t is the sequence number of the year (the first year in the time series is set at 1); is the share of electric vehicles in sales at time ; is the parameter that determines the growth rate; is the parameter that affects the change in the curvature of the function (function value at the inflection point), and thus the function's growth rate at the asymptotes.	- A generalised sigmoid function with flexibly adjusting S-curve. The S-curve flexibly adjusts to match the historical data; the function's inflection point has a floating ordinate value. - Low probability of complying with the declared deadlines for banning sales of internal combustion cars. - Gradual increase in the share of BEVs and decrease in the share of PHEVs.	Assessing the level of motorisation in China (Huo, Wang, 2012)
Scenario 2. The Gompertz function		
$s(t) = e^{-be^{-ct}}$ Where t is the sequence number of the year (the first year in the time series is set at 1); is the share of electric vehicles in sales at time ; is the parameter that determines the growth rate; is the parameter which determines the function's shift along the abscissa axis.	- A type of asymmetric (relative to the inflection point) sigmoid function which reflects rapid growth at the initial stage of technology adoption, followed by a smooth slowdown after reaching the inflection point. - A slower adoption of electric vehicles when government support initiatives are curtailed. - Low probability of complying with the declared deadlines for banning sales of internal combustion cars. - Gradual increase in the share of BEVs and decrease in the share of PHEVs.	- Modeling the size of the automobile market in China (Qian, Soopramanien, 2014) - Modeling electric vehicle sales in 20 large countries (Kumar et al., 2022) - Modeling the level of motorisation in 59 countries (Rota et al., 2016)
Scenario 3. Standard logistic function		
$s(t) = \frac{1}{1+ae^{-bt}}$ Where t is the sequence number of the year (the first year in the time series is set at 1); is the share of electric vehicles in sales at time ; is the parameter that determines the function's intersection point with the ordinate axis (the shift along the abscissa axis); and is the parameter that determines the growth rate.	- Standard logistic function with a symmetrical S-curve relative to the inflection point, with a constant ordinate value of 50% and a steeper slope on the modeled time horizon. - Faster growth rates of the share of electric vehicles, and of abandoning ICE vehicles, in some cases matching the declared deadlines for the complete decarbonisation of transport. - Faster growth in the share of BEVs, and decrease in the share of PHEVs.	- Modeling the size of the automobile market in China (Qian, Soopramanien, 2014) - Modeling electric vehicle sales in 20 major countries (Kumar et al., 2022) - Modeling the electric vehicle fleet in 26 countries in various regions of the world (Rietmann et al., 2020)
Source: authors.		

[4] https://www.acea.auto/nav/?content=publications, accessed on 15.03.2025.

Table 2. **Regional Electric Vehicle Markets and Their Specific Features: The Passenger Car Segment**

Regional market	Specific features
China	The world's largest electric vehicle market in absolute terms, the global component production hub
Scandinavia	Leading countries in electric vehicle penetration. Includes Denmark, Iceland, Norway, Finland, and Sweden
Europe with a mature electric vehicle market	A mature electric vehicle market comprising major Western and Central European economies
Rest of Europe	An emerging electric vehicle market, primarily comprising Eastern European and smaller Western and Central European nations
Japan and South Korea	Highly developed Asian countries with established electric vehicle markets
US and Canada	North American nations actively adopting electric vehicles. Regional features include long routes, and a car-centric culture/
Australia and New Zealand	These countries promote electric vehicles adoption, and experience energy limitations due to their isolated geographic location
Rest of the world	Other countries with low EV penetration

Source: authors.

growth rate of sales to that of GDP. The current estimates of the long-term real GDP growth until 2060 were published by the Organisation for Economic Cooperation and Development (OECD) in 2023.[5] This indicator was chosen because the commercial segment is more dependent on the overall economic situation and foreign trade flows. The modeling was carried out separately for each region and vehicle type; details are presented in Tables 2 and 3, the complete results are in Appendix 1.[6]

At the second stage, the share of electric vehicles in total vehicle sales was modeled, using the S-curve concept. The choice of modeling a relative value was due to the need to adjust for the limiting factor - sales of all vehicle types. This allowed the authors to avoid unrealistic predictions exceeding market demand and the automobile industry's production capacity.

Various modifications of the sigmoid functions with a distinctive S-shaped form were applied to map three growth trajectories for the electric vehicle market (Table 1).At the second stage, the share of electric vehicles in total vehicle sales was modeled, using the S-curve concept. The choice of modeling a relative value was due to the need to adjust for the limiting factor - sales of all vehicle types. This allowed to avoid unrealistic predictions exceeding market demand and the automobile industry's production capacity.

Various modifications of sigmoid functions with a distinctive S-shaped form were applied to map three growth trajectories for the electric vehicle market (Table 1).

The flexibility of the function applied in Scenario 1 allowed for adjusting the S-curve to historical data, setting the baseline electric vehicle market growth trajectory while maintaining current trends. The Gompertz function applied in Scenario 2 reflects a rapid growth at the lower asymptote, followed by a gradual slowdown after the inflection point (fixed 1/e value). This allowed for modeling a market slowdown after the curtailing of government demand support programs.

Scenario 3 represents an optimistic market growth option. Electric vehicle penetration can be promoted and accelerated by several factors:

Table 3. **Regional Electric Vehicle Markets and Their Specific Features: Commercial Segment**

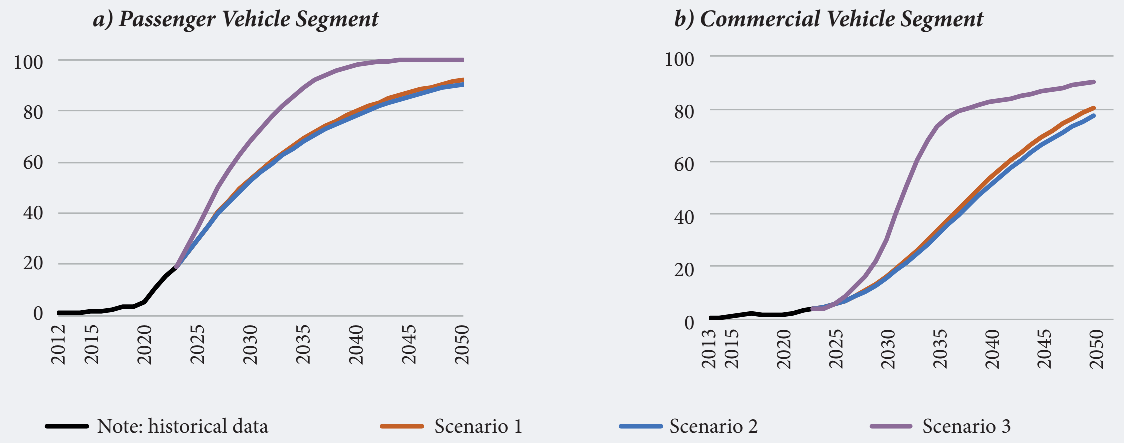
Regional market	Specific features
China	World leader in commercial electric transport, a high rate of public transport electrification
Europe (EU + EFTA)	Large EU and EFTA economies are the second commercial electric transport development hub. Active market scaling is taking place in Western and Central Europe
Japan and South Korea	Asian nations with growing commercial electric transport segments; their leading automakers have sufficient competences in the production of electric trucks
Rest of the world	Countries with rudimentary or non-existent commercial electric vehicle market

Source: authors.

[5] https://www.oecd.org/en/data/indicators/real-gdp-long-term-forecast.html?oecdcontrol-ed8cfcbb26-var3=2005&oecdcontrol-ed8cfcbb26-var4=2060, accessed on 15.03.2025.

[6] Appendices are available at the separate file (see the link on the article webpage https://foresight-journal.hse.ru/article/view/24480

Figure 5. **Electric Vehicles' Shares in Global Passenger and Commercial Vehicle Sales (%)**



Note: actual (historical) data until 2023, followed by modeling results until 2050.
Source: authors, based on (IEA, 2024; OICA, 2024) data.

1) fluctuations in hydrocarbon fuel prices and progress in renewable energy generation, which can facilitate relevant changes in consumer preferences;

2) increased investments in research and development (R&D) to reduce the key battery component costs and the per kWh cost of energy produced by the batteries;

3) the implementation of ambitious plans to ban fossil fuel vehicles due to the priority of the climate agenda;

4) increased attention to energy security, along with a wider range of energy sources.

At the modeling stage, the functions' lower asymptote is assumed to be 0 (the smallest possible share in sales) and the upper one - 1 (the largest possible share). The analysis of the passenger car segment was based on historical data for 2012-2023 and of the commercial segment - on historical data for 2013-2023. Models for the three scenarios were trained using the nonlinear least square method applied to fit nonlinear curves.

At the final stage of the calculations, the target variable was computed using the results of modeling total vehicle sales and the share of electric vehicles: new electric vehicle sales in absolute terms. The results of modeling the electric vehicles' share in sales by world region are presented in Appendix 2. The growth of electric vehicles' shares in global passenger and commercial vehicle sales is shown in Figure 5.

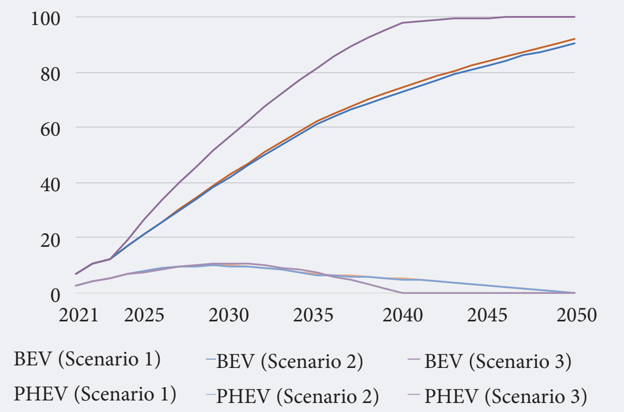
At the third stage total global sales of electric vehicles were examined. The ratio of BEV to BEV+PHEV was calculated using historical data for 2012-2023. To forecast this ratio for the period until 2050, IEA estimates for 2025, 2030, and 2035 (IEA, 2023) and regression analysis were used. On the basis of the obtained proportions, global sales of new electric vehicles were broken down into BEVs and PHEVs.

Thus, in Scenario 1 in the passenger car segment, the share of BEVs in global vehicle sales will increase to 42.8% by 2030, to 74.5% by 2040, and to 91.7% by 2050. Meanwhile the share of PHEVs will peak at 10.1% in 2029 and then gradually decline until 2050. In the commercial segment, the share of BEVs in total sales will reach 76.1% by 2050; while PHEVs will only amount to 3.8% (Figures 5 and 6).

The growth of the EV market under Scenario 2 has turned out to be very close to the trajectory obtained in Scenario 1. In the passenger car segment, the share of BEVs in global sales could reach 42.2% in 2030, 73.1% in 2040, and 90.3% in 2050. The share of PHEVs will reach its top value of 10% in 2029, and then gradually decline. In the commercial segment, the share of BEVs in total vehicle sales will increase to 73.1% by 2050; and that of PHEVs decrease to 3.7% (Figures 5 and 6). This similarity of the scenario results suggests that the historical sales data largely reflects the pattern of initial rapid growth of electrical vehicles' share in sales, followed by a slowdown after reaching 37%, which corresponds to the ordinate value of the Gompertz function's inflection point.

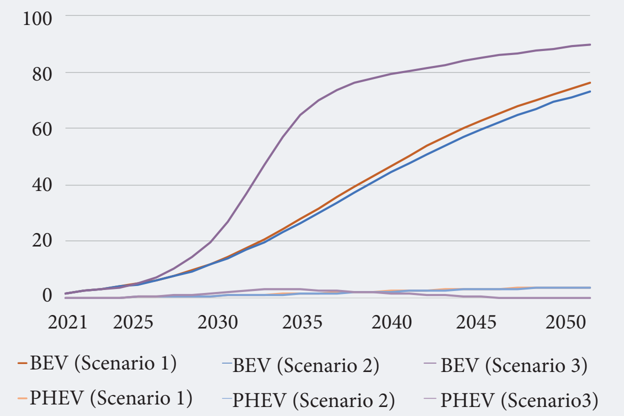
Under Scenario 3, the penetration of both electric vehicle types is expected to accelerate: the share of BEVs in global car sales could reach 56.8% by 2030, 97.7% by 2040, and 100% by 2050. The share of PHEVs will increase from 6.9% in 2024 to 10.9% in

Figure 6. **Shares of Passenger BEVs and PHEVs in Global Vehicle Sales until 2050, All Scenarios (%)**



Source: authors.

Figure 7. **Shares of Commercial BEVs and PHEVs in Global Vehicle Sales until 2050, All Scenarios (%)**



Source: authors.

2030, and then gradually decline in favor of BEVs. In the commercial segment, the share of BEVs could reach 90% of all vehicle sales by 2050, with PHEV sales ceasing completely from 2045 onwards (Figures 6 and 7).

Long-Term Demand for Non-Ferrous Metals for Electric Vehicle Components

Non-ferrous metals are used to make various electric vehicle components. The ones which could significantly affect raw material markets as the adoption of electric vehicles accelerates include batteries and related electrical conductors[7].

Electric vehicle batteries vary in the chemical composition of their components, but lithium-ion ones are the most popular. The most common batteries are lithium-nickel-cobalt-manganese-oxide (NCM), lithium-nickel-cobalt-aluminium-oxide (NCA) or their mixtures (more than 90% of the market in 2020), and lithium-ferrum-phosphate (LFP) batteries used in early electric vehicle models, which are gaining popularity again given the rising prices of nickel and cobalt (IEA, 2022). Battery type is determined by the composition of the cathode, while the anode is usually made of graphite.

In addition to lithium-ion batteries, lithium-sulphur and sodium-ion ones have good prospects since they offer a number of advantages (Kumar, 2024). Lithium-sulphur batteries have a relatively high energy density, while sodium-ion ones boast a long service life. Plus, they are potentially more economical and environmentally friendly than their lithium-ion analogues. Currently, these battery types are just beginning to enter the electric vehicle market (mass production of sodium-ion battery electric vehicles was launched for the first time only in 2023)[8], which makes it difficult to forecast demand in the medium and long term.

The development of electric vehicles can change the market situation not only for metals used in battery cathodes, but also for copper and other non-ferrous metals. Electrification of the automotive industry will require a significant increase in the share of materials with high electrical conductivity. The list of key non-ferrous metals markets for which are affected by the proliferation of electric vehicles, is presented in Table 4.

Now we will estimate electric vehicles' impact on the non-ferrous metal markets described above until 2050, using a scenario approach. The relevant effects were in several stages:

1. The market for lithium electric vehicle batteries quickly changes due to active R&D, which lead to replacing some of the chemical components with others. Two battery types with the largest potential were identified: NCX (NCM and NCA), and LFP (Xu et al., 2020; Maisel et al., 2023).

[7] https://about.bnef.com/blog/lithium-ion-battery-pack-prices-hit-record-low-of-139-kwh/, accessed on 15.03.2025.

[8] https://carnewschina.com/2023/12/27/volkswagen-backed-jac-yiwei-ev-powered-by-sodium-ion-battery-starts-mass-production-in-china/, accessed on 15.03.2025.

Table 4. **List of Non-Ferrous Metals under Consideration, Their Specific Characteristics, and Application in Electric Vehicles**

Non-ferrous metal	Application in electric vehicles	Specific characteristics
Lithium	A key cathode component in all types of lithium-ion batteries (positively charged ions carry electric charge)	About 95% of the production and 80% of the reserves are concentrated in four countries: Australia (4 enterprises), China (3), Argentina (2), and Chile (2). More than 90% of battery and component production capacities are located in Asian countries, first of all China (over 70%).
Nickel	Cathode component in NCM- and NCA-type batteries	The main application is the production of steel and alloys. The largest producers are Indonesia and the Philippines (about 60% of global output). Russia, Australia, and Brazil also have significant reserves. Russia is a leading supplier of high-quality nickel for electric vehicle batteries (20% of global supply).
Cobalt	Cathode component in NCM- and NCA-type batteries	More than 70% of global production is concentrated in the Congo, which has almost half of the world's reserves. Global supply chains are controlled by China, which is the world leader in the production of industry-ready cobalt.
Manganese	Cathode component in NCM-type batteries	The main consumer is metallurgy (steel production). Global reserves are estimated as significant; about 85% of profitable reserves are located in South Africa, Australia, Brazil, China, and Ukraine. Can be replaced by aluminium in the widely used NCA technology.
Aluminium	Cathode component in NCM-type batteries; also applied to make elements and packaging (electrode foil, case material) for all battery types	Applied in areas where the weight of the product is critical. About 90% of bauxite (raw material) mining is concentrated in Australia, Guinea, China, Brazil, Indonesia, and India. More than 50% of the enrichment and primary metal production are carried out in China; other countries' shares do not exceed 6%-7%. Can be easily recycled many times over.
Copper	The main cable and wire material in all electric vehicle types	The largest global players are Chile and Peru. Reserves have been discovered and explored on all inhabited continents and are estimated to be sufficient.

Source: authors, based on (US Geological Survey, 2024; Xu et al., 2020; Yao, Luman, 2021).

The shares of each battery type were determined on the basis of estimates available in (Maisel et al., 2023). The scenarios presented in this study, initially built for the period until 2040, were extrapolated to 2050 maintaining the original logic. The authors built two battery market growth scenarios depending on the prevailing electric vehicle technology. The NCM scenario assumes the dominance of NCM-type batteries, with a gradually increasing share of nickel. The key metals here are lithium, nickel, cobalt, manganese, and aluminium. The LFP scenario is based on the predominance of LFP-type batteries, with key metals being lithium and aluminium.

Each scenario assumes similar battery designs for both the passenger and commercial segments; the only difference being in capacity.

Data on different battery types' metal content in relation to their power, used to calculate battery composition and build the scenarios, is presented in (Maisel et al., 2023). Data on battery power required for passenger and commercial BEVs is available in the IEA reports for 2023 and 2024 (IEA, 2023; IEA, 2024). Considering that the commercial segment includes three vehicle types (light commercial vehicles, trucks, and buses), the market structure data for 2023 was used to calculate the average battery power (IEA, 2023). In the end, the required power for passenger BEVs was set at 60 kW, for passenger PHEVs at 15 kW, for commercial BEVs 211 kW, and for commercial PHEVs at 50 kW. The composition of various battery types is described in Appendix 3.

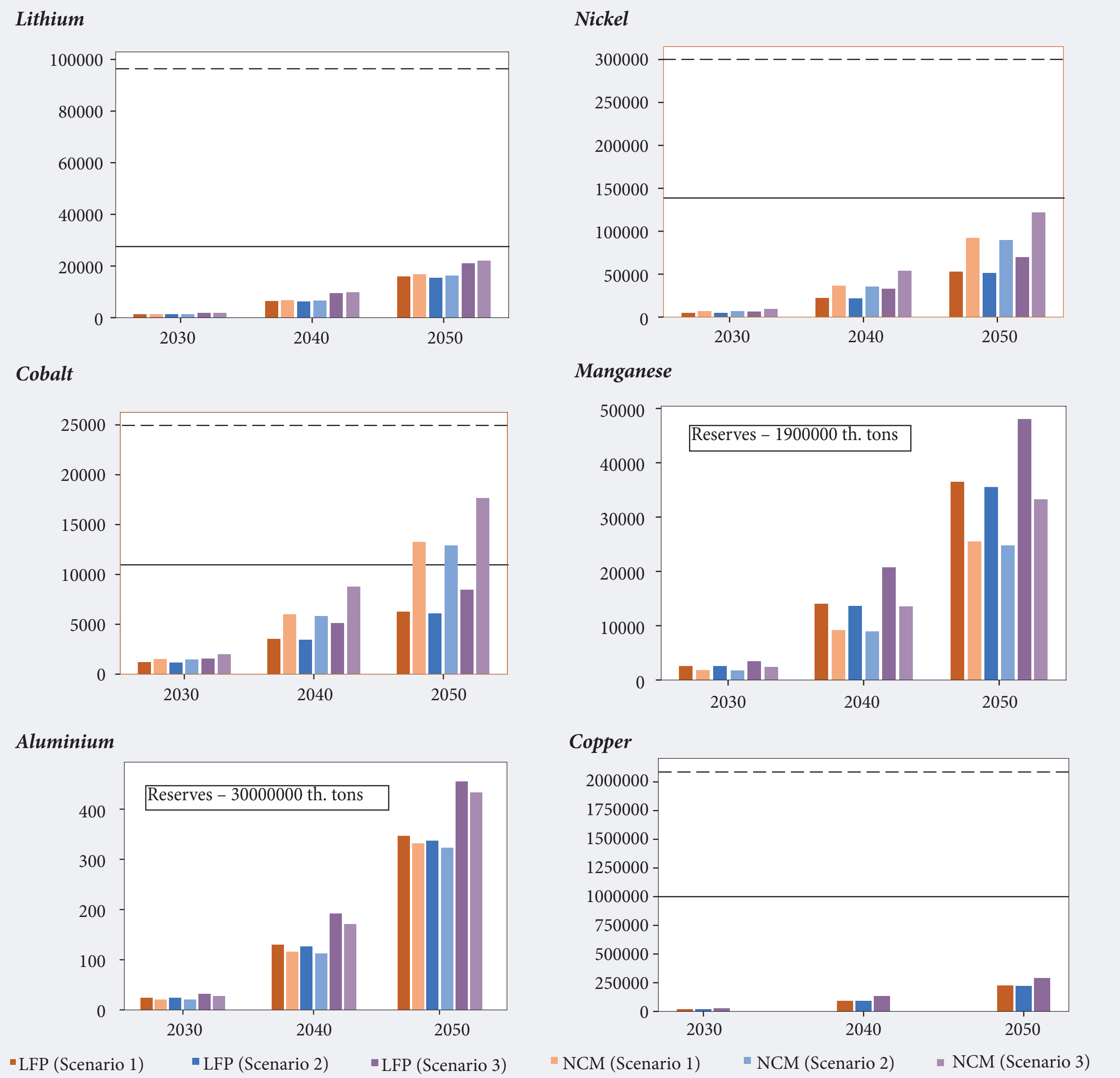
Composition was considered at the battery level, so materials needed to make wiring and casing, including copper and aluminium, have not been directly taken into account when building the scenarios.

2. Empirical data was used to calculate the amount of copper in an electric vehicle. A passenger BEV contains 89 kg, a commercial one 200 kg, a passenger PHEV 40 kg, and a commercial PHEV 89 kg (ICA, 2017). Unlike other metals, which have been taken into account only regarding their application in batteries, copper content values were calculated at the level of the entire battery pack ready for installation in the vehicle.

3. At the final modeling stage, scenarios for cumulative demand for each non-ferrous metal for 2024-2050 were built, on the basis of the following estimates::

1) chemical composition of electric vehicle batteries;
2) non-ferrous metals' content in batteries, fuel cells, and conductors;
3) new electric vehicle sales.

Figure 8. **Cumulative Demand for Non-ferrous MetalsApplied in Electric Vehicle Batteries, Under Different Scenarios (thousand tons)**



Note: solid line denotes reserves, dotted one resources.

Source: authors.

For metals applied in batteries, an additional breakdown into NCM and LFP was made.

4. The obtained estimates of demand for non-ferrous metals were then compared with the data on their explored reserves and available resources. The latter was understood as the availability of the chemical elements in the earth's crust in a form and quantity, which would economically justify mining, now or in the future. Reserves were understood as the part of available resources mining which would be feasible in the current economic situation, given the present-day requirements for raw materials' physical and chemical characteristics and the technology level.

Graphs for comparative analysis are presented in Figure 8, numerical values in Appendix 4.

The electric vehicles' impact on non-ferrous metal markets can be minimal, moderate, significant, or substantial. The following criteria were used to classify the metals into these categories:

1) how much metal is needed to meet the demand for electric vehicles;
2) country structure of metal production, reserves, and available resources;
3) possibility of metal recycling and secondary use.

Substantial Market Impact: Cobalt

Under the NCM scenario, demand for cobalt may exceed the available reserves. Even under the LFP scenario, demand would reach 55%-77% of the reserves. Given that 74% of the current production and 55% of proven reserves are in the Democratic Republic of the Congo, significant price discrimination is possible if the shortage increases.

Currently, recycling lithium-ion batteries is often less profitable and riskier than mining and purchasing the metal. The main reasons include commodity markets' volatility, the remote location of recycling plants, problems with transporting batteries, and their diverse designs. Shipping batteries to a recycling site accounts for about 40% of the overall process costs (Slattery et al., 2021). This is due to their large weight and the high technical requirements for transportation. Sometimes it is easier for car dealers to ship the entire electric vehicle to the recycling site than extract and transport the battery.[9]

Given that battery production is expected to keep growing, not only for electric vehicles but also for energy storage systems, its impact on the cobalt market could be significant).

Significant Market Impact: Lithium and Nickel

Total demand for lithium to manufacture electric vehicles could reach 55%-78% of the current reserves, which is significant given the high demand for lithium-ion batteries in other industries. Lithium-free alternatives do exist, but their technological readiness remains low. An additional factor is the fact that 79% of reserves are concentrated in four countries, while more than 90% of production capacities are located in the Asia-Pacific region and South America. This strengthens their negotiating positions in the dialogue with North American and European manufacturers.

The demand for nickel may amount to 40%-94% of the reserves, while batteries currently account for about 7% of this metal consumption (IEA, 2022). The share of nickel in NCM-type batteries will grow, replacing more expensive elements, first of all cobalt (Barber, Marshall, 2021). The future of the nickel market will be affected by multidirectional factors: about 20% of the world's battery-grade nickel is produced in the Russian Federation, which in the current geopolitical situation creates market pressure (IEA, 2022). On the other hand, recycling and reuse capacities are being developed in nickel's main application area, alloy production.

Recycling used batteries to recover lithium and nickel has the same limitations as in the case of cobalt, but lithium and nickel recovery is even less cost-effective (Barber, Marshall, 2021).

Moderate Market Impact: Copper

By 2050, cumulative demand for copper for use in electric vehicles may amount to 23%-30% of its reserves. Despite the availability of sufficient processing capacities, this value is significant, since the main consumers of copper are the energy and construction sectors where the development of renewable energy sources and distributed generation support high demand.[10] Growing demand for copper in the automotive industry may lead to a structural change in the market, and the emergence of competition for available supply with the traditional consumers of the metal.

Minimal Market Impact: Manganese and Aluminium

Aluminium and manganese markets were estimated to be minimally affected by the increased adoption of electric vehicles because of the small aggregate demand for these metals relative to their reserves in 2050: less than 0.1% for aluminium, and 1.3%-2% for manganese. Though only aluminium directly used in batteries was considered in this paper, this metal's reserves significantly exceed the demand for it. Also, aluminium is relatively easy to recycle and is already among the most recycled and reused materials. About 75% of mined aluminium still remain in circulation. [11] Aluminium and manganese

[9] https://www.wired.com/story/cars-going-electric-what-happens-used-batteries/, accessed on 15.03.2025.
[10] https://ar2020.nornickel.com/commodity-market-overview/copper, accessed on 15.03.2025.
[11] https://www.aluminum.org/Recycling, accessed on 15.03.2025.

reserves are sufficient to meet the demand for electric vehicle batteries.

Conclusion

The study analyzed how increased the adoption of alternative-fuel vehicles will affect global non-ferrous metal markets until 2050.

Electric vehicles (BEVs and PHEVs) have the greatest potential to dominate the alternative-fuel vehicle segment. They are characterized by a near-zero direct carbon footprint, growing penetration of global markets, and steadily declining prices and TCO supported by incentives offered by national governments and created by economies of scale.

According to our scenario analysis, by 2050 the share of passenger BEVs in sales may reach 90%-100%, while the share of PHEVs will reach a peak of 10%-11% around 2030 and then begin to decline. In the commercial segment, the share of BEVs by 2050 may reach 73%-90%, while that of PHEVs will not exceed 4% throughout the entire period under consideration. The demand for non-ferrous metals to manufacture electric vehicles was compared with the main characteristics of these metals' markets: the amount of reserves and resources, the country structure of production, and major industry consumers. It was established that in the long term, wide adoption of electric vehicles can significantly impact the cobalt market, moderately impact the lithium, nickel, and copper ones, and only minimally affect the manganese and aluminium markets.

Setting up a network of enterprises recycling electric vehicle components, which would cover major electric vehicle development hubs; increasing the density of electric charging station networks to allow the use of smaller-capacity batteries; and reusing spent electric vehicle batteries for stationary energy storage could facilitate balancing non-ferrous metal markets. The risk of significant shortages of nickel and cobalt can be overcome by redistributing the market in favor of LFP-type batteries that do not use these metals. Today, NMC batteries are being actively replaced by LFP ones. In particular, according to some estimates, the share of cobalt-containing batteries in China in 2024 will be 31%, compared to 44% in 2022.12 The sustainability of the copper market can be improved by increasing investments in secondary processing, and in exploring ore deposits currently classified as available resources.

The results of electric vehicle sales modeling are consistent with emerging market trends and the specifics of regional automotive markets, but the presented scenarios have a number of limitations and uncertainties, in particular:

1) highly uncertain prospects for the hydrogen segment, due to hydrogen-powered vehicles' being significantly inferior to PHEVs in terms of TCO and infrastructure availability parameters, which are key for consumers;

2) the rate of electric vehicle penetration into developing countries' markets with weak CO2 emission regulations and low economic and technological development;

3) potential disruptions in related industries, such as electricity generation and distribution;

4) potential disruptions in global component and material supply chains due to growing geopolitical tensions.

For energy storage and transmission technologies, key uncertainties are related to the possibility of radical changes in their components (e.g., the introduction of new lithium-sulphur and lithium-air batteries to the market) and the improvement in their recycling.

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References

BloombergNEF (2023) *Electric Vehicle Outlook 2023,* New York: BloombergNEF. https://about.bnef.com/electric-vehicle-outlook/, accessed 15.03.2025.

BloombergNEF (2024) *Electric Vehicle Outlook 2024,* New York: BloombergNEF. https://about.bnef.com/electric-vehicle-outlook/, accessed 15.03.2025.

Foster R. (1986) Working The S-Curve: Assessing Technological Threats. *Research Management*, 29(4), 17–20. https://doi.org/10.1080/00345334.1986.11756976

Geroski P.A. (2000) Models of Technology Diffusion. *Research Policy*, 29(4–5), 603–625. https://doi.org/10.1016/s0048-7333(99)00092-x

[12] https://www.mining.com/web/worlds-biggest-cobalt-miner-is-gloomy-on-the-ev-metals-future/, accessed on 15.03.2025.

Huo H., Wang M. (2012) Modeling Future Vehicle Sales and Stock in China. *Energy Policy*, 43, 17–29. https://doi.org/10.1016/j.enpol.2011.09.063

IPCC (2022) *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change,* Geneva: Intergovernmental Panel on Climate Change. https://www.ipcc.ch/report/ar6/wg3/, accessed 15.03.2025.

ICA (2017) *The Electric Vehicle Market and Copper Demand*, McLean, VA: International Copper Association. https://internationalcopper.org/wp-content/uploads/2017/06/2017.06-E-Mobility-Factsheet-1.pdf, accessed 15.03.2025.

IEA (2020) *Global EV Outlook 2020*, Paris: International Energy Agency. https://www.iea.org/reports/global-ev-outlook-2020, accessed 15.03.2025.

IEA (2022) *Global EV Outlook 2022*, Paris: International Energy Agency. https://www.iea.org/reports/global-ev-outlook-2022, accessed 15.03.2025.

IEA (2023) *Global EV Outlook 2023*, Paris: International Energy Agency. https://www.iea.org/reports/global-ev-outlook-2023, accessed 15.03.2025.

IEA (2024) *Global EV Outlook 2024*, Paris: International Energy Agency. https://www.iea.org/reports/global-ev-outlook-2024, accessed 15.03.2025.

Khomutov I.A., Lishnevetskaya A.I., Kwon K.P., Kukuruz G.G. (2021) *Green revolution in Europe: What it brings to Russia. Part 1. Vehicles*, Moscow: IG Petromarket. http://www.petromarket.ru/upload/iblock/c1e/Petromarket-Climate-Policy-Cars.pdf, accessed 18.01.2025 (in Russian).

Krajinska A. (2021) *Magic Green Fuels,* Brussels: European Federation for Transport and Environment. https://www.transportenvironment.org/wp-content/uploads/2021/11/2021_12_TE_e-fuels_cars_pollution.pdf, accessed 15.03.2025.

Kumar R.R., Guha P., Chakraborty A. (2022) Comparative Assessment and Selection of Electric Vehicle Diffusion Models: A Global Outlook. *Energy*, 238(C), 1–16. https://doi.org/10.1016/j.energy.2021.121932

Kumar A. (2024) A Comprehensive Review of an Electric Vehicle Based on the Existing Technologies and Challenges. *Energy Storage*, 6(5), e70000. https://doi.org/10.1002/est2.70000

Liang Y., Zhao C., Yuan H., Chen Y., Zhang W., Huang J.Q., Yu D., Liu Y., Titirici M., Chueh Y., Yu H., Zhang Q. (2019) A Review of Rechargeable Batteries for Portable Electronic Devices. *InfoMat*, 1, 6–32. https://doi.org/10.1002/inf2.12000

Mahajan V., Muller E. (1979) Innovation Diffusion and New Product Growth Models in Marketing. *Journal of Marketing*, 43(4), 55–68. https://doi.org/10.2307/1250271

Maisel F., Neef C., Marscheider-Weidemann F., Nissen N.F. (2023) A Forecast on Future Raw Material Demand and Recycling Potential of Lithium-ion Batteries in Electric Vehicles. *Resources, Conservation and Recycling*, 192, 106920. https://doi.org/10.1016/j.resconrec.2023.106920

OICA (2024) *Global Sales Statistics*. https://www.oica.net/category/sales-statistics/, accessed 15.03.2025.

Qian L., Soopramanien D. (2014) Using Diffusion Models to Forecast Market Size in Emerging Markets with Applications to the Chinese Car Market. *Journal of Business Research*, 67 (6), 1226–1232. https://doi.org/10.1016/j.jbusres.2013.04.008

Rietmann N., Hugler B., Lieven T. (2020) Forecasting the Trajectory of Electric Vehicle Sales and the Consequences for Worldwide CO2 Emissions. *Journal of Cleaner Production*, 261, 121038. https://doi.org/10.1016/j.jclepro.2020.121038

Rota M.F., Carcedo J.M., Garcia J.P. (2016) Dual Approach for Modeling Demand Saturation Levels in the Automobile Market. The Gompertz Curve: Macro Versus Micro Data. *Investigacion Economica*, 75 (296), 43–72. https://doi.org/10.1016/j.inveco.2016.07.003

S&P Global (2024) *Light Vehicle Sales Forecast*, Washington, D.C.: S&P Global.

Slattery M., Dunn J., Kendall A. (2021) Transportation of Electric Vehicle Lithium-Ion Batteries at End-of-Life: A Literature Review. *Resources, Conservation and Recycling*, 174, 105755. https://doi.org/10.1016/j.resconrec.2021.105755

US Geological Survey (2023) *Mineral Commodity Summaries 2023*, Reston, VA: US Geological Survey. https://doi.org/10.3133/mcs2023

US Geological Survey (2024) *Mineral Commodity Summaries 2024*, Reston, VA: US Geological Survey. https://doi.org/10.3133/mcs2024

Xu C., Dai Q., Gaines L., Hu M., Tukker A., Steubing B. (2020) Future Material Demand for Automotive Lithium-Based Batteries. *Communications Materials*, 1, 99. https://doi.org/10.1038/s43246-020-00095-x

Exploring the Relationship Dynamics in Entrepreneurial Ecosystems and Their Impact upon Innovation

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Abstract

This study investigates how key entrepreneurial ecosystem (EE) factors interact and are reconfigured in response to economic turbulence. Using Russia as a case study, we analyze the systemic dynamics of EE through the lens of the Complex Adaptive Systems (CAS) theory, identifying the most influential factors driving ecosystem resilience. A quantitative approach was employed using the fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) method. Data were collected from highly experienced experts, including academics and market professionals with extensive knowledge of urban EEs in Russia. Their evaluations provided a robust understanding of causal relationships and the adaptability of EE factors under economic instability. The regulatory environment emerged as the primary driver of EE reconfiguration, significantly influencing other factors. Human capital and access to capital were also critical for sustaining entrepreneurship in turbulent contexts, whereas innovation was highly dependent on external conditions rather than acting as an independent driver. These findings highlight the need for adaptive policies to enhance EE resilience, offering a novel methodological framework for understanding EE adaptability in emerging economies.

Keywords: entrepreneurial ecosystems; complex adaptive systems; strategies; complex interaction; human capital; innovation; self-organization: economic turbulence; fuzzy DEMATEL; Russia

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Introduction

The concept of an entrepreneurial ecosystem has been widely used to gain a better understanding of the phenomenon of high-growth entrepreneurship, as well as the complex interactions between entrepreneurs and their environments (Vedula, Kim, 2019). The interacting elements of ecosystems encompass systemic factors as well as entrepreneurs, considering the synergy between stakeholders and the institutional aspects that shape the context for entrepreneurial initiatives (Audretsch et al., 2019; Stam, 2015).

The Russian entrepreneurial ecosystem faces unique challenges and opportunities in the global political disputes and the current conflict. In this context, with global turbulence influencing domestic policies and economic structures, innovation plays a key role in economic development (Aeeni, Saeedikiya, 2019; Arici et al., 2024). By using the theoretical framework of entrepreneurial ecosystems to analyze this situation, it is possible to have a profound understanding of future directions in the face of the complexities and uncertainties experienced by companies (Altshuller, 2017; Ansell et al., 2017; Brondoni, 2022).

With regard to complexity, Complex Adaptive Systems (CAS) and Entrepreneurial Ecosystems (EE) involve several interacting agents, resulting in unpredictable emergent behaviors due to their extensive interconnectivity (Daniel et al., 2022). Such agents adapt and evolve in response to disturbances, altering their properties or environment. Crises accentuate their interconnectivity and interdependence, accelerating co-evolution and requiring rapid adaptation (Cloutier, Messeghem, 2022; Phillips, Ritala, 2019). Path dependence is crucial in this debate, where initial advantages can result in entrenchment. The CAS theory can address gaps in understanding the development of EE by integrating structural and dynamic approaches.

Yet, empirical evidence in this context remains scarce, and current studies primarily focus on the early stages of EE development (Han et al., 2021; Carter, Pezeshkan, 2023). Hence, although the EE literature encompasses a systemic view of entrepreneurial events, the bulk of contributions remain oriented towards assessments that look into EE dimensions as separate blocks, not as interrelated elements that simultaneously affect and are affected by one another, constantly coevolving and shaping dynamic conditions that enable (or hinder) entrepreneurship. In light of these considerations, this research aims to identify the main factors that impact the development of EE in cities and, more importantly, how these factors relate to each other. Accordingly, our research question can be stated as follows: How do key entrepreneurial ecosystem factors interact and reconfigure in contexts of economic turbulence? This question emphasizes the systemic nature of EE, shifting the focus from individual components to their relational dynamics.

Our empirical setting involves the case of Russia. The analysis conducted by Shirokova et al. (2022) reveals that, notwithstanding the present challenges, the Russian milieu offers distinct opportunities for entrepreneurship research. This underscores the necessity of adopting a novel approach that delves into local specificities, thereby enhancing the applicability of EE on a global scale. Our analytical approach relies on the fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) method based on primary data collection with 25 EE experts in this country.

Theoretical Background

Entrepreneurial Ecosystems Factors

Isenberg (2010) underscores the need for solutions that originate locally and are tailored to the specific conditions of well-known EEs. The EE is seen as a dynamic community comprising interdependent actors and systemic contexts, emphasizing both the contextual realm and individual decision-making (Audretsch et al., 2019). Therefore, the EE differs across regions and entrepreneurial stakeholder groups, leading to the formulation of hypotheses about the perceived robustness of sustainable and resilient EE (Spigel, Harrison, 2018). The significance of adapting the development of EEs to local conditions is highlighted, reinforcing the multi-scalar and multi-actor nature of these systems (Brown Mason, 2017).

As described by Stam and van de Ven (2021), the factors of the EE consist of six pivotal pillars essential for the development and sustainability of an EE: regulatory environment, infrastructure, market, innovation, access to capital, human capital, and entrepreneurial culture. The regulatory environment, influenced by legal and political forces, plays a central role in the development of the EE, impacting marketing strategies and presenting challenges and opportunities for entrepreneurs (Zhao et al., 2023). Beyond physical conditions, the infrastructure includes digital assets and various amenities that foster an environment conducive to entrepreneurial activities (Audretsch, Belitski, 2017; Stam, van de Ven, 2021). Market dynamics, driven by potential demand for innovative products or services, require strategic market direction for entrepreneurial success (Stam, 2015; Zhao et al., 2023).

Innovation, involving the proactive generation and implementation of new ideas, processes, and collaborations, is essential for nurturing nascent firms and fostering alliances within the EE (Kuratko et al., 2017). Access to capital, including human, social, and financial assets influenced by entrepreneurial decisions, is critical for sustained entrepreneurship, emphasizing reliance on personal financial resources and substantial financial backing for development (Zhao et al., 2023). Human capital, providing intellectual support and entrepreneurial knowledge closely linked to innovation, is an essential contributor to entrepreneurial activities (Stam, van de Ven, 2021; Zhao et al., 2023). Lastly, entrepreneurial culture shapes entrepreneurial intentions and perceptions. An entrepreneurial culture is identified as substantial for EE prosperity, influencing motivation, innovativeness, and risk-taking (Audretsch, Belitski, 2017; Stam, van de Ven, 2021; Vicentin et al., 2024).

Complex Adaptative Systems

The CAS theory was first proposed by Simon (1962), as a reaction to the mechanistic and equilibrium-based view of the world, and was widely adopted by many scholars focused on entrepreneurial systems (van De Ven, 1993; Stam, van de Ven, 2021). By definition, CAS are characterized by numerous interacting elements or agents, resulting in emergent behaviors that are inherently difficult to predict solely by observing individual interactions (Bone, 2016; Fredin, Lidén, 2020). The complexity within these systems arises from their extensive interconnectivity and the challenges associated with predicting their behavior. CAS are large-scale systems whose behaviors can change, evolve, or adapt in response to disturbances, thereby maintaining a stable state by modifying their properties or the surrounding environment (Cloutier, Messeghem, 2022; Phillips, Ritala, 2019).

The complexity of a CAS results from the interaction and interconnectivity between its elements and the environment. Similarly, EEs consist of a diverse set of agents, such as entrepreneurs, investors, educational institutions, government entities, and customers, interacting in complex and interdependent ways (Daniel et al., 2022). In both CAS and EEs, there is no single centralized control mechanism (Aeeni, Saeedikiya, 2019). During a crisis, the interconnectivity, and interdependence of the elements within the system become even more pronounced (Fredin, Lidén, 2020). For instance, economic sanctions, political instability, and changes in government policies directly impact businesses, investors, and consumers within the EE (Khurana et al., 2022).

As highlighted by Roundy et al. (2018), CAS theory can address gaps in the characterization of EE trajectories by integrating structural and dynamic approaches that consider the continuous evolution of sub-ecosystems (Carter, Pezeshkan, 2023; Malecki, 2018). These approaches help one understand how EEs develop through phases of impulse, creation, and structuring, revealing the inherent complexity of their functioning and evolution (Cantner et al., 2021). Nevertheless, these conceptual approaches have not produced empirical evidence of EE framed within the complexity of CAS, and they have mainly concentrated on the early stages of EE development (Han et al., 2021).

In the context of EE, turbulence is defined as a state of tension and transformation and includes a wide range of disruptive events and changes, not just crises but also social, economic, and political transformations. Therefore, the concept of turbulence from the perspective of an EE provides a lens for examining the challenges and opportunities arising in an EE characterized by constant flux. It empowers us to analyze complexity and uncertainty as essential elements in understanding and navigating the collective future of organizations within transforming ecosystems (Aeeni, Saeedikiya, 2019; Arici et al., 2024).

Method

Given the proposed goals, the methodology adopted in this study is based on field research with exploratory, explicative, and propositional research characteristics. This study adopts a quantitative approach utilizing the fuzzy DEMATEL method to systematically identify and analyze the primary factors influencing the development of EEs in urban areas, with a particular focus on the Russian context. Our goal is to elucidate the relationships among these factors, assess their impact, and determine the most influential ones within the dynamic environments of urban EE.

The Russian Context

In the current Russian context, which is marked by significant political changes and international conflicts, unique challenges and opportunities for entrepreneurship arise. Global turbulence dynamics directly impact domestic policies and economic systems, creating an environment where innovation becomes a important driver for economic development (Altshuller, 2017; Ansell et al., 2017; Brondoni, 2022; Nowinska et al., 2025).

Since 2000, Russia has undertaken reforms to strengthen state control and clarify bureaucratic guidelines, often through ambiguous regulations (Yakovlev, 2006). This complex and ever-changing regulatory environment requires entrepreneurs to carefully navigate a series of regulatory and bureaucratic challenges to maintain operational legitimacy.

Simultaneously, the government has encouraged the strengthening of the economy through innovation, aiming to diversify economically and achieve competitive advantages (Shakib et al., 2023). Innovation, substantially supported by public funding, is seen as essential for economic growth, with approximately 70% of this funding coming from the public sector.[1] This focus on innovation has helped Russia improve its position in the Global Competitiveness Index, demonstrating progress in various innovation indicators (Davidson et al., 2018; Shakib et al., 2023).

A literature review by Shirokova et al. (2022) highlights that, despite adversities, the Russian context offers unique opportunities for research and development in entrepreneurship, influenced by geographical, socioeconomic, and ethnic disparities. The need for a

[1] https://www.forbes.ru/tehnologii/366587-put-k-innovaciyam-rossiya-tratit-na-nauku-1-vvp-hvatit-li-etogo, accessed 19.03.2025.

'third wave' of contextualization in entrepreneurship research is emphasized, aiming for a deeper understanding of the local nuances that shape entrepreneurship theories and promoting an expanded dialogue between local and global researchers.

Data Collection

In 2024, an electronic survey (Google Forms) was administered to 25 Russian experts specializing in urban EEs to gather information about the relevance of various factors within these systems in Russian urban contexts.[2] All respondents held postgraduate degrees in entrepreneurship and innovation, and had over six years of practical market experience, ensuring a high level of expertise in both academic and professional domains. Subsequently, the survey introduced seven factors based on the frameworks provided by Stam and van de Ven (2021): regulatory environment, infrastructure, market, access to capital, innovation, human capital, and entrepreneurial culture. The experts then assessed the relevance of these factors to the EE in the cities, completing the statement, "Indicate, in your opinion, the relevance of each of the following elements for a city's entrepreneurial ecosystem." Following this assessment, they analyzed the influence of each factor upon one another in the EE analysis.

Fuzzy DEMATEL Method

The fuzzy logic and DEMATEL models are combined to create a decision-making framework. This model processes the vague assessments of experts into precise values using fuzzy sets for a direct influence matrix. The evaluation starts with experts employing a fuzzy linguistic scale to determine mutual influences between factors, defining causal relationships despite judgment imprecision. Terms such as "None (No), Very Low Influence (VLI), Low Influence (LI), Moderate Influence (MI), High Influence (HI), Very High Influence (VHI)" are employed, with each expert contributing their influence matrix, as demonstrated in Table 1. Also, Figure 1 illustrates the membership functions for fuzzy linguistic terms and their corresponding fuzzy numbers. Consequently, given n factors represented by the set $F = \{F_1, F_2,..., F_n\}$ to be evaluated by l experts represented by the set $E= \{E_1, E_2,..., E_l\}$, each expert must assess the pairwise influence of factor F_i on factor F_j. This procedure generates an individual direct influence fuzzy matrix $\tilde{Z}_k = [\tilde{z}^k_{ij}]_{n\times}$, in which $\tilde{z}^k_{ij} = (z^k_{ij1}, z^k_{ij2}, z^k_{ij3})$, represents the fuzzy evaluation from an expert k (Zhang et al., 2023).

In the second step, we combine the evaluations of experts to create the collective direct-influence fuzzy matrix $\tilde{Z}$. After forming the individual matrices $\tilde{Z}_k$ (k= 1,2,...,l), the composite direct-influence fuzzy matrix $\tilde{Z}_k = [\tilde{z}^k_{ij}]_{n\times n}$ is derived by amalgamating the assessments from all experts. Here, $\tilde{z}_{ij}$ is treated as a Triangular Fuzzy Number (TFN) (0,0,0), and $\tilde{z}_{ij}$ is computed as:

$$\tilde{z}_{ij} = (z^k_{ij1}, z^k_{ij2}, z^k_{ij3}) = (1/l)\Sigma^l_{k=1}\tilde{z}^k_{ij} = ((1/l)\Sigma^l_{k=1}z^k_{ij1}, (1/l)\Sigma^l_{k=1}z^k_{ij2}, (1/l)\Sigma^l_{k=1}z^k_{ij3}) \quad (1)$$

In the third step, fuzzy evaluations are defuzzified using the CFCS (Converting Fuzzy Data into Crisp Scores) method to form the crisp direct-influence matrix Z .

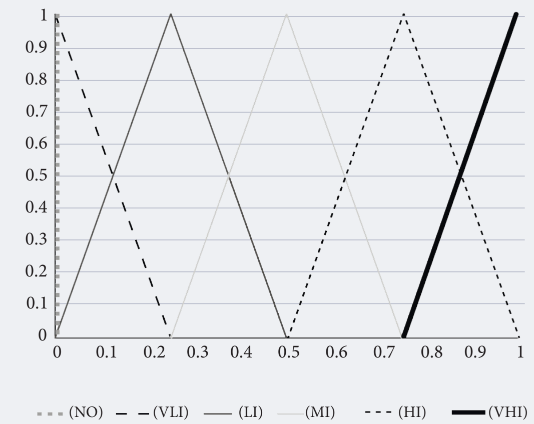
In the fourth step, this matrix is used with the DEMATEL method to create the normalized direct-influence matrix X and the total-influence matrix T, which are essential for developing the influential relation map (IRM). The derivation of the normalized direct-influence matrix X is achieved by:

Table 1. **Fuzzy Linguistic Terms with Related Fuzzy Numbers**

Linguistic terms	Triangular fuzzy numbers
None 0 (No)	(0, 0, 0)
Very Low Influence (VLI)	(0, 0, 0.25)
Low Influence (LI)	(0, 0.25, 0.5)
Moderate Influence (MI)	(0.25, 0.5, 0.75)
High Influence (HI)	(0.5, 0.75, 1)
Very High Influence (VHI)	(0.75, 1, 1)

Source: adapted from (Singh, Sarkar, 2020; Zhang et al., 2023).

Figure 1. **Membership Function of All Linguistic Terms from Fuzzy DEMATEL**



Source: authors.

[2] Of the 25 interviewees, 60% were female and 40% were male. On average, experts have 6.9 years of professional experience. Regarding the areas of work, 24% work in information technology, 12% in education, 12% in business and 12% in innovation, and the rest of the sample belongs to the following areas: technology transfer, public policy, electronic device development, energy, entrepreneurship and marketing, project management, accounting, and analytics.

$$X = Z/s,\ s = max(max_{1\le i\le n} \sum^{n}_{j=1} z_{ij}, max_{1\le i\le n} \sum^{n}_{i=1} z_{ij}), \quad (2)$$

Where all elements are adhered to $0 \le x_{ij} < 1.0 \le \sum^{n}_{j=1} x_{ij} \le 1$ and at least one i such that $i \sum^{n}_{j=1} z_{ij} \le s$.

Subsequently, the total-influence matrix T is computed using:

$$T = X + X^2 + ... + X^h = X\,(I - X)^{-1}, \quad (3)$$

When h → ∞, in which I is represented as an identity matrix (Rouhani et al., 2013).

Finally, the formulation of an IRM is facilitated with the horizontal axis denoted by ($R + C$) and the vertical axis by ($R - C$), depicting the sum of the rows and columns from the total-influence matrix T, defined respectively by:

$$R = [r_i]_{n\times 1} = \sum^{n}_{j=1} t_{ij}]_{n\times 1},\ C = [c_j]_{1\times n} = \sum^{n}_{i=1} t_{ij}]^{T}_{1\times n}, \quad (4)$$

Where, r_i represents the sum of influences a factor F_i exerts on others, while c_j totals the influences received by factor F_j. These calculations determine each factor's centrality as the horizontal axis vector ($R + C$) (named Prominence) and its role as either a net influencer or influenced entity as the vertical axis vector ($R - C$) (named Relation) within the network. These values are visualized in an IRM by plotting the dataset of ($R + C$, $R - C$), which plots the combined influence scores to aid in decision-making.

Steps for Using the Fuzzy DEMATEL Method

The steps to develop the fuzzy DEMATEL method are shown in Figure 2. Initially, data collection was performed with the identification of entrepreneurship ecosystem factors (IT_{ij}) and the opinion of the 25 Russian experts specializing in urban EEs about the relationships and interactions between these factors. After identifying key criteria, the influence matrix is created using linguistic terms and fuzzy numbers to represent the complex relationships as identified by EE experts. Subsequently, each decision-maker attributes scores based on the expert evaluations among the EE factors.

Thereafter, the matrix of relationship influences, designated as "Z", is computed using the CFCS method. The traditional DEMATEL method is then applied in the subsequent steps. Consequently, the "Z" matrix is normalized to form a new matrix "X". Following this, the "T" matrix, which synthesizes the direct influences among the EE factors in the Russian context, is calculated to construct the IRM. The vertical axis vectors "R" and "C", named "Relation", are calculated to visualize and analyze both direct and indirect influences among the factors, thereby facilitating the understanding of the dynamics of the EE in the Russian context.

Results

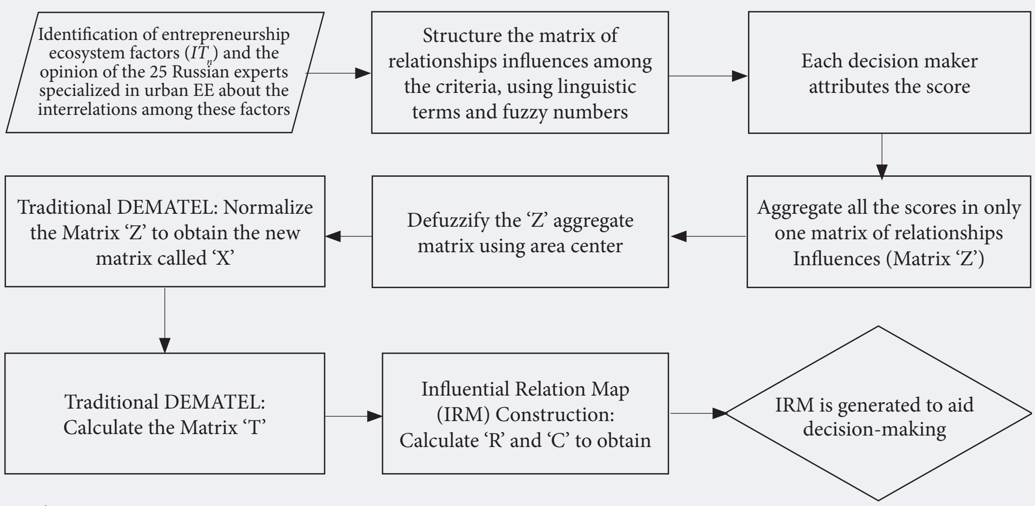
Initially, the variables of the fuzzy DEMATEL model are expressed by an assessment of EE factors and descriptions, as discussed by Stam and van de Ven (2021), as detailed in Table 2, while applying the proposed framework.

As previously stated, empirical data were gathered on seven factors about EEs, categorized as IT_1 through IT_7. A total of 25 specialists in EEs responded to the questionnaire, providing insights into the relationships among these factors and their influence upon EEs within urban settings, with a particular focus on the Russian context.

In this context, we utilize the CFCS (Converting Fuzzy data into Crisp Scores) technique to convert fuzzy assessments into precise values. Fuzzy assessments for these dimensions are presented in Appendices 1 and 2, with their corresponding fuzzy numbers detailed in Table 1.

Applying our proposed method, we present the paired importance and cause-effect outcomes from varied

Figure 2. **Steps for Using the Fuzzy DEMATEL method**



Source: authors.

Table 2. **The Influential Factors in EE**

Factor	Description
IT_1	Regulatory Environment
IT_2	Infrastructure
IT_3	Market
IT_4	Access to Capital
IT_5	Innovation
IT_6	Human Capital
IT_7	Entrepreneurial Culture

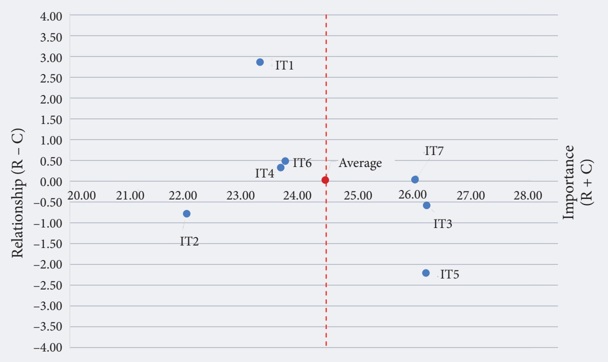
Source: authors.

Table 3. **Defuzzified Relationship Matrix Z**

	IT_1	IT_2	IT_3	IT_4	IT_5	IT_6	IT_7
IT_1	0.000	0.670	0.663	0.640	0.623	0.557	0.583
IT_2	0.293	0.000	0.513	0.417	0.660	0.630	0.443
IT_3	0.500	0.513	0.000	0.680	0.677	0.550	0.717
IT_4	0.440	0.623	0.687	0.000	0.653	0.467	0.517
IT_5	0.400	0.527	0.720	0.573	0.000	0.427	0.720
IT_6	0.547	0.407	0.553	0.460	0.737	0.000	0.683
IT_7	0.637	0.477	0.687	0.497	0.750	0.650	0.000

Source: authors.

Figure 3. **Distribution of the Studied Factors within the Quadrants according to the Degree of Importance and Impact**



Source: authors.

Table 4. **Relation Matrix T**

	IT_1	IT_2	IT_3	IT_4	IT_5	IT_6	IT_7
IT_1	1.461	**1.780**	**2.062**	**1.812**	**2.167**	**1.790**	**1.986**
IT_2	1.263	1.320	1.673	1.453	**1.795**	1.493	1.613
IT_3	1.553	1.716	**1.875**	**1.788**	**2.138**	**1.755**	**1.978**
IT_4	1.445	1.635	**1.908**	1.527	**2.004**	1.633	**1.820**
IT_5	1.441	1.617	**1.918**	1.663	**1.859**	1.628	**1.863**
IT_6	1.483	1.605	**1.900**	1.652	**2.039**	1.536	**1.871**
IT_7	1.605	1.736	**2.062**	1.780	**2.186**	**1.803**	**1.849**

Note: The table highlights represent the values obtained higher than the relation matrix T average of the 1.743. Thus, it is possible to observe how the factors relate to each other, and which are most influenced by the others, as in the case of IT5, IT3 and IT7 which have values greater than the average of the T matrix, representing a significant influence of other factors.

Source: authors.

perspectives, alongside their average performance, in Appendix 3.

Subsequently, all scores were aggregated into a single matrix of relationship influences, called matrix "Z". The aggregation process can be carried out using simple arithmetic averages of the judgments to generate the corresponding fuzzy numbers, as shown in Table 3.

After defuzzification, the traditional DEMATEL steps were followed, employing equations (1-4) and presenting Tables 4 and 5.

In Table 5 and Table 6, it is evident that the regulatory environment factor is the primary driver, followed by human capital, access to capital, and entrepreneurial culture whereas innovation emerges as the most impacted factor. To simplify the assessment, Figure 3 graphically illustrates the cause-and-effect relationship of EE factors in the Russian context.

Analyzing the positions of the most influential and influenceable factors within the EE in the Russian context, based on the results obtained and their positions on the fuzzy DEMATEL interrelationship graph, a detailed interpretation of each factor can be provided, as per the four-quadrant IRM diagram presented and observed in Figure 4. Accordingly, the regulatory environment factor (IT_1) is positioned in Quadrant I, representing a driving factor with a powerful relationship. Consequently, the regulatory environment has a high capacity to influence other factors. The human capital factor (IT_6) also belongs in Quadrant I, functioning as a driving factor and influencing another factor. The access to capital factor (IT_4) is also located in Quadrant I, although with a lower capacity to influence other factors. The entrepreneurial culture (IT_7) is positioned in Quadrant II, identified as a central factor, although

Table 5. **Traditional DEMATEL**

Factor	R	C	R + C	R – C
IT1 – Regulatory Environment	13.058	10.250	23.308	2.809
IT2 – Infrastructure	10.610	11.409	22.019	-0.799
IT3 – Market	12.804	13.398	26.201	-0.594
IT4 – Access to Capital	11.972	11.675	23.647	0.297
IT5 – Innovation	11.987	14.189	26.176	-2.202
IT6 – Human Capital	12.085	11.636	23.722	0.449
IT7 – Entrepreneurial Culture	13.020	12.980	26.000	0.040

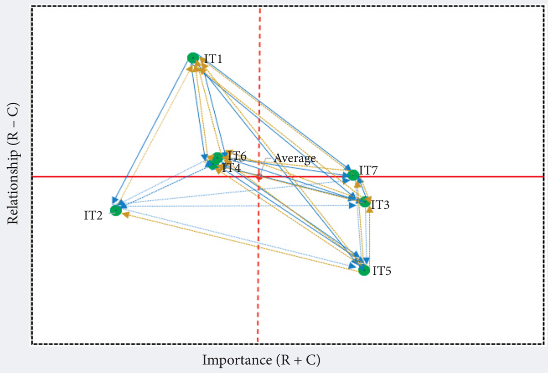
Source: authors.

Table 6. **Ordering of Factors**

Position	Factor	R – C
1	IT_1	2.809
2	IT_6	0.449
3	IT_4	0.297
4	IT_7	0.040
5	IT_3	-0.594
6	IT_2	-0.799
7	IT_5	-2.202

Source: authors.

Figure 4. **The Relationship and Prominence**



Source: authors.

its value appears minimal compared to the other factors in Quadrant I. Meanwhile, the innovation factor (IT_5) is situated in Quadrant III, presenting itself as highly prominent but with low impact. This indicates how significant innovation is and that it is primarily influenced by other factors. Strategies to improve innovation should consider strengthening the regulatory environment, human capital, access to capital, and entrepreneurial culture, which all influence it directly.

In Figure 4, it is noted that the arrows represent the relationships between the factors. The blue arrows represent the relationship of influence of the factors on others, in which it is possible to observe that the factor IT_1 exerts influence over all factors, as it occupies the first position. The yellow arrows represent the relationship of influence that they receive from other factors; as we can see, the IT_5 factor receives influence from all other factors.

Discussions

In this study, we aimed to understand the main factors that impact the development of EE in the Russian context and how these factors relate to one another using the fuzzy DEMATEL method. As approached in our theoretical background, through the lens of the CAS theory, it is possible to have a holistic and intertwined view regarding the geography and evolution of entrepreneurship as the interplay between the system and its environment (Fredin, Lidén, 2020).

The EE is considered a complex system that involves multiple entities and levels and a diversity of interactions between components, individuals, and social contextual factors (Carter, Pezeshkan, 2023). EEs are also considered open systems with feedback loops characterized by non-linear relationships (Fredin, Lidén, 2020) and the notion of path dependence by incorporating continuity and change (Cloutier, Messeghem, 2022). As a consequence, a large number of scholars consider that EEs are CASs (Fredin, Lidén, 2020; Cloutier, Messeghem, 2022; Carter, Pezeshkan, 2023), mainly because entrepreneurs can be considered agents that affect the development of an EE (Carter, Pezeshkan, 2023), and simultaneous and parallel actions occur, making these EEs pursue self-organizing behavior (Fredin, Lidén, 2020). Yet, systematic assessments about how EE dimensions are interconnected are rare, hampering a thorough examination of the systemic nature of contextual conditions leading to entrepreneurship.

In this respect, self-organization is a process by which agents spontaneously mutually adjust their behavior in a way that allows them to cope with changing internal or external environmental forces (Fredin, Lidén, 2020). During periods of crisis and turbulence, CASs, characterized by internal interactions and feedback processes, learning, and adaptability, serve as controlling mechanisms. Thus, CASs are self-organizing, capable of reaching order without external management (Fredin, Lidén, 2020). In this inquiry, the Russian context illustrates a case in which there are simultaneously incentives for entrepreneurial activities and growth of the country's competitive advantage, while entrepreneurs face significant regulatory and bureaucratic challenges to maintain operational legitimacy. This case, through the lens of the CAS theory, reinforces the influence of the self-organizing behavior of an EE.

In other words, Russian entrepreneurs consistently faced economic instability and turbulence throughout the nation's history. However, nowadays, the government is taking meaningful steps to help entrepreneurs start and run their businesses in a less bureaucratic way. Our results reflected such conditions regarding the regulatory environment as the main factor affecting the Russian EE. Following (Fredin, Lidén, 2020), for example, higher-level regulations are often the result of simple rules and local interactions at the lower level.

Although Russian incentives toward entrepreneurship are focused on innovation (Davidson et al., 2018; Shakib et al., 2023), our analysis indicates that innovation dynamics are the less important factor impacting an EE in this country. We can consider, thus, that for Russian entrepreneurs to be innovative, it is primarily critical to be part of an adaptative system, as it is a factor affected by all ecosystem elements. These systems enabling them to create, replace, develop, restructure, or adapt from within so that they can respond to environmental changes and affect their surroundings.

In the same vein, it is possible to argue that the self-organizing behavior of a Russian EE allows these entrepreneurs to maintain their competitive advantage even in turbulent times, exposing them to a coevolutionary process of identifying, exploiting, and creating new opportunities. In accordance with Carter and Pezeshkan (2023), these dynamics indeed support and explain the emergence of sustainable viability of an enterprise or segment of enterprises in turbulent times.

Based on our findings, this study offers significant contributions. Regarding our methodological approach, we can summarize the main advantages of using the fuzzy DEMATEL method, which employs an innovative approach to handling diffuse assessments. This approach allows for the preservation of more comprehensive information throughout the analysis of relationships among the factors within the EE in the Russian context. As a result, we can analyze the cause-and-effect relationships from various perspectives, taking into account the expertise and knowledge of specialists in EEs. Therefore, the findings indicate that, in crisis conditions, such as those found in Russia, the regulatory environment, human capital, access to capital, and entrepreneurial culture impact innovation in EE more significantly than in more stable economic contexts, thereby corroborating Hypothesis 1 of this study.

Furthermore, the method accounts for the uncertainty in expert information, addressing this practical and inevitable issue in real-world situations, especially during turbulent times. Through this approach, it becomes possible to analyze the interrelations among EE factors in the Russian context, a perspective that has not yet been explored in the literature. Thus, this suggests that, in turbulent times, both the regulatory environment and human capital should be prioritized in terms of actions and public policies to foster innovation in EE, especially in the Russian context.

Additionally, by merging the theoretical characteristics of CAS theory and EE, we could understand a case in a specific context, the Russian one, and the significant influence of a self-organizing behavior (Carter, Pezeshkan, 2023). Thus, managerially, this innovative study contributes to expanding analytical possibilities and decision-making in EEs during turbulent periods. It also facilitates a deeper and more comprehensive exploration of the regulatory environment, human capital, access to capital, entrepreneurial culture to promote greater innovation.

Concluding Remarks

This study contributes to advancing scientific knowledge in its field and provides valuable insights for professionals working with EEs. It introduces an innovative approach to understanding the main factors influencing the development of EEs in cities and elucidates how these factors relate to each other through the application of the fuzzy DEMATEL method. By identifying the regulatory environment, human capital, access to capital, and entrepreneurial culture as the most influential factors in fostering innovation in EEs, this study highlights the effectiveness and robust performance of the proposed approach in turbulent times.

Recognizing the practical application context, it is presumed that there is significant interdependence among these factors within EEs. However, it is important to note that the sampling procedure in this study differs from traditional multivariate analysis, as it involves samples extracted based on expert insights. Additionally, it is essential to observe that this research is limited by its application within a specific geographic and contextual context, namely Russia. Thus, it would be beneficial for future research to explore analogous problems using the fuzzy DEMATEL method and conduct comparative analyses across different countries or models.

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References

Aeeni Z., Saeedikiya M. (2019) Complexity Theory in the Advancement of Entrepreneurship Ecosystem Research: Future Research Directions. In: *Eurasian Business Perspectives* (eds. B.M.H. Bilgin, H. Danis, E. Demir, U. Can), Heidelberg, Dordrecht, London, New York: Springer International Publishing, pp. 19–37.

Altshuller M. (2017) Another Forgotten War: The Lack of a Western Response to the Ukrainian Conflict. *Harvard International Review*, 38(S1), 7–8. http://www.jstor.org/stable/26445588

Ansell C., Jarle T., Ogard M. (2017) *Governance in Turbulent Times*, Oxford: Oxford University Press. https://doi.org/10.1093/acprof:oso/9780198739517.001.0001

Arici T., Gok M. (2024) Ambiguous Effect of Environmental Turbulence on Innovation and Performance: Analyzing Technology Sectors. *Journal of Innovations in Business and Industry*, 2(1), 13–23. https://doi.org/10.61552/jibi.2024.01.003

Audretsch D.B., Belitski M. (2017) Entrepreneurial ecosystems in cities: Establishing the framework conditions. *The Journal of Technology Transfer*, 42(5), 1030–1051. https://doi.org/10.1007/s10961-016-9473-8

Audretsch D.B., Cunningham J.A., Kuratko D.F., Lehmann E.E., Menter M. (2019) Entrepreneurial ecosystems: Economic, technological, and societal impacts. *The Journal of Technology Transfer*, 44(2), 313–325. https://doi.org/10.1007/s10961-018-9690-4

Bone C. (2016) A complex adaptive systems perspective of forest policy in China. *Technological Forecasting and Social Change*, 112, 138–144. https://doi.org/https://doi.org/10.1016/j.techfore.2016.08.024

Brondoni S.M. (2022) Russian-Ukrainian War, Innovation, Creative Imitation & Sustainable Development. Symphonya. *Emerging Issues in Management*, 1, 4–9. https://doi.org/10.4468/2022.1.02brondoni

Brown R., Mason C. (2017) Looking inside the spiky bits: a critical review and conceptualisation of entrepreneurial ecosystems. *Small Business Economics*, 49(1), 11–30. https://doi.org/10.1007/s11187-017-9865-7

Cantner U., Cunningham J.A., Lehmann E.E., Menter M. (2021) Entrepreneurial ecosystems: A dynamic lifecycle model. *Small Business Economics*, 57(1), 407–423. https://doi.org/10.1007/s11187-020-00316-0

Carter W., Pezeshkan A. (2023) The complexity of entrepreneurial ecosystem evolution and new venture policy: The case of the U.S. commercial space ecosystem. *Technological Forecasting and Social Change*, 192, 122568. https://doi.org/https://doi.org/10.1016/j.techfore.2023.122568

Cloutier L., Messeghem K. (2022) Whirlwind model of entrepreneurial ecosystem path dependence. *Small Business Economics*, 59(2), 611–625. https://doi.org/10.1007/s11187-021-00553-x

Colovic A., Schruoffeneger M. (2022) Entrepreneuring for deprived urban communities: Exploring the role of micro-entrepreneurship. *European Management Review*, 19(3), 450–461. https://doi.org/https://doi.org/10.1111/emre.12458

Daniel L.J., de Villiers Scheepers M.J., Miles M.P., de Klerk S. (2022) Understanding entrepreneurial ecosystems using complex adaptive systems theory: getting the big picture for economic development, practice, and policy. *Entrepreneurship & Regional Development*, 34(9–10), 911–934. https://doi.org/10.1080/08985626.2022.2083691

Fredin S., Lidén A. (2020) Entrepreneurial ecosystems: Towards a systemic approach to entrepreneurship? *Geografisk Tidsskrift – Danish Journal of Geography*, 120(2), 87–97. https://doi.org/10.1080/00167223.2020.1769491

Fuentelsaz L., Maicas J.P., Montero J. (2023) The social status of entrepreneurs: An analysis of informal and formal institutional determinants. *European Management Review*, 12616 (ahead-of-print). https://doi.org/10.1111/emre.12616

Han J., Ruan Y., Wang Y., Zhou H. (2021) Toward a complex adaptive system: The case of the Zhongguancun entrepreneurship ecosystem. *Journal of Business Research*, 128, 537–550. https://doi.org/https://doi.org/10.1016/j.jbusres.2019.11.077

Isenberg D. (2010) How to start an entrepreneurial revolution. *Harvard Business Review*, 88, 40–51.

Khurana I., Dutta D.K., Singh Ghura A. (2022) SMEs and digital transformation during a crisis: The emergence of resilience as a second-order dynamic capability in an entrepreneurial ecosystem. *Journal of Business Research*, 150, 623–641. https://doi.org/https://doi.org/10.1016/j.jbusres.2022.06.048

Kuratko D.F., Fisher G., Bloodgood J.M., Hornsby J.S. (2017) The paradox of new venture legitimation within an entrepreneurial ecosystem. *Small Business Economics*, 49(1), 119–140. https://doi.org/10.1007/s11187-017-9870-x

Malecki E.J. (2018) Entrepreneurship and entrepreneurial ecosystems. *Geography Compass*, 12(3), e12359. https://doi.org/https://doi.org/10.1111/gec3.12359

Moraes G.H.S.M., Schaeffer P.R., Alves A.C., Heaton S. (2025) Exploring a link between faculty intrapreneurship, student entrepreneurship and ecosystem dynamism. *Journal of Entrepreneurship in Emerging Economies*, 17(2), 336–356. https://doi.org/10.1108/JEEE-09-2023-0356

Phillips M.A., Ritala P. (2019) A complex adaptive systems agenda for ecosystem research methodology. *Technological Forecasting and Social Change*, 148, 119739. https://doi.org/10.1016/j.techfore.2019.119739

Rouhani S., Ashrafi A., Afshari S. (2013) Segmenting critical success factors for ERP implementation using an integrated fuzzy AHP and fuzzy DEMATEL approach. *World Applied Sciences Journal,* 22, 1066–1079. https://doi.org/10.5829/idosi.wasj.2013.22.08.631

Roundy P.T., Bradshaw M., Brockman B.K. (2018) The emergence of entrepreneurial ecosystems: A complex adaptive systems approach. *Journal of Business Research*, 86, 1–10. https://doi.org/10.1016/j.jbusres.2018.01.032

Shakib M., Sohag K., Mariev O., Samargandi N., Ferraris A. (2023) Innovation and credit market deepening: Evidence from Russian region. *Journal of Innovation & Knowledge*, 8(3), 100391. https://doi.org/10.1016/j.jik.2023.100391

Shirokova G., Beliaeva T., Manolova T.S. (2022) The Role of Context for Theory Development: Evidence From Entrepreneurship Research on Russia. *Entrepreneurship Theory and Practice*, 47(6), 2384–2418. https://doi.org/10.1177/10422587221138226

Simon H.A. (1962) The Architecture of Complexity. *Proceedings of the American Philosophical Society*, 106(6), 467–482.

Spigel B., Harrison R. (2018) Toward a process theory of entrepreneurial ecosystems. *Strategic Entrepreneurship Journal*, 12(1), 151–168. https://doi.org/10.1002/sej.1268

Stam E. (2015) Entrepreneurial Ecosystems and Regional Policy: A Sympathetic Critique. European Planning Studies, 23(9), 1759–1769. https://doi.org/10.1080/09654313.2015.1061484

Stam E., van de Ven A. (2021) Entrepreneurial ecosystem elements. *Small Business Economics*, 56(2), 809–832. https://doi.org/10.1007/s11187-019-00270-6

Valdez M.E., Richardson J. (2013) Institutional Determinants of Macro-Level Entrepreneurship. *Entrepreneurship Theory and Practice*, 37(5), 1149–1175. https://doi.org/10.1111/etap.12000

Van De Ven H. (1993) The development of an infrastructure for entrepreneurship. *Journal of Business Venturing*, 8(3), 211–230. https://doi.org/10.1016/0883-9026(93)90028-4

Vedula S., Kim P.H. (2019) Gimme shelter or fade away: The impact of regional entrepreneurial ecosystem quality on venture survival. *Industrial and Corporate Change*, 28(4), 827–854. https://doi.org/10.1093/icc/dtz032

Vicentin D.C., Moraes G.H.S.M., Fischer B.B., Campello B.S.C., Prado N.B., Anholon R. (2024) The interdependence between the Entrepreneurial Ecosystem and Entrepreneurial Culture – An analysis with sustainable and traditional entrepreneurs. *Journal of Cleaner Production*, 466, 142821. https://doi.org/10.1016/j.jclepro.2024.142821

Yakovlev A. (2006) The Evolution of Business: State Interaction in Russia: From State Capture to Business Capture? *Europe-Asia Studies*, 58(7), 1033–1056. http://www.jstor.org/stable/20451287

Zhang Z.-X., Wang L., Wang Y.-M., Martínez L. (2023) A novel alpha-level sets based fuzzy DEMATEL method considering experts' hesitant information. *Expert Systems with Applications*, 213, 118925. https://doi.org/10.1016/j.eswa.2022.118925

Zhao X., Xu Y., Vasa L., Shahzad U. (2023) Entrepreneurial ecosystem and urban innovation: Contextual findings in the lens of sustainable development from China. *Technological Forecasting and Social Change*, 191, 122526. https://doi.org/10.1016/j.techfore.2023.122526

Appendix 1. **Fuzzy Relationship Matrix (IT01)**

	IT_1 - IT_1	IT_1 - IT_2	IT_1 - IT_3	IT_1 - IT_4	IT_1 - IT_5	IT_1 - IT_6	IT_1 - IT_7
R1	[0.0,0.0,0.0]	[0.25,0.5,0.75]	[0.75,1,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.75,1,1]
R2	[0.0,0.0,0.0]	[0.75,1,1]	[0.0,0.25,0.5]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]
R3	[0.0,0.0,0.0]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.75,1,1]
R4	[0.0,0.0,0.0]	[0.0,0.25,0.5]	[0.25,0.5,0.75]	[0.0,0.25,0.5]	[0.25,0.5,0.75]	[0.0,0.25,0.5]	[0,0.25,0.5]
R5	[0.0,0.0,0.0]	[0.5,0.75,1]	[0.75,1,1]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.25,0.5,0.75]
R6	[0.0,0.0,0.0]	[0.5,0.75,1]	[0.5,0.75,1]	[0.75,1,1]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.25,0.5,0.75]
R7	[0.0,0.0,0.0]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.5,0.75,1]
R8	[0.0,0.0,0.0]	[0.25,0.5,0.75]	[0.75,1,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.75,1,1]	[0.25,0.5,0.75]
R9	[0.0,0.0,0.0]	[0.75,1,1]	[0.0,0.25,0.5]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]
R10	[0.0,0.0,0.0]	[0.75,1,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.75,1,1]	[0.75,1,1]	[0.25,0.5,0.75]
R11	[0.0,0.0,0.0]	[0.5,0.75,1]	[0.5,0.75,1]	[0.0,0.25,0.5]	[0.0,0.25,0.5]	[0.0,0.25,0.5]	[0.25,0.5,0.75]
R12	[0.0,0.0,0.0]	[0.5,0.75,1]	[0.5,0.75,1]	[0.75,1,1]	[0.75,1,1]	[0.25,0.5,0.75]	[0.0,0.25,0.5]
R13	[0.0,0.0,0.0]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.5,0.75,1]
R14	[0.0,0.0,0.0]	[0.5,0.75,1]	[0.75,1,1]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.25,0.5,0.75]
R15	[0.0,0.0,0.0]	[0.5,0.75,1]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.25,0.5,0.75]
R16	[0.0,0.0,0.0]	[0.5,0.75,1]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.25,0.5,0.75]
R17	[0.0,0.0,0.0]	[0.5,0.75,1]	[0.0,0.25,0.5]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.0,0.25,0.5]	[0.0,0.25,0.5]
R18	[0.0,0.0,0.0]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.5,0.75,1]
R19	[0.0,0.0,0.0]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.75,1,1]	[0.25,0.5,0.75]	[0.0,0.25,0.5]	[0.0,0.25,0.5]
R20	[0.0,0.0,0.0]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.5,0.75,1]
R21	[0.0,0.0,0.0]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.75,1,1]	[0.25,0.5,0.75]	[0.25,0.5,0.75]
R22	[0.0,0.0,0.0]	[0.0,0.0,0.25]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]
R23	[0.0,0.0,0.0]	[0.5,0.75,1]	[0.75,1,1]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.75,1,1]
R24	[0.0,0.0,0.0]	[0.75,1,1]	[0.0,0.25,0.5]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]
R25	[0.0,0.0,0.0]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.0,0.25,0.5]	[0.0,0.0,0.25]	[0.25,0.5,0.75]	[0.25,0.5,0.75]
Aggregate	[0.0,0.0,0.0]	[0.44,0.68,0.89]	[0.43,0.68,0.88]	[0.40,0.65,0.87]	[0.39,0.63,0.85]	[0.32,0.56,0.79]	[0.35,0.59,0.81]

Source: authors.

Appendix 2. **Fuzzy Relationship Matrix (IT07)**

	IT_1 - IT_1	IT_1 - IT_2	IT_1 - IT_3	IT_1 - IT_4	IT_1 - IT_5	IT_1 - IT_6	IT_1 - IT_7
R1	[0.5,0.75,1]	[0.0,0.25,0.5]	[0.75,1,1]	[0.0,0.0,0.25]	[0.75,1,1]	[0.75,1,1]	[0.0,0.0,0.0]
R2	[0.5,0.75,1]	[0.0,0.25,0.5]	[0.5,0.75,1]	[0.0,0.25,0.5]	[0.75,1,1]	[0.25,0.5,0.75]	[0.0,0.0,0.0]
R3	[0.5,0.75,1]	[0.0,0.25,0.5]	[0.5,0.75,1]	[0.0,0.25,0.5]	[0.75,1,1]	[0.75,1,1]	[0.0,0.0,0.0]
R4	[0.0,0.0,0.25]	[0.0,0.0,0.25]	[0.25,0.5,0.75]	[0.0,0.25,0.5]	[0.5,0.75,1]	[0.5,0.75,1]	[0.0,0.0,0.0]
R5	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.0,0.0,0.0]
R6	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.5,0.75,1]	[0.0,0.0,0.0]
R7	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.0,0.0,0.0]
R8	[0.5,0.75,1]	[0.0,0.25,0.5]	[0.75,1,1]	[0.0,0.25,0.5]	[0.75,1,1]	[0.75,1,1]	[0.0,0.0,0.0]
R9	[0.5,0.75,1]	[0.0,0.25,0.5]	[0.5,0.75,1]	[0.0,0.25,0.5]	[0.75,1,1]	[0.25,0.5,0.75]	[0.0,0.0,0.0]
R10	[0.75,1,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.75,1,1]	[0.75,1,1]	[0.0,0.0,0.0]
R11	[0.5,0.75,1]	[0.5,0.75,1]	[0.0,0.25,0.5]	[0.0,0.25,0.5]	[0.0,0.25,0.5]	[0.0,0.25,0.5]	[0.0,0.0,0.0]
R12	[0.75,1,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.75,1,1]	[0.0,0.0,0.0]
R13	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.0,0.0,0.0]
R14	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.0,0.0,0.0]
R15	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.0,0.0,0.0]
R16	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.0,0.0,0.0]
R17	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.75,1,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.0,0.25,0.5]	[0.0,0.0,0.0]
R18	[0.0,0.25,0.5]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.75,1,1]	[0.25,0.5,0.75]	[0.0,0.0,0.0]
R19	[0.5,0.75,1]	[0.5,0.75,1]	[0.75,1,1]	[0.75,1,1]	[0.75,1,1]	[0.75,1,1]	[0.0,0.0,0.0]
R20	[0.25,0.5,0.75]	[0.0,0.0,0.25]	[0.25,0.5,0.75]	[0.0,0.25,0.5]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.0,0.0,0.0]
R21	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.5,0.75,1]	[0.0,0.0,0.0]
R22	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.0,0.25,0.5]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.0,0.0,0.0]
R23	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.25,0.5,0.75]	[0.5,0.75,1]	[0.0,0.0,0.0]
R24	[0.5,0.75,1]	[0.0,0.25,0.5]	[0.5,0.75,1]	[0.0,0.25,0.5]	[0.75,1,1]	[0.25,0.5,0.75]	[0.0,0.0,0.0]
R25	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.25,0.5,0.75]	[0.0,0.0,0.0]
Aggregate	[0.40,0.64,0.87]	[0.24,0.47,0.72]	[0.46,0.70,0.91]	[0.27,0.49,0.73]	[0.53,0.78,0.94]	[0.42,0.67,0.86]	[0.0,0.0,0.0]

Source: authors.

Appendix 3. **Fuzzy Relationship Aggregated Matrix**

	IT_1	IT_2	IT_3	IT_4	IT_5	IT_6	IT_7
IT_1	[0.0,0.0,0.0]	[0.44,0.68,0.89]	[0.43,0.68,0.88]	[0.4,0.65,0.87]	[0.39,0.63,0.85]	[0.32,0.56,0.79]	[0.35,0.59,0.81]
IT_2	[0.09,0.27,0.52]	[0.0,0.0,0.0]	[0.28,0.52,0.74]	[0.2,0.41,0.64]	[0.43,0.66,0.89]	[0.39,0.63,0.87]	[0.23,0.43,0.67]
IT_3	[0.26,0.51,0.73]	[0.27,0.52,0.75]	[0.0,0.0,0.0]	[0.44,0.69,0.91]	[0.44,0.69,0.9]	[0.31,0.56,0.78]	[0.49,0.73,0.93]
IT_4	[0.24,0.43,0.65]	[0.38,0.63,0.86]	[0.46,0.71,0.89]	[0.0,0.0,0.0]	[0.43,0.67,0.86]	[0.23,0.46,0.71]	[0.27,0.52,0.76]
IT_5	[0.16,0.4,0.64]	[0.29,0.53,0.76]	[0.49,0.74,0.93]	[0.34,0.58,0.8]	[0.0,0.0,0.0]	[0.2,0.42,0.66]	[0.5,0.75,0.91]
IT_6	[0.32,0.55,0.77]	[0.19,0.4,0.63]	[0.31,0.56,0.79]	[0.23,0.46,0.69]	[0.51,0.76,0.94]	[0.0,0.0,0.0]	[0.55,0.8,0.933]
IT_7	[0.4,0.64,0.87]	[0.24,0.47,0.72]	[0.45,0.7,0.91]	[0.27,0.49,0.73]	[0.53,0.78,0.94]	[0.42,0.67,0.86]	[0.0,0.0,0.0]

Source: authors.

Modeling and Forecasting the Diffusion of Unicorn Startups

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Abstract

Unicorn startups have become symbols of entrepreneurial success and fundamental drivers of innovation and wealth creation. This study examines the diffusion process of unicorns across eight countries (the US, China, India, the UK, Germany, France, the Netherlands, and Sweden) and three industries (Fintech, Health, and Transport). The aim of this research is to model and forecast the diffusion of unicorn startups using three- and four-parameter Logistic and Gompertz sigmoid growth models, leveraging data from the Dealroom database. By addressing this research gap, the study seeks to provide valuable information for policymakers and investors regarding the ultimate potential number of unicorns and the time to saturation. The findings indicate that the Gompertz model generates highly optimistic estimates of unicorn saturation levels, while the Logistic model produces more realistic projections for both fitting existing data and forecasting future trends. Specifically, the three- parameter Gompertz model is suited for analyzing unicorn diffusion in China. The three-parameter Logistic model is appropriate for analyzing unicorn diffusion in the USA, the UK, and all studied sectors. Meanwhile, the four-parameter Logistic model is the best model for explaining unicorn diffusion in India, Germany, France, the Netherlands, and Sweden. The results also reveal that India has the highest estimated speed of unicorn diffusion (97%), while the US exhibits the highest saturation level (6,241 unicorns). Sectoral analysis shows that Fintech has the lowest estimated diffusion speed (43.1%), but the highest saturation level (1,630 unicorns). Our forecasting analyses suggest that all selected countries and sectors — except the US and Fintech — are likely to reach unicorn saturation by around 2030. These findings provide critical insights for planning, regulation, policy formulation, and portfolio decision-making.

Keywords: unicorn startups; innovation diffusion; forecasting; entrepreneurial performance; Logistic model; Gompertz model

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Introduction

Over the past decade, the term "unicorn startup", referring to privately held companies valued at over $1 billion, has become a symbol of entrepreneurial success and technological innovation. Since its introduction by Aileen Lee in 2013,[1] the global number of unicorns has increased exponentially, from just 38 in 2013 to over 2,600 by early 2023.[2] Despite this rapid expansion, unicorns remain rare phenomena. In Europe, for instance, only one in 100 seed-funded startups achieves this valuation milestone[3].

Unicorns typically emerge at the nexus of disruptive technologies and highly scalable business models, reshaping traditional industries by offering more efficient, accessible, and often digital solutions (Stadler, 2016; Meek, Cowden, 2023; WIPO, 2023). Their rise was particularly accelerated in the wake of the COVID-19 crisis: 472 new unicorns were created in 2021 alone, fueled by global digitization, abundant venture capital, and increasingly supportive regulatory frameworks. This surge translated to nearly one new unicorn per day in the United States, approximately every ten days in India and China, almost every 15 days in Germany and the UK; every month in France; and every two months in the Netherlands and Sweden.

While most unicorns take at least five years on average to reach this valuation (Venâncio et al., 2023), a subset — including ClickHouse (US), Gorillas (EU), and iCarbonX (China) — achieved unicorn status in in less than a year, highlighting the exceptional agility of certain ventures during periods of systemic disruption (Kuckertz et al., 2020; Rodrigues, 2021).This rapid emergence raises an important question: **Is the unicorn phenomenon sustainable or is it approaching a saturation point?**

Despite the high failure rate of startups and growing macroeconomic volatility, the proliferation of unicorns represents both a strategic challenge and a major opportunity for innovation-driven economies. The concept of creative destruction (Schumpeter, 1943) remains particularly relevant for understanding the disruptive force of these firms. Yet the scale, speed, and uneven distribution of unicorn emergence remain poorly understood and insufficiently theorized.

A growing body of literature has attempted to identify the key drivers of unicorn success. For instance, Guo and Zhang (2021), using fuzzy set qualitative comparative analysis, highlight the role of emerging industries, enabling ecosystems, platform-based business models, and access to capital in unicorn development in China. Venâncio et al. (2023), analyzing 766 unicorns across 39 countries, emphasize the importance of innovation capacity, infrastructure, and resource availability. Kutsenko et al. (2022) add an important dimension by examining founder mobility, showing that nearly 40% of unicorns involved foreign entrepreneurial talent.

While these studies offer valuable insights, they often fall short of providing analytical frameworks capable of systematically modeling or forecasting unicorn diffusion across countries and industries. Although some scholars acknowledge the non-linear and abrupt nature of unicorn growth, analyses often rely on anecdotal evidence or descriptive analyses of individual business models (Urbinati et al., 2018; Trabucchi et al., 2019). Consequently, they offer limited guidance for anticipating future trends or for benchmarking national innovation ecosystems.

This research aims to address this gap by modeling the diffusion dynamics of unicorn startups across eight countries — namely the United States, China, India, the United Kingdom, Germany, France, the Netherlands, and Sweden — and three major sectors: fintech, healthtech, and transportation. Drawing on data from the Dealroom database, which tracks the cumulative number of unicorns from 2000 to 2022, we apply three- and four-parameter Logistic and Gompertz growth models to estimate the diffusion trajectories of unicorn startups. This methodological approach represents an advance over previous studies by offering a robust, quantifiable framework for capturing non-linear growth and forecasting saturation points.

The study is guided by the following research questions:

1. Can unicorn growth be effectively modeled using S-curve diffusion models?
2. Which model variant — logistic vs. Gompertz, three- vs. four-parameter — best captures the diffusion dynamics of unicorns across countries and industries?
3. How do diffusion trajectories differ across national and sectoral contexts?
4. What explains these differences?
5. What are the projected saturation points or upper limits of unicorn creation in each country or sector?
6. What strategic insights can be derived for investors, policymakers, and innovation ecosystem stakeholders?

This study makes several key contributions to the literature. First, to our knowledge, it is the first to apply Logistic and Gompertz growth models — tradition-

[1] https://techcrunch.com/2013/11/02/welcome-to-the-unicorn-club/, accessed 12.09.2024.
[2] https://dealroom.co/, accessed 18.01.2025.
[3] https://2020.stateofeuropeantech.com/chapter/state-european-tech-2020/, accessed 06.02.2025.

ally used in technology adoption studies — to the diffusion of unicorn startups. Grounded in Rogers' (1962) innovation diffusion theory, our study extends the applicability of S-curve models from product-level to firm-level valuation phenomena. Contrary to critiques regarding the incompatibility of sigmoid curves with rapid, exponential startup growth (Urbinati et al., 2018), our results show that these models effectively capture the core dynamics of unicorn proliferation with Logistic models outperforming Gompertz in most national and sectoral contexts

Second, by employing both three- and four-parameter specifications, we improve the precision and flexibility of diffusion modeling. Prior studies (e.g., Akin et al., 2020; Korkmaz, 2020) indicate that four-parameter models provide more accurate forecasts in scenarios characterized by delayed take-off or early saturation. Our results support this conclusion, showing that four-parameter models most effectively capture the unique growth dynamics of unicorn startups.

Third, the study offers a comparative, cross-country, and cross-sectoral perspective. By linking estimated diffusion trajectories to contextual variables such as venture capital intensity, regulatory landscape, and entrepreneurial mobility, we identify why certain countries (e.g., the US and China) and sectors (e.g., fintech) exhibit faster unicorn proliferation. The comparative lens also enables us to identify countries and industries approaching saturation, versus those with untapped growth potential.

From a practical standpoint, our findings yield actionable insights for investors, policymakers, and entrepreneurs. Reliable forecasting of unicorn emergence can inform venture capital allocation, guide innovation policy formulation, and scaling strategies for high-growth ventures. For instance, our results indicate that fintech unicorns are likely to reach saturation more gradually than those in the health tech and transportation sectors — suggesting differentiated approaches for public support and investment strategy. Entrepreneurs can benchmark their growth trajectories against diffusion curves, optimizing their scaling approaches, while corporate strategists can use these insights to anticipate market disruptions and refine acquisition or partnership strategies.

Although some scholars caution against overemphasizing unicorns as representative of entrepreneurship (Aldrich, Ruef, 2018), there is strong evidence that unicorns play a critical role in advancing innovation, creating jobs, and driving economic dynamism (Shane, 2009; OECD, 2021; Testa et al., 2022; Shahid, 2023). In 2021 alone, Europe's unicorns generated over 135,000 jobs (Huebl et al., 2022). Furthermore, unicorn density has become a core indicator in global innovation rankings (WIPO, 2023). Supporting their emergence is thus a matter of strategic importance for national development agendas (Kuratko, Audretsch, 2021; Kuckertz et al., 2020, 2023).

In an increasingly competitive and innovation-driven global economy, the ability to model and forecast unicorn diffusion is of critical strategic value. By bridging innovation diffusion theory with the empirical realities of startup ecosystems, this study offers a novel, data-driven framework for understanding and anticipating the trajectories of high-growth firms.

Theoretical Framework and Hypothesis Development

This study is anchored in the Diffusion of Innovation (DoI) theory and utilizes the logistic and Gompertz diffusion models as its principal analytical frameworks for modeling the growth trajectories of unicorn startups.

The conceptualization of innovation diffusion was first systematically articulated by Rogers (1962). According to Rogers, diffusion is defined as the process by which an innovation — understood as a new idea, practice, or technology — is communicated over time through specific channels among members of a social system. He identifies five core elements that shape this process: the innovation itself, communication channels, time, the social system, and the adoption decision process. Rogers also proposed a classification of adopters into five groups — innovators, early adopters, early majority, late majority, and laggards — laying the foundation for understanding how and why innovations spread unevenly within populations.

Building on this theoretical base, subsequent research has introduced quantitative models to capture the temporal dynamics of innovation diffusion. Among the most prominent are the Logistic and the Gompertz models, both of which exhibit the characteristic S-shaped curve of cumulative adoption. This curve typically unfolds in three phases: (1) a slow initial uptake, (2) a rapid acceleration phase as the innovation gains legitimacy and traction, and (3) a deceleration as the market approaches saturation.

Originally rooted in 19th century biological and demographic studies, the Gompertz and the Logistic model have been widely adopted in fields ranging from marketing and technology forecasting to epidemiology. Their empirical relevance was notably reaffirmed during the COVID-19 pandemic, where they were extensively employed to simulate the spread of infection (Pelinovsky et al., 2022; Satoh, 2021).

While these models have proven robust in many contexts, their suitability for modeling digital-era, high-velocity innovations, such as unicorn startups, has been the subject of scholarly debate. Unicorns often embody unique dynamics: platform-based scalability, global scalability, and substantial venture capital infusion — factors that may generate diffusion patterns deviating from traditional S-curves (Urbinati et al., 2018; Trabucchi et al., 2019).

However, historical evidence shows that even paradigm-shifting innovations — such as the automobile, electricity, or television — can be effectively modeled using growth-based frameworks when appropriately parameterized (Meade, Islam, 2015). This underscores the adaptability and enduring relevance of these models, even in the face of disruptive technological change.

As previously noted, unicorn startups share key features of transformative innovations: they are digitally native, disruptive, and rapidly adopted, often reshaping entire industries. These characteristics make them particularly well-suited for empirical modeling through non-linear diffusion curves, especially the Logistic and Gompertz functions.

By leveraging both models, this study conducts a comparative analysis of diffusion patterns across countries and sectors, enabling the estimation of critical parameters such as maximum market potential (M), growth rate (α), and inflection point (β). The Logistic model, which assumes a symmetrical S-curve, is optimal for contexts with balanced early and late adoption, while the Gompertz model — characterized by an asymmetrical S-curve — is better suited to scenarios where early adoption is gradual but followed by a rapid acceleration in later stages.

Recent studies (e.g., Akin et al., 2020; Korkmaz, 2020) have shown that four-parameter extensions of the Gompertz and Logistic models often outperform their three-parameter counterparts in terms of fit and forecasting accuracy. The three-parameter model (Logistic or Gompertz) constrains the curve to start at zero, which may not accurately represent the data. In reality, some countries might already have a baseline level of entrepreneurial activity or an existing tech ecosystem. The four-parameter model, with its lower asymptote, accounts for this non-zero starting point. This model offers greater flexibility in fitting the data, even if the initial data points are not perfectly accurate.

Accordingly, following the methodologies of Jha & Saha (2020) and Akin et al. (2020), this study employs both three-parameter and four-parameter versions of the Logistic and Gompertz models, as detailed in the subsections below.

Logistic Model

The Logistic curve is symmetrical about its inflection point. The three-parameter logistic model (LM3P) is as follows:

$$U(t) = \frac{M}{1+e^{-\alpha(t-\beta)}}, \tag{1}$$

M, β and α, are all positive parameters.

M is the market potential or the maximum number of possible unicorns, α is the growth rate or the pace of unicorn adoption and β is the inflection point, which indicates the point at which the growth of unicorn adoption reaches its peak and begins to decline. This is generated when the diffusion of unicorns has reached half of its maximum level (*M / 2*).

The Logistic model with four parameters (LM4P) is as follows:

$$U(t) = A + \frac{B}{1+e^{-\alpha(t-\beta)}}, \tag{2}$$

Where *A* is a location parameter and acts as the lower asymptote, *B* is the asymptotic amount of unicorn growth that occurs as *t* increases, and *A+B=M.*

Gompertz Model

The Gompertz curve has the property of being asymmetric about the inflection point. The three parameter Gompertz model (GM3P) is:

$$U(t) = Me^{-e^{-\alpha(t-\beta)}}, \tag{3}$$

M is the market potential or the maximum number of possible unicorns, α is the growth rate or the pace of unicorn adoption, and β is the inflection point, which indicates the point in time at which the growth of unicorn adoption peaks and begins to decline. This occurs when the diffusion of unicorns reaches the share *1/e* ≈ 36.8% of its maximum level (*M/e*).

The Gompertz model with four parameters (GM4P) is as follows:

$$U(t) = C + De^{-e^{-\alpha(t-\beta)}}, \tag{4}$$

Where C is a location parameter and acts as a lower asymptote, *D* is the asymptotic amount of unicorn growth that occurs as *t* increases, and *C+D=M.*

Research Hypotheses

By operationalizing unicorn diffusion through established growth models, this study empirically evaluates the extent to which Logistic and Gompertz functions can capture the cross-national and cross-sectoral trajectories of unicorn startup proliferation. The following hypotheses are proposed and tested :

H1: The diffusion of unicorn startups follows an S-shaped growth trajectory that can be effectively modeled using either the Logistic or Gompertz function, consistent with classical innovation diffusion theory.

H2: The Gompertz model provides a superior fit in contexts characterized by rapid early-stage growth followed by premature saturation, often influenced by regulatory or structural constraints.

H3: The Logistic model is better suited for countries where structural, economic, and institutional conditions support balanced, sustained scaling, aligning with its assumptions of symmetrical growth around an inflection point.

H4: Unicorn diffusion patterns differ significantly across countries, driven by heterogeneity in institutional frameworks, innovation capacity, access to venture capital, and national entrepreneurship ecosystems.

H5: Sector-specific factors — such as regulatory barriers, technological maturity, and product lifecycle dynamics — significantly influence the shape, speed, and ultimate ceiling of unicorn diffusion trajectories.

Methodology and Data

Our analysis begins with a descriptive examination of the dataset (detailed in the following subsection) to provide a preliminary assessment of our first hypothesis concerning the applicability of the Logistic and Gompertz diffusion models to the context of unicorn startups. Following this, we adopt a three-stage methodological approach.

Stage 1: Model Estimation. We estimate the parameters of the diffusion models outlined in Equations (1) through (4) for each country and industry in the sample using Nonlinear Least Squares (NLS) regression. For each case, the model with the highest adjusted R^2 and the lowest Root Mean Square Error (RMSE) is selected as the best-fitting model for historical data.

Stage 2: Forecasting and Validation. Using the estimated parameters, we forecast the diffusion of unicorns by country and industry for the period 2023–2033. To evaluate forecasting accuracy, we rely on two primary error metrics: the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE). The model exhibiting the lowest MAE and MAPE is considered the most reliable for projection purposes.

Stage 3: Comparative Analysis of Diffusion Dynamics. To explore heterogeneity in diffusion patterns, we compare the fitted parameters — such as growth rate, inflection point, and market potential — across countries and sectors. This comparison enables us to assess the influence of institutional frameworks, digital infrastructure, and innovation ecosystems on unicorn diffusion by country, and the role of technological maturity, regulatory complexity, and innovation cycles at the sectoral level.

Data and Descriptive Analysis

This paper focuses on assessing the goodness of fit and predictive ability of the Logistic and Gompertz models for the diffusion of unicorns. To this end, we use time series data on cumulative unicorns from the Dealroom database, specifically the so-called “Unicorn Club”. Launched in 2013, the Dealroom database provides information on technology companies founded since 1990, with a particular focus on the EU market. Dealroom is recognized as a leading data provider for high-growth companies, offering detailed funding round histories, valuation milestones, and investor networks (Veugelers, Amaral-Garcia, 2025). It is one of the most widely cited and used databases for tracking startups, scaleups, and unicorns, making it highly relevant for studying their diffusion process. Several previous studies have relied on this database, such as (Burstrom et al., 2023; El-Dardiry, Vogt, 2023; Testa et al., 2022). Furthermore, its transparent methodology for identifying unicorns — defined as privately held startups exceeding a $1 billion valuation — ensures consistency in firm classification, making it well-suited for analyzing the diffusion patterns of these companies across different geographies and industries.

The Unicorn Club is particularly well suited for research as it is updated daily and is structured in an accessible way (Retterath, Braun, 2020). It enables near real-time tracking of new unicorns, exits, and funding activities. Unlike traditional data sources, Dealroom provides up-to-date information, minimizing delays in data availability (van Meeteren et al., 2022). Dealroom offers granular data on the number of new and cumulative unicorns by continent, country, and industry since 2000. Compared to other databases (e.g., CB Insights, Crunchbase, PitchBook), Dealroom stands out for its global scope, particularly on emerging markets, and its integration of proprietary and publicly available data sources. It gathers information using multiple methods including automated harvesting of public data (e.g., press releases, VC reports, job boards, domain registries), partnerships with government agencies to supplement startup records, and manual verification to ensure data accuracy (El-Dardiry, Vogt, 2023). Furthermore, Dealroom provides broader sectoral tags and deeper coverage of European ecosystems (Burstrom et al., 2023; Leendertse et al., 2022).

Despite its strengths, Dealroom — like other venture capital databases — has limitations. As with many commercial startup data providers, its datasets can be incomplete due to the private nature of many investment deals, inconsistent reporting by some investors, or selective reporting of certain deal types (Testa et al., 2022). Moreover, while Dealroom offers extensive global coverage, regional gaps persist, particularly in the Asia-Pacific ecosystem. However, van Meeteren et al. (2022) validated Dealroom’s coverage by comparing it with Crunchbase. Their findings revealed similar sectoral and geographical distribution patterns in both datasets, with most companies concentrated in North America and Europe. This suggests that while some limitations exist, Dealroom remains a reliable source for studying unicorn diffusion on a global scale.

According to the Dealroom database, there are currently 2,615 unicorn companies worldwide, 90% of which are in just 15 countries. Among these countries, the US and China alone account for 54% and 12.42% of the total number of unicorns, respectively. The most represented industries are fintech, with 517 companies in this category, healthcare with 433 unicorns and transportation with 234 unicorns.

The dataset used for this paper was downloaded in December 2022. It covers the period 2000-2022 and includes information on the number of cumulative unicorns in eight countries (US, China, India, UK, Germany, Sweden, France and the Netherlands) and three industries (fintech, health, and transport). Our database represents 80% of the world's unicorns. The size of this database is consistent with diffusion and forecasting studies such as (Armstrong, 2001; Michalakelis et al., 2008; Lee et al., 2011).

Figures 1 and 2 describe the growth paths of the unicorns in the eight countries and three sectors selected during the study period. As can be seen from these figures, the shapes of the unicorn curves follow an S-curve pattern. Therefore, using forecasts based on linear extrapolation may lead to under- or overestimation. The distribution of unicorns varies considerably across countries and sectors. As noted above, Figure 1 shows that most unicorns are concentrated in the US and China, with the former leading the pack. Among European countries, the UK has the most unicorns, followed by Germany, the Netherlands, Sweden, and France. However, India seems to outperform the EU27 countries in terms of the number of unicorns, especially from 2020 onwards. Figure 1 also shows that the number of unicorns has increased continuously since 2014 in all the countries examined.

The largest increase in unicorns came in 2021, when all countries except China, the Netherlands, Sweden, and the UK saw the highest rate of unicorn growth. However, it appears that the growth rate of European and Indian unicorns in 2021 outpaced that of their US and Chinese counterparts. The same patterns are observed for the growth rate of unicorns in the three sectors examined (Figure 2). Figure 2 shows that most unicorns are active in the health and fintech sectors followed by unicorns active in the transportation sector. A continuous increase in the number of unicorns has been observed since 2014, reaching a peak in 2021.

Results and Discussions

Logistic and Gompertz models with three and four parameters are used as growth models in this research. We use the non-linear least squares (NLS) and STATA 15 software to estimate the parameters in (1), (2), (3), and (4), after providing appropriately chosen initial values, since the two curves are non-linear in the parameters of interest. The estimated parameters can then be used to obtain forecasts of the variable *U*.

The quality of the fit to the data is excellent for each model. All models show a high accuracy with an adjusted coefficient of determination (Adj_R^2) greater than 95%. All the parameters of the models are almost statistically significant at the 1% level. In the following sections, we detail our results by country and by sector.

Analysis of Unicorn Diffusion by Country

The results of the analysis for the eight countries are summarized in Table 1. The models obtained for all countries in the study are statistically significant and all the parameters of the models are statistically significant at the 1% level, except for the saturation point parameter in the case of the USA, UK, and Germany (Table 1). From Table 1, we can conclude that the Logistic model is suitable for analyzing the diffusion of unicorns in the USA, India, Germany, the UK, France, the Netherlands, and Sweden. Indeed, this model yields a lower RMSE and a higher adjusted R^2 than the Gompertz model. In the case of China, however, the Gompertz model is more appropriate to describe unicorn diffusion.

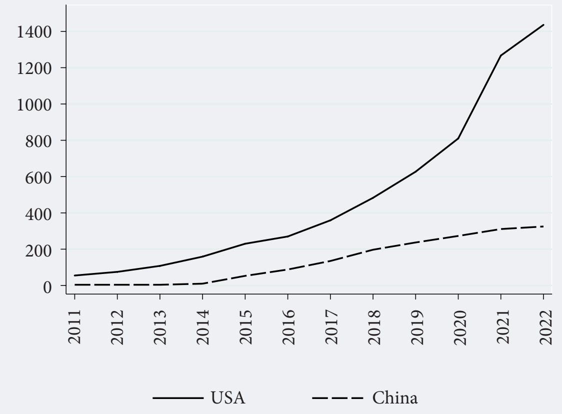
Our Logistic model results for unicorn diffusion in the USA indicate a maximum level of 6,241.574. The speed of convergence to the saturation level is 0.322, and half of the maximum level will be reached in 2026. Using the Logistic model with four parameters, we find almost the same results as those reported above. The results of the Gompertz model indicate an overestimation of the potential maximum number of unicorns and a very low speed of diffusion (0.017). The values of adjusted R^2, RMSE, MAE, and MAPE indicate that the three-parameter Logistic model is the best to describe and forecast unicorn diffusion in the USA. Our forecasting analysis shows that the saturation of unicorn diffusion in the USA, generated by the Logistic model, is predicted to be reached in 2052.

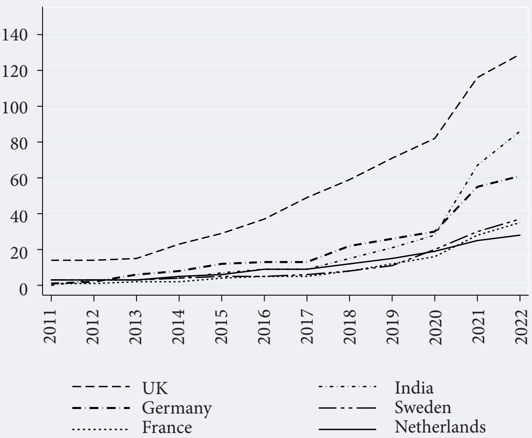
The results of the Logistic model for the diffusion of unicorns in China indicate a maximum level of 335.796, with a convergence speed to the saturation level of 0.694. According to the model, unicorn diffusion reached half of its maximum level in 2018. The Gompertz model results suggest a maximum diffusion level of 380.713, a diffusion speed of 0.378, and that 36.8% of the maximum level was achieved in 2017. Based on the values of adjusted R^2, RMSE, MAE, and MAPE, the three-parameter Gompertz model demonstrates superior performance in both describing and forecasting unicorn diffusion in China. Our forecasting analysis predicts that the saturation of unicorn diffusion in China, as estimated by the Gompertz model, will be reached in 2032.

For the UK, our results from the three-parameter Logistic model for unicorn diffusion show a maximum level of 545.113 (but not statistically significant). The speed of convergence to the saturation level is 24.5% (significant at 1%) and half of the maximum level will be achieved in 2027. Using the Gompertz model, we find similar results to the USA case. The potential maximum number of unicorns is also overestimated, while the speed of diffusion is underestimated. The values of adjusted R^2, RMSE, MAE, and MAPE indicate that the Logistic model is the best to describe and forecast unicorn diffusion in the UK. Our forecasting analysis shows that the saturation of unicorn diffusion in the UK, as generated by the Logistic model, is predicted to be reached after 2032.

For India, the results of the four-parameter Logistic model for unicorn diffusion indicate a maximum

Figure 1. **Growth Path of Unicorns by Country**





Source: authors.

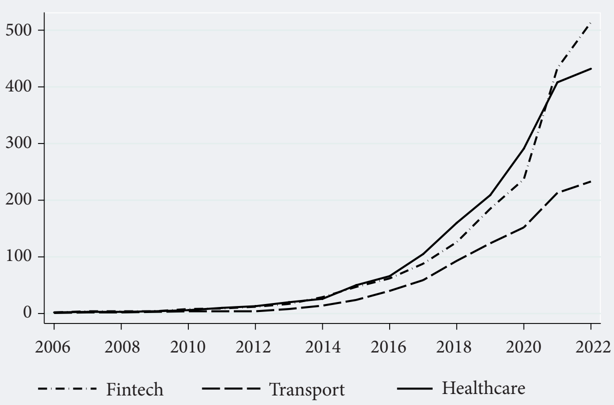
level of 139.889 and the speed of convergence to the saturation level is 97%. Unicorn diffusion reached half of its maximum level in 2021. The results of the Gompertz model indicate a maximum diffusion level of 313.211 (but not statistically significant), the speed of diffusion is 0.298 and 36.8% of its maximum level was achieved in 2022. From Table 1, we can conclude that the four-parameter Logistic model provides more accurate results in describing and forecasting the unicorn diffusion in India, which is reflected in its high adjusted R^2 and low RMSE, MAE, and MAPE. Our forecasting analysis shows that the saturation point of unicorn diffusion in India, as generated by the Logistic model, is predicted to be reached in 2030.

The results of the four-parameter Logistic model for the diffusion of unicorns in France show a maximum level of 91.9 and the speed of convergence to the saturation level is 0.496. Unicorn diffusion achieved half of its maximum level in 2023. The Gompertz model strongly overestimates the ultimate potential number of unicorns and underestimates the speed of diffusion. The four-parameter ogistic model is found lto be suitable for describing the process of unicorn diffusion in France, while the Gompertz model is the best for predicting unicorn diffusion. However, given that the predictive performance of the Logistic and Gompertz models is not significantly different and considering that the ultimate market potential estimate of the Logistic model is more realistic (91.9), we choose the Logistic model over the Gompertz model to forecast the unicorn diffusion in France. According to our forecast results generated by the Logistic model, the saturation of unicorn diffusion in France will be reached in 2032.

The four-parameter Logistic model also performs well in describing and forecasting the diffusion process of unicorns in Sweden and the Netherlands. In Sweden, the maximum potential number of unicorns is 48 and half of this number was reached in 2021. In the Netherlands, it took a year longer to reach half of the maximum potential number of unicorns, which is 57. Our results also show that unicorns in Sweden are diffusing at 2.4 times the speed of unicorn diffusion in the Netherlands. Regarding our forecasting results, we find that while Sweden will achieve its saturation point of unicorn diffusion in 2027, the Netherlands will need five more years to reach its maximum potential number of unicorns.

For the case of Germany, the performance analysis of non-linear growth models based on adjusted R^2 and RMSE shows that the three-parameter Gompertz model is more suitable for describing and forecasting the diffusion of German unicorns. However, the saturation value is strongly overestimated, while the speed of growth is underestimated, and these values do not seem plausible with the German data. This estimation problem has also been identified by several previous researchers such as (Gamboa, Otero, 2009; Jha, Saha, 2020) in the telecommunications industry.

Figure 2. **Growth Path of Unicorns by Sector**



Source: authors.

Table 1. **Estimated Parameters of the Unicorn Diffusion Models by Country**

Parameter	Country							
	USA (n=23)		China (n=12)		UK (n=13)		India (n=13)	
Model	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**
M_3P	6241.574	8.94e+09	335.796 *	380.713*	545.113	452195.2	196.359*	6.94e+08
M_4P	5 545,489	-	342,582*	378,268*	381.833	2 358,319	139.889*	313.211
_3P	0.322 *	0.017*	0.694*	0.378*	0.245*	0.024	0.678*	0.028*
_4P	0.331*	-	0.637*	0.385*	0.276**	0.066	0.97*	0.298**
_3P	2025.629*	2182.154*	2017.603*	2016.996 *	2026.676*	2109.214*	2021.719*	2121.446*
_4P	2025.065*	-	2017.574*	2017.007*	2024.435*	2038.416*	2020.835*	2022.305*
In-sample								
Adj R^2_3P	0.995	0.995	0.998	0.999	0.997	0.996	0.987	0.985
Adj R^2_4P	0.993	-	0.996	0.998	0.991	0.991	0.988	0.983
RMSE_3P	34.047	34.978	8.122	5.119	3.683	3.727	4.532	4.849
RMSE_4P	34.825	-	7.583	5.304	3.853	3.841	3.685	4.386
Out-of-sample								
MAE_3P	15.412	16.437	5.898	3.791	2.252	2.339	3.227	3.309
MAE_4P	15.685	-	5.194	3.6	2.181	2.151	2.37	2.745
MAPE_3P	0.132	0.135	0.415	0.238	0.063	0.068	0.465	0.373
MAPE_4P	0.417	-	0.467	0.19	0.055	0.052	0.451	0.483

Parameter	Country							
	Germany (n=13)		France (n=13)		Sweden (n=13)		Netherlands (n=14)	
Model	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**
M_3P	2648.196	3.59e+08	15139.13	4.64e+08	81455.96	1.82e+08	186.937	1.26e+08
M_4P	301,384	1.08e+08	91.9**	1.11e+08	48,308*	88,65***	56,765**	236,871
_3P	0.285*	0.017*	0.355*	0.021*	0.319*	0.021*	0.236*	0.013*
_4P	0.349	0.020*	0.496*	0.024*	0.834*	0.295**	0.347*	0.091***
_3P	2035.042*	2182.009*	2039.03*	2157.377*	2046.163	2153.066*	2029.22	2224.1 *
_4P	2025.92 *	2154.355 *	2022.98*	2132.8*	2020.632*	2021.679*	2022.15*	2030.601*
In-sample								
Adj R^2_3P	0.982	0.984	0.991	0.991	0.983	0.985	0.995	0.996
Adj R^2_4P	0.955	0.960	0.991	0.990	0.990	0.985	0.992	0.991
RMSE_3P	3.557	3.408	1.117	1.124	1.982	1.865	0.837	0.82
RMSE_4P	4.138	3.888	0.950	0.980	1.131	1.39	0.776	0.794
Out-of-sample								
MAE_3P	2.48	2.461	0.817	0.894	1.456	1.488	0.603	0.618
MAE_4P	2.59	2.594	0.546	0.572	0729	0.937	0.523	0.541
MAPE_3P	0.4	0.344	0.338	0.399	0.246	0.306	0.108	0.112
MAPE_4P	0.235	0.226	0.143	0.123	0.260	0.301	0.084	0.086

Note: Significance level: *, p < 1%; **, p < 5%; ***, p < 10%. Some values are not reported since the modeling failed to achieve the convergence criteria even after thousands of iterations..

Source: authors.

Furthermore, we find that the NLS estimation procedure requires more than two thousand iterations to reach the convergence criteria, in contrast to the Logistic model, which requires only a few iterations. Since the maximum potential number of unicorns estimated with the Logistic model is more realistic, we chose the Logistic model over the Gompertz model to describe and forecast the diffusion processes of unicorns in Germany. For the choice between a Logistic model with three or four parameters, we refer to Figure 3. We find that the Logistic model with four parameters best fits the real adoption curve. Therefore, we consider this model to be the most suitable for describing and predicting the diffusion of unicorns in Germany. The results show that the growth rate is 34.9%, the saturation level is 301.384, and half of this saturation level will be reached in 2026. According to our forecasting analysis results, generated by the four-parameter Logistic model, unicorn diffusion in Germany will reach 128 in 2025.

Comparing the estimated parameters of the best fitted models for our sample of countries, the results show that India has the highest estimated speed of diffusion (97%), followed by Sweden (83.4%) and China (37.8%). As for the maximum diffusion of unicorns, our results show that the US has the highest level (6,241.574), followed by the UK (545.13) and China (380.713). Therefore, the US will continue to be the top country for unicorns. We also find that China, India, France, Sweden, and the Netherlands have already reached half of their maximum diffusion of unicorns. Conversely, the US, UK, and Germany still need one to two years to reach this level. Furthermore, we find that all the countries selected in our analysis, except the US, will reach their maximum level of unicorn diffusion around 2030.

Results of the Unicorn Diffusion Analysis by Sector

In this section, we report the results of our analysis of the unicorn diffusion process by sector. The results of the analysis, for the three selected sectors, are summarized in Table 2.

The models obtained for all the sectors in the study are statistically significant and almost all the parameters of the models are statistically significant at the 1% level. From Table 2, we can conclude that the Logistic model is suitable for analyzing the diffusion of unicorns in all three sectors, as it provides a lower RMSE and a higher adjusted R^2 than the Gompertz model.

For the fintech sector, our Logistic model results indicate a maximum level of 1,630.231. The speed of convergence to the saturation level is 0.431 and half of the maximum level will be reached in 2024. Using the Logistic model with four parameters, we find similar results. The Gompertz model results indicate an overestimation of the potential maximum number of unicorns and a very low speed of diffusion (0.022). The adjusted R^2 and RMSE values indicate that the three-parameter Logistic model is well-suited for describing unicorn diffusion in the fintech sector, while the Gompertz model performs better for predicting diffusion. However, given the Logistic model's more realistic estimate of the ultimate market potential (1,630.231), as illustrated in Figure 4, we have chosen the three-parameter Logistic model for forecasting unicorn diffusion in the fintech sector. According to our analysis, unicorn diffusion in the fintech sector is expected to reach saturation by 2040.

For the health sector, the three-parameter Logistic model results indicate a maximum level of 619.390 unicorns, with a convergence speed to the saturation level of 50.8%. Unicorn diffusion reached half of its maximum level in 2020. The Gompertz model results indicate a maximum diffusion level of 1,440.596, a diffusion speed of 15.9%, and 36.8% of the maximum level reached in 2023. Based on the adjusted R^2, RMSE, MAE, and MAPE values, we find that the three-parameter Logistic model performs best in describing and forecasting unicorn diffusion in the health sector. Our forecasting analysis predicts that the saturation of unicorn diffusion in the health sector will be reached in 2030.

For the transport sector, the three-parameter Logistic model results indicate a maximum level of 318.955 unicorns, with a convergence speed to the saturation level of 50.4%. Unicorn diffusion reached half of its maximum level in 2020. The Gompertz model results indicate a maximum diffusion level of 615.22, a diffusion speed of 17.6%, and 36.8% of the maximum level reached in 2022. From Table 2, we can conclude that the three-parameter Logistic model provides more accurate results in describing and forecasting unicorn diffusion in the transport sector, as reflected in its high adjusted R^2, low RMSE, MAE and MAPE. Our forecasting analysis predicts that the saturation of unicorn diffusion in the transport sector will be reached in 2030.

Comparing the estimated parameters of the best-fit models for our selected sectors, the results show that the fintech sector has the lowest estimated speed of diffusion (43.1%) but the highest saturation level (1,630). We also find that selected sectors have already reached half of their maximum diffusion of unicorns. Furthermore, the transportation and health sectors are expected to reach their maximum unicorn diffusion in seven years, while the fintech sector will need ten more years to reach this level.

Discussion

This study is the first to systematically apply Logistic and Gompertz models to analyze the diffusion of unicorn startups across major countries and sectors. The findings provide several key insights into growth trajectories, ecosystem maturity, and the influence of institutional environments on entrepreneurial success.

Validation of S-Curve Dynamics. First, we confirm H1: the diffusion of unicorns follows an S-shaped curve, consistent with established patterns in product and technology adoption. Contrary to earlier concerns (e.g., Urbinati et al., 2018), S-curve models effectively capture the early acceleration and eventual saturation of unicorn creation. In line with previous studies (Akin et al., 2020; Korkmaz, 2020), four-parameter models improve forecasting accuracy, particularly in cases of delayed take-off or early saturation.

Model Performance: Logistic vs. Gompertz. Consistent with H2 and H3, the Logistic models generally outperform Gompertz, especially in market-oriented ecosystems such as the US, India, and most European nations. These environments are characterized by steady access to venture capital and organic entrepreneurial growth, making the symmetric nature of the Logistic curve an appropriate fit. In contrast, the Gompertz model is better suited for China, where unicorn creation is front-loaded due to state-driven initiatives like "Made in China 2025," followed by a sharp decline owing to regulatory constraints. This explains China's early saturation point (2032) and lower ceiling (381 unicorns), as supported by recent analyses on the revival challenges of Chinese unicorns (Jian et al., 2024). Conversely, the United States exhibits consistent annual growth of 32.2%, progressing toward a saturation ceiling of 6,241 unicorns — a pattern well aligned with Logistic dynamics.

Country-Level Diffusion Patterns. As predicted by H4, unicorn diffusion dynamics vary significantly across countries. The US leads in saturation (6,241 unicorns), with the highest saturation ceiling, supported by mature financial markets, extensive R&D networks, and robust startup ecosystems. India demonstrates the fastest annual growth rate (97%), driven by a large market and rapid tech adoption (Startup Genome, 2022), though its ultimate ceiling is lower

Table 2. **Estimated parameters of the unicorn diffusion models by sector**

Parameter	Sector					
	Fintech (n=21)		Healthcare (n=19)		Transport (n=17)	
Model	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**	**Logistic**	**Gompertz**
M_3P	1630.231***	3.11e+09	619.390*	1440.596**	318.955*	615.22*
M_4P	1 373,545**	239 642,95	599,396*	1 179,559**	315,394*	541,338*
_3P	0.431*	0.022*	0.508*	0.159*	0.504*	0.176*
_4P	0.459*	0.052	0.532*	0.184*	0.512*	0.196*
_3P	2023.707*	2148.927*	2020.128*	2022.922 *	2019.911*	2021.68 *
_4P	2023.045 *	2056.553*	2020.007*	2021.828 *	2019.87*	2021.032*
In-sample						
Adj R^2_3P	0.992	0.992	0.996	0.994	0.998	0.997
Adj R^2_4P	0.989	0.988	0.995	0.993	0.996	0.996
RMSE_3P	14.75	15.026	9.925	12.301	4.598	5.098
RMSE_4P	14.967	15.639	9.986	12.062	4.750	4.905
Out-of-sample						
MAE_3P	6.961	6.538	5.457	7.447	2.674	3.210
MAE_4P	6.678	6.732	5.191	6.814	2.5	2.501
MAPE_3P	0.334	0.295	0.302	0.492	0.249	0.392
MAPE_4P	0.474	0 .415	0.402	0.768	0.154	0.219

Note: Significance level: *, p < 1%; **, p < 5%; ***, p < 10%.

Source: authors.

due to limitations in capital, depth, and infrastructure. This contrast illustrates a classic trade-off: rapid diffusion may come at the cost of long-term scalability. European countries exhibit moderate diffusion patterns and mid-range saturation potential. While their capital markets are more fragmented, stable institutional environments provide a foundation for sustained, but slower, unicorn development (Testa et al., 2022).

Sectoral Dynamics and H5 Validation. H5 is also validated. The fintech sector demonstrates the slowest diffusion rate but the highest projected long-term potential (1,630 unicorns), reflecting persistent regulatory hurdles and trust concerns (CB Insights, 2023). By contrast, health and transportation sectors display faster adoption, fueled by clear demand signals and fewer institutional constraints. These differences underscore the need for sector-specific policy and investment strategies.

*Theoretical Contributions and Diffusion Mechanisms***.** These findings affirm Rogers' diffusion of innovations theory, emphasizing the role of social systems and institutional factors in shaping S-curve trajectories. In market-oriented environments (e.g., the US, India, Europe), unicorn diffusion typically proceeds through the classic phases of slow initiation, rapid acceleration, and eventual saturation. These patterns align with the Logistic model. Conversely, in state-led ecosystems such as China, diffusion is asymmetric, with strong early-stage support followed by regulatory constraints — well captured by the Gompertz model.

Implications for Policymakers and Investors. This study offers practical implications for both policymakers and investors. For investors, understanding cross-country saturation levels and sectoral adoption speeds is critical for timing entry and exit strategies. In China, regulatory volatility presents a key risk, whereas in the US, market saturation could limit future returns. Geographic diversification — balancing high-growth potential in China and India with the stability of the U.S. and Europe — can help mitigate these risks.

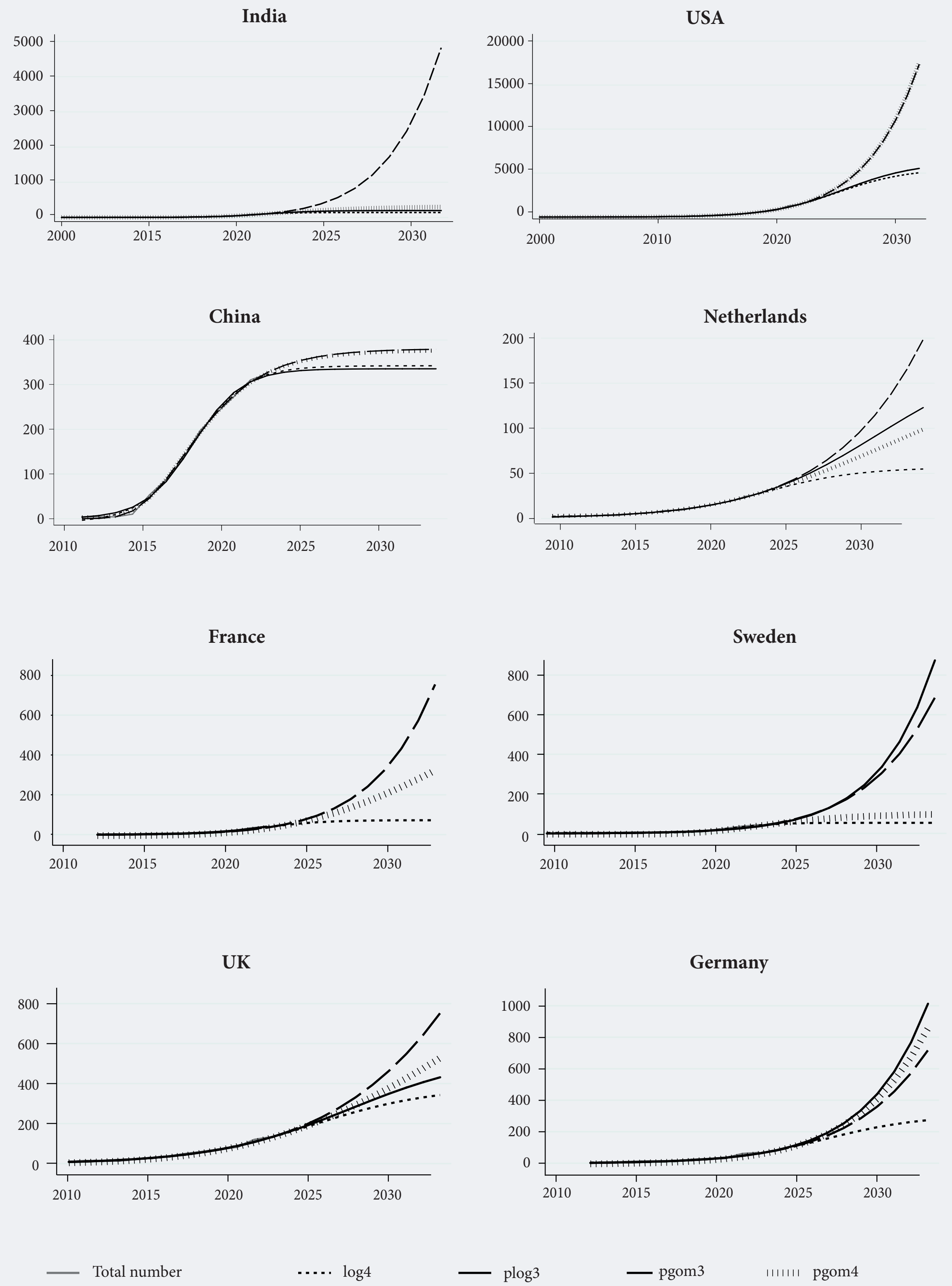
Policymakers should anticipate market saturation and support unicorn scaling through targeted reforms. In the US, continued investment in venture capital infrastructure and innovation leadership is essential. China must transition toward more market-oriented policies to enable long-term scaling, beyond the initial growth push. Its lower saturation ceiling (estimated at 335–380 unicorns) underscores the need for sectoral deregulation and deeper capital markets. Europe, meanwhile, must address its scale-up gap by harmonizing policies, improving cross-border investment flows, and supporting regional innovation clusters.

To accelerate unicorn diffusion, governments should focus on sector-specific enablers — such as regulatory reform in fintech, increased R&D investment in health, and risk-sharing mechanisms for early-stage ventures in all high-potential sectors.

Conclusion

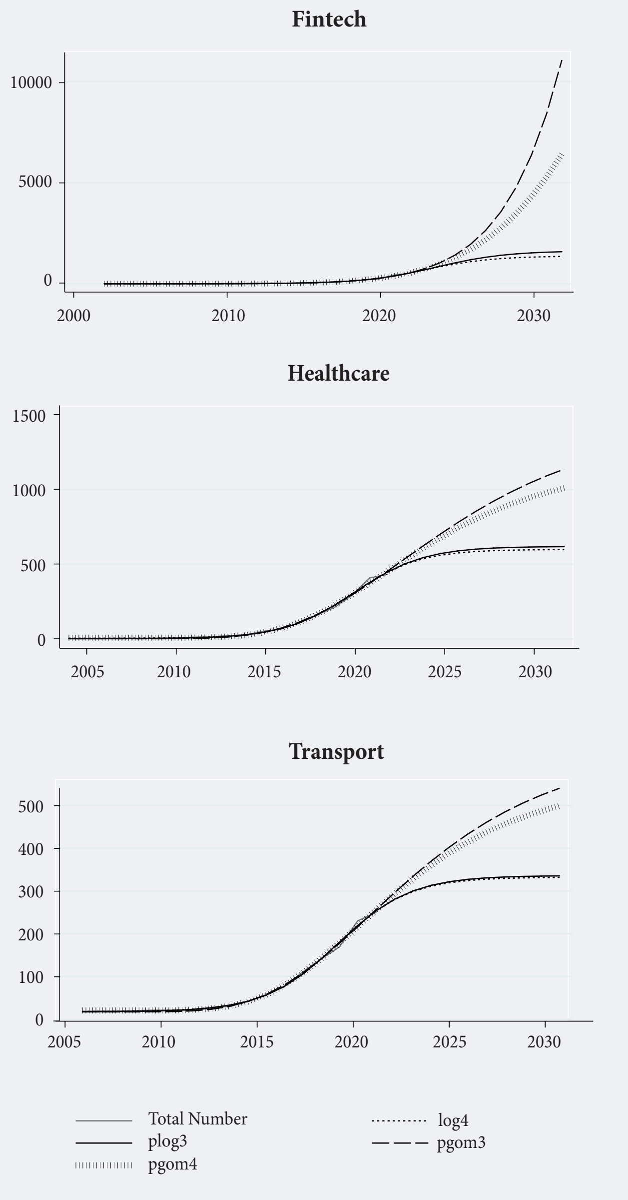
This study investigates the global diffusion of unicorn startups through the lens of Logistic and Gompertz models, offering a novel application of innovation diffusion theory to the startup ecosystem. By analyzing cross-country and sectoral trends — particularly

Figure 3. **Unicorn Diffusion and Forecasting by Country**



Note: plog4= forecasting by LM4P, plog3 = forecasting by LM3P, pgom3= forecasting by GM3P, pgom4 = forecasting by GM4P.
Source: authors.

Figure 4. **Unicorn Diffusion and Forecasting by Sector**



Note: plog4= forecasting by LM4P, plog3 = forecasting by LM3P, pgom3= forecasting by GM3P, pgom4 = forecasting by GM4P..
Source: authors.

in the United States, China, India, and key European countries, as well as in the fintech, health, and transportation sectors — the research uncovers significant insights into the dynamics shaping unicorn emergence and growth.

The results demonstrate that Logistic models outperform Gompertz models in market-driven ecosystems such as the US, India, and most European nations, where organic entrepreneurial activity and venture capital access are prominent. Conversely, China's diffusion pattern aligns more closely with the Gompertz model, reflecting early saturation due to centralized policy controls and regulatory constraints. The use of four-parameter models further improves forecasting accuracy, particularly in contexts with delayed take-off or premature saturation.

Country-specific findings reveal pronounced heterogeneity. The United States remains the global leader in unicorn creation, supported by deep financial markets, a robust innovation infrastructure, and sustained startup scaling. India exhibits remarkable growth velocity but faces a lower saturation threshold. Europe presents a more fragmented landscape — while countries such as Germany, France, and Sweden show solid growth trajectories, fragmented capital markets, regulatory heterogeneity, and limited cross-border scaling hinder broader continental convergence.

Sectoral analysis confirms that diffusion dynamics vary significantly. Fintech lags in adoption speed due to regulatory complexity and trust barriers but holds the highest long-term potential. In contrast, the health and transportation sectors benefit from strong demand drivers and relatively streamlined institutional environments, leading to faster uptake.

These findings carry meaningful implications. For policymakers, tailored interventions are essential: market-driven economies should focus on reinforcing venture capital ecosystems and nurturing regional innovation hubs, while state-led economies may need to adopt regulatory reforms that support entrepreneurial scaling. Sector-specific strategies, such as reducing barriers in fintech or investing in R&D for health and transportation, are also vital.

For investors and startup founders, understanding the interplay between sectoral adoption speeds and country-specific saturation levels can help optimize strategic decisions. Identifying inflection points in growth trajectories enables better timing for market entry, scaling, or exit.

While this study breaks new ground by modeling unicorn diffusion globally, several limitations suggest directions for further research. First, although Logistic and Gompertz models capture broad patterns effectively, they could be extended — for example, through five-parameter or hybrid models — to account for more nuanced dynamics. Second, incorporating a longitudinal dimension by categorizing unicorns based on the year they attained unicorn status could offer deeper insights into cohort-specific behaviors and lifecycle patterns. Third, future research could develop a more comprehensive framework integrating macroeconomic variables, institutional quality, digital infrastructure, and policy environments to better explain cross-country and cross-sector diffusion differences.

By advancing both the theoretical and empirical understanding of how unicorns emerge and scale, this study lays the groundwork for more data-driven and context-sensitive policy and investment strategies aimed at fostering inclusive and sustainable innovation ecosystems globally.

References

Akin E., Pelen N.N., Tiryaki I.U., Yalcin F. (2020) Parameter Identification for Gompertz and Logistic Dynamic Equations. *PLoS ONE*, 15, 0230582. https://doi.org/10.1371/journal.pone.0230582

Aldrich H.E., Ruef M. (2018) Unicorns, Gazelles, and Other Distractions on the Way to Understanding Real Entrepreneurship in America. *Academy of Management Perspectives*, 32(4), 458–472. https://doi.org/10.5465/amp.2017.0123

Armstrong J.S. (ed.) (2001) *Principles of Forecasting*, Dordrecht: Kluwer Academic Publishers.

Burström T., Lahti T., Parida V., Wartiovaara M., Wincent J. (2023) A definition, review, and extension of global ecosystems theory: Trends, architecture and orchestration of global VCs and mechanisms behind unicorns. *Journal of Business Research*, 157, 113605. https://doi.org/10.1016/j.jbusres.2022.113605

CB Insights (2023) *State of Fintech 2023 Report,* New York: CB Insights.

El-Dardiry R., Vogt B. (2023) How far do Gazelles run? Growth patterns of regular firms, high growth firms and startups. *Applied Economics*, 55(37), 4304–4318. https://doi.org/10.1080/00036846.2022.2128184

Gamboa L.F., Otero J. (2009) An estimation of the pattern of diffusion of mobile phones: The case of Colombia. *Telecommunications Policy*, 33, 611–620. https://doi.org/10.1016/j.telpol.2009.08.004

Guo K., Zhang T. (2021) Research on the Development Path and Growth Mechanism of Unicorn Enterprises. *Mathematical Problems in Engineering*, 7, 9960828. https://doi.org/ 10.1155/2021/9960828

Huebl S., Does R., Orlova A., Heckova E., Aschauer D., Kojalek M. (2022) *The 2022 European Unicorn & Soonicorn Report*, San Francisco, CA: 5Invest.

Jha A., Saha D. (2020) Forecasting and analyzing the characteristics of 3G and 4G mobile broadband diffusion in India: A comparative evaluation of Bass, Norton-Bass, Gompertz, and logistic growth models. *Technological Forecasting and Social Change*, 152, 119885.

Korkmaz M. (2020) A study over with four-parameter Logistic and Gompertz growth models. *Numerical Methods for Partial Differential Equations*, 37(3), 2023–2030. https://doi.org/10.1002/num.22641

Kuckertz A., Bernhard A., Berger E.S.C., Dvouletý O., Harms R., Jack S., Kibler E. (2023) Creating and maintaining hope through social entrepreneurship in light of humanitarian crises. *Journal of Business Venturing Insights*, 19, e00356. https://doi.org/10.1016/j.jbvi.2022.e00356

Kuckertz A., Brandle L., Gaudig A., Hinderer S., Reyes C.A.M., Prochotta A., Steinbrink K.M., Berger E.S.C. (2020) Startups in times of crisis – A rapid response to the COVID-19 pandemic. *Journal of Business Venturing Insights*, 13, e00169. https://doi.org/10.1016/j.jbvi.2020.e00169

Kutsenko E., Tyurchev K., Ostashchenko T. (2022) Relocation as a Driver of Innovative Activity: A Global Study of Unicorn Founders' Migration. *Foresight and STI Governance*, 16 (4), 6–23. https://doi.org/10.17323/2500-2597.2022.4.6.23

Kuratko D.F., Audretsch D.B. (2021) The future of entrepreneurship: The few or the many? *Small Business Economics*, 59, 269–278. https://doi.org/10.1007/s11187-021-00534-0

Lee S., Marcu M., Lee S. (2011) An empirical analysis of fixed and mobile broadband diffusion. *Information Economics and Policy*, 23(3–4), 227–233. https://doi.org/10.1016/j.infoecopol.2011.05.001

Leendertse J., Schrijvers M., Stam E. (2022) Measure Twice, Cut Once: Entrepreneurial Ecosystem Metrics. *Research Policy*, 51(9), 104336. https://doi.org/10.1016/j.respol.2021.104336

Meade N., Islam T. (2015) Forecasting in telecommunications and ICT-A review. *International Journal of Forecasting,* 31(4), 1105–1126. https://doi.org/10.1016/j.ijforecast.2014.09.003

Meek S., Cowden B.J. (2023) Strategies of Unicorn startups: How these positive deviants compare to early-stage and Fortune 500 ventures. *Journal of Small Business and Enterprise Development*, 30(6),1109–1128. https://doi.org/10.1108/JSBED-02-2023-0069

Michalakelis C., Dimitris V., Sphicopoulos T. (2008) Diffusion models of mobile telephony in Greece. *Telecommunications Policy*, 32(3–4), 234–245. https://doi.org/10.1016/j.telpol.2008.01.004

OECD (2021) *Understanding Firm Growth: Helping SMEs Scale Up,* Paris: OECD.

Pelinovsky E., Kokoulina M., Epifanova A., Kurkin A., Kurkina O., Tang M., Kirillin M. (2022) Gompertz model in COVID-19 spreading simulation. *Chaos, Solitons and Fractals,* 154, 111699. https://doi.org/10.1016/j.chaos.2021.111699

Retterath A., Braun R. (2020) *Benchmarking Venture Capital Databases* (SSRN Paper 3706108). https://doi.org/10.2139/ssrn.3706108

Rodrigues C.D. Noronha M.E.S.D. (2023) What companies can learn from unicorn startups to overcome the COVID-19 crisis. *Innovation & Management Review*, 20(3), 211–226. https://doi.org/10.1108/INMR-01-2021-0011

Rogers E.M. (1962) *Diffusion of Innovations,* New York: Free Press.

Rossi M., Martini E. (2019) Venture capitalists and value creation: The role of informal investors in the growth of smaller European firms. *International Journal of Globalisation and Small Business*, 10(3), pp. 233–247. https://doi.org/10.1504/IJGSB.2019.100123

Satoh D. (2021) Discrete Gompertz equation and model selection between Gompertz and logistic models. *International Journal of Forecasting*, 37(3), 1192–1211. https://doi.org/10.1016/j.ijforecast.2021.01.005

Schumpeter J.A. (1943) *Capitalism, Socialism and Democracy*, London, New York: Routledge.

Shahid Y. (2023) *Can Fast Growing Unicorns Revive Productivity and Economic Performance?,* Washington, D.C.: Center for Global Development.

Shane S. (2009) Why encouraging more people to become entrepreneurs is bad public policy. *Small Business Economics*, 33(2), 141–149. https://doi.org/10.1007/s11187-009-9215-5

Stafeev A. (2024) What makes a successful unicorn startup founder. *International Journal of Professional Business Review*, 9(5), 4638. https://doi.org/10.26668/businessreview/2024.v9i5.4638

Startup Genome (2022) *The Global Startup Ecosystem Report 2022,* San Francisco, CA: Startup Genome.

Testa G., Compañó R., Correia A., Rückert E. (2022) *In search of EU unicorns – What do we know about them?*, Luxembourg: Publications Office of the European Union. https://doi.org/10.2760/843368

Trabucchi D., Talenti L., Buganza T. (2019) How do Big Bang Disruptors look like? A Business Model perspective. *Technological Forecasting and Social Change*, 141, 330–340. https://doi.org/10.1016/j.techfore.2019.01.009

Urbinati A., Chiaroni D., Chiesa V., Frattini F. (2018) The Role of Business Model Design in the Diffusion of Innovations: An Analysis of a Sample of Unicorn-Tech Companies. *International Journal of Innovation and Technology Management*, 16(1), 1950011. https://doi.org/10.1142/S0219877019500111

Van Meeteren M., Trincado-Munoz F., Rubin T.H., Vorley T. (2022) Rethinking the digital transformation in knowledge-intensive services: A technology space analysis. *Technological Forecasting and Social Change*, 179, 121631. https://doi.org/10.1016/j.techfore.2022.121631

Venâncio A., Picoto W., Pinto I. (2023) Time-to-unicorn and digital entrepreneurial ecosystems. *Technological Forecasting and Social Change*, 190, 122425. https://doi.org/10.1016/j.techfore.2023.122425

Veugelers R., Amaral-Garcia S. (2025) *Financing EU Health Innovation: The Role of Venture Capital*, Seville: JRC.

WIPO (2023) *Global Innovation Index 2023: Innovation in the Face of Uncertainty,* Geneva: World Intellectual Property Organization. https://doi.org/10.34667/tind.48220

The Role of Digital Leadership Capabilities in Enterprise-Wide Digital Transformation

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Abstract

In a situation of rapid technological development and the world's transition to a new technological regime, organizations are faced with the need for digital transformation (DT). This process goes beyond the simple implementation of advanced technologies and involves the management of processes of increased complexity, deep recombinations of business processes, structures, methods of external communications, and so on. However, these factors are not considered by most organizations. In other words, DT is underestimated in terms of complexity, duration, and intensity of adaptation stress. Only 10%-20% of organizations succeed in such a transformation at the first attempt, with large companies failing most often. This study analyzes the reasons why most of these initiatives fail to achieve their goals. Particular emphasis is placed on the link between digital competencies of managers and the impact of technological reforms. For this purpose, an array of relevant publications on the topic of DT over the last five years was analyzed. According to the results, the majority of organizations enter DT without proper preparation in the form of early revision of competencies and corporate culture, going beyond the established models of thinking and behavior, which previously provided competitiveness, but in the new context cease to work. Principles that increase the chances of successful digital transformation are formulated. This article contributes to the growing body of knowledge on management practices in transformational transitions.

Keywords: digital transformation, digital competencies of managers; new management models; dynamic capabilities; transition management; sustainable competitiveness

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Introduction

In the context of dynamic technological progress, organizations are faced with the need to move to more complex development models, including the digital economy. According to the UN, in 2019, the volume of the global digital economy already reached an impressive $22.5 trillion (UNCTAD, 2019), and the pandemic crisis has become a powerful driver of its further growth.

The key to the transition to a digital economy is a comprehensive digital transformation (DT), which, when done correctly, can provide organizations with significant benefits in terms of increasing value and maintaining sustainability and competitiveness in an uncertain business environment (Ciao et al., 2024). At the same time, the requirements for entrepreneurship standards and business conduct in general are becoming more stringent.

The main goal of DT is to change value creation practices along the entire value chain: from digitizing production processes to increasing the transparency of relationships in production and supply chains (Kirti et al., 2022), which optimizes management practices (Klos et al., 2021). Thus, the ultimate goal of DT is not simply to go digital, but rather to ensure sustainable growth and value creation. In general, the implementation of DT implies a long-term, comprehensive strategy. Digital technologies are becoming tools for organizations to modernize production models, management, customer service, and marketing strategies. Based on these observations, governments are rethinking laws and policies related to data security, intellectual property, and the formation of digital competencies (Mergel et al., 2019; Nambisan et al., 2019).

The human factor remains the key driver of adaptation to new technological cycles (Schiuma et al., 2024). Whether an organization can master opportunities of a fundamentally different level depends on personnel with the appropriate competencies, including dynamic capabilities, especially for executive management. Despite its importance, the role of management in the implementation of DT is an insufficiently studied factor (Trenerry et al., 2021). The philosophy of resource renewal and competencies aimed at implementing complex DT processes differ significantly from traditional management patterns (Veeraya et al., 2024). The shortage of such a set of skills is demonstrated by the fact that in more than 80% of cases, digital transformations do not achieve the desired goals (Oludapo et al., 2024). The problem is particularly characteristic of large organizations due to the difficulties they experience in moving away from traditional management models that once ensured competitiveness (Oludapo et al., 2024; Trenerry et al., 2021). Removing this barrier requires a radically different perception of the dynamism of change and increased persistence in proactive action (Oludapo et al., 2024).

In-depth research is needed to better understand the aspects that determine the effectiveness of corporate digital transformation. Our article contributes to this process by analyzing the latest literature on the topic and is aimed at identifying the links between transformation processes at organizations, their management practices, effectiveness, and development strategies.

Research Methodology

To select relevant publications, a set of search terms in combination with Boolean operators (AND/OR) was used, namely: “digital transformation”, “digital literacy of managers”, “dynamic potential”, and “company management and efficiency”. The search was performed in the Web of Science database due to its authority and representativeness. In accordance with the specified criteria, 14,895 materials were included in the search results, which were filtered by the following criteria:

- open access;
- review publications;
- articles in English;
- published in the last five years (2021–2025);
- belong to the corresponding Web of Science categories (business, management, environmental science, computer science, support staff).

After applying the above criteria, 48 studies remained, of which five studies were subjected to in-depth analysis (see Table 1), the rest supplemented the literature review.

As the analysis shows, China holds the lead in the number of scientific publications on the topic under consideration (3158), more than twice exceeding Germany, which ranks second (Table 2). Its lead is due to the large-scale development of science, technology, and entrepreneurship in the country. A number of European countries (Germany, Great Britain, Italy, and Spain, the BRICS countries (India, Brazil, Russia), and Australia) are also notably active.

Figure 1 shows the dynamics of the number of publications in recent years. It is noteworthy that if about 2,000 articles were published in 2021, then just three years later this figure doubled. There has been a significant shift toward the digitalization of organizational functions, which has led to the interest of researchers in the relevant topic. A large body of work is devoted to the relationship between digital technology and management and the dynamic capabilities, innovative activity, and efficiency of companies.

Figure 2 shows the direct links between DT and other aspects of management.

Table 1. **Publications that Formed the Basis of the Literary Analysis**

a) Schiuma et al., 2024

Topics	• The role of managers in managing digital knowledge and digital technologies of the organization • Human-centered approach to DT
Author's keywords	Leader - Organizational Transformer; Digital Knowledge; Digital Transformation; Leadership Competencies
Methodology	• Grounded Theory Method • Deductive analysis of literature followed by inductive empirical research • Semi-structured interviews
Key findings	Need for deep awareness of the practical aspects of DT at senior management levels

b) Oludapo et al., 2024

Topics	Analysis of problems associated with DT, the frequency of failures of this process and the main reasons
Author's keywords	Digital transformation; failures; organizational transformation; information system; competence transformation
Methodology	• Bibliometric analysis • Thematic mapping of literature
Key findings	• More than 80% of DT initiatives end in failure • Modern research operates with broad categories such as "technology," "information system," and "management," which results in a simplified understanding of the digital transformation ecosystem and leaves the causes of failures unidentified. • Insufficient awareness and understanding of the reasons for the failure of the DT

c) Gouveia et al., 2024

Topics	• Value creation mechanisms and strategic management in the context of digital transformation • The contribution of digital entrepreneurship to sustainable business development • Innovative business models • Digital transformation of SMEs
Author's keywords	Strategic management; digital transformation; c value creation
Methodology	Systematic review, bibliometric and cluster analysis of literature
Key findings	Changes in industry value creation mechanisms under the influence of digital transformation require adaptation of development strategies and technological potential of companies

d) Espina-Romero et al., 2023

Topics	• Evolution of digital management competencies (2018-2023) with a focus on the impact of the pandemic crisis • Study of the geography of the authors of the relevant studies • Specifics of digital management competencies in education and industry • contexts • Dependence of the effectiveness of the digital transformation on the level of technology development • Adaptation of management competencies to the specifics of the digital environment
Author's keywords	Digital management competencies ; digital transformation; technology; adaptation to change; innovation; technical skills; change management; effective communications; strategic decision making
Methodology	Quantitative bibliometric analysis
Key findings	• The pandemic crisis has significantly increased the importance of digital transformation and the role of technological competencies of managers in this process • The main publication activity on the topic under consideration was demonstrated by European and Asian countries, and the top three were the USA, Germany and China

e) Mrugalska, Ahmed, 2021

Topics	Flexibility of organizations; Industry 4.0 Technologies; Intelligent manufacturing; Internet of Things (IoT); Cyber-physical systems; Big data analytics; Cloud computing
Author's keywords	Industry 4.0; organizational agility; Industry 4.0 ecosystem; environment
Methodology	Systematic literature review
Key findings	Strategic flexibility is becoming critical for managing change in organizations in conditions of increased uncertainty. The introduction of Industry 4.0 technologies facilitates the development of this competence in different dimensions. The main technological tools include intelligent manufacturing, the Internet of Things, cyber-physical systems, big data analytics, and cloud computing.

Source: compiled by the authors.

The Main Results of the Literary Analysis

Definition of the Digital Transformation

DT goes beyond the simple implementation of advanced technologies and involves the management of highly complex processes, including the deep recombination of business processes, structures, and external communication methods (Oludapo et al., 2024; Bresciani et al., 2021). The basic condition for its successful completion is the creation of a new culture that allows for flexible adaptation to emerging technologies and effective operation in a variety of interconnected, rapidly changing contexts (Plekhanov et al., 2023).

DT is developing in three stages: digitalization, the transformation of management models, and value creation (Kraus et al., 2022; Zhu et al., 2021). The first two stages involve the digitalization of data and business processes, respectively, becoming the basis for the deep integration of digital technologies into management mechanisms (Pagani, 2013; Piepponen et al., 2022; Verhoef et al., 2021). Digital technologies improve communication and collaboration, reduce the costs of implementing business processes, increase the efficiency of logistics, capital movement, and the circulation of information flows (Heredia et al., 2022; Nambisan, 2019), and facilitate value creation under conditions of uncertainty (Ferreira et al., 2019). However, it is necessary to take into account that DT is a continuous and long-term process (Bharadwaj et al., 2013), requiring maintaining a focus on creating innovation (Gao et al., 2022; Hinings et al., 2018). The stumbling block for DT is outdated organizational practices and rigid corporate culture (Correani et al., 2020).

Digital Competencies of Managers

The penetration of digital technologies into all aspects of business makes the relevant competencies of management personnel critically important. We are talking about the skills of managing organizations as complex systems and their adaptation to a changing environment (Karakose, Tulubas, 2023), in which new technological solutions create opportunities of a fundamentally different level. DT involves going beyond the technological dimension into the area of strategic and cultural aspects, and, consequently, reformatting thinking and behavioral patterns (Veeraya et al., 2024; Oludapo et al., 2024; Trenerry et al., 2021; Peng et al., 2024).

Managers with such competencies are able to become powerful motivators of innovative activity and transmit the relevant skills and knowledge to all levels of personnel (Karakose et al., 2022; Wang et al., 2024) and integrate technical capabilities and social systems into

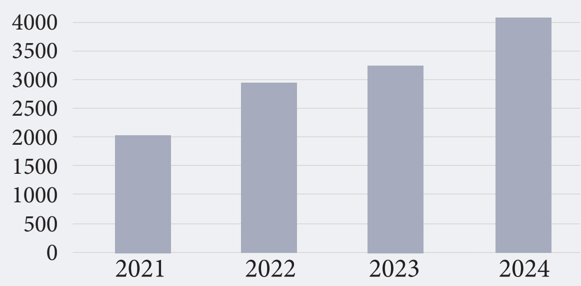
Table 2. **Number of Publications by Country and Region**

Country	Number of Publications
China	3158
Germany	1204
USA	1083
United Kingdom	914
Italy	840
Spain	746
Russia	657
India	570
Australia	497
Brazil	467

Note: the number of publications is calculated on the basis of initial sample.

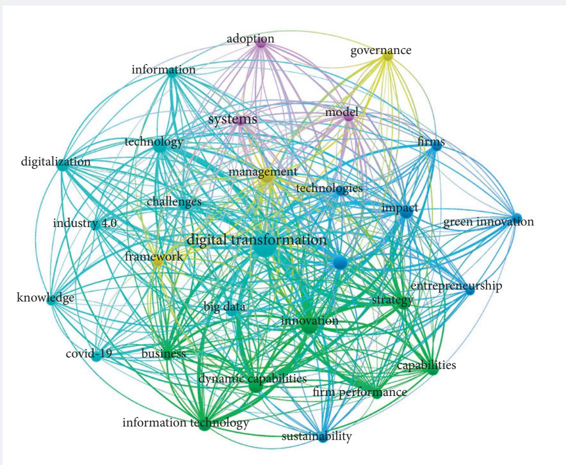
Source: authors.

Figure 1. **Number of Publications by Year**



Source: authors.

Figure 2. **The Relationship between Digital Transformation and Digital Competencies of Managers**



Source: authors.

a single strategic framework (Qiao et al., 2024). Digital competencies, superimposed on the previous skill base and corresponding to emerging opportunities, help to effectively implement more complex technological solutions (Schiuma et al., 2024) and create innovations.

Strategic agility and dynamic capabilities enable the acceleration of an organization's digital transformation. Interdisciplinary collaboration enables the coordination of DT initiatives with different areas of the organization's activities (Mrugalska, Ahmed, 2021).

Leaders with digital competencies can ensure their organizations are better positioned strategically to both seize digital opportunities and to address challenges and manage the risks associated with technological change (Mollah et al., 2024). As a result, their competitiveness, operational efficiency and customer base indicators improve (Karippur, Balaramachandran, 2022).

Managers with such competencies are able to become powerful stimulators of innovation and transmit the relevant skills and knowledge to all levels of staff (Feliciano et al., 2023).

Factors of DT Failure at Organizations

Change management and technology adoption initiatives represent a significant expense in today's organizations. Despite this, failure rates remain high, especially at large companies (Oludapo et al., 2024). A McKinsey study of a sample of over 800 traditional enterprises worldwide shows that while 70% have started using digital transformation, 71% of that number are still in the experimentation stage. For example, as of 2021, only 16% of Chinese enterprises achieved their initial digital transformation goals (Ciao et al., 2024). The key constraints to digital transformation include cultural and structural barriers, the importance of which is often underestimated. In the context of large-scale contextual changes, organizations can no longer rely on established management models (which ensured success in previous conditions) and incremental transformations. There is a need for a shift in the strategic paradigm. The previously noted 80% failure rate in the implementation of digital transformation is only an average figure. In large organizations, it can reach 90% (Ramesh, Delen, 2021)[1], which can partly be associated with their larger scale of operations and ambitious goals. However, the decisive contribution to this increased figure is made by: rigid hierarchical structures, inflexible business models and cultural inertia (O'Brien et al., 2023). Let us consider the listed factors in more detail.

Structural complexity. An important prerequisite for effective digital transformation is: significant systemic changes based on a holistic strategic approach, taking into account technological, process, and personnel components. As a rule, several initiatives are implemented simultaneously, related to the distribution of roles and responsibilities, as well as the creation of special digital units. This implies changes in the organizational culture aimed at adapting personnel to new forms of work (Jöhnk et al., 2020). Large organizations typically have numerous interdependent units that are semi-autonomous and build their own operating models. Any changes in their activities, especially within the framework of DT, which is complex, spread to other business units, causing a cascading effect of changes. Thus, efforts to direct this process onto the right path inevitably go beyond local adjustments (Karakose et al., 2022). At the same time, they should vary in scope, since, for example, in some cases it is impossible to ignore taking into account local specifics (different regulatory requirements may apply in different regions of the company's operations, etc.).

Significant barriers to DT arise at the operational and strategic levels due to the slow speed of decision-making, which is caused by *cultural inertia* and the complexity and rigidity of organizational structures. Some culturally homogeneous organizations with a rich history demonstrate reluctance to change their patterns, despite changed external circumstances (Haskamp et al., 2021). This is especially true in cases where established models have been successful for a long time. A conflict of interests arises between the different levels of the hierarchy: middle management begins to perceive radical changes, including DT, as a threat to their status quo.

Initiatives to experiment and implement new approaches can also be held back by such "convincing" arguments of their opponents as excessively high costs of modernization. Another significant factor determining the failure of digital transformation is the lack of a knowledge base that is not adapted to the modern context, since most existing theories of organizational transformation were created before the advent of the Internet (Haskamp et al., 2021). In modern conditions, the dynamics of the spread of new technologies requires their prompt coordination with existing products, processes, and strategies.

The scale of the required changes. The digital transformation of large organizations affects many stakeholders, including hundreds of employees located in different territories. As a result, the process is extended over

[1] The remaining 10% of initiatives can be considered successful because they are implemented within the planned budget and within the planned time frame.

a long period, during which the market situation may change unpredictably. Despite this, the organization is still expected to provide acceptable economic indicators. Overcoming such a multidimensional challenge requires thorough preparation.

Limitations of Traditional Approaches to Change Management

Linear nature of management models. Traditional change management tools are based on the idea of the predictable and linear nature of change. There are many approaches that assume a step-by-step logical progression, including Kotter's eight-stage model (Kotter, 1995). However, the modern context makes them irrelevant due to the failure to take into account such aspects as complexity, non-linearity, the iterative nature of transformational transitions, and the need for rapid adaptation.

Limitations on flexibility and pace. Risk mitigation and structured planning are the core components of traditional models. However, DT requires the integration of aspects such as rapid prototyping, adaptive reconfiguration, and strategic flexibility. Large organizations tend to have entrenched, difficult-to-adjust risk management mechanisms and planning cycles, making these challenges difficult.

Fragmented transformation management. DT is not limited to the implementation of technologies, but assumes their holistic synthesis with cultural and operational dimensions. In turn, with the traditional approach to modernization, the implementation of technologies and organizational changes are considered as separate areas (Verhoef et al., 2021). However, the lack of connectivity between the mentioned aspects hinders successful digital transformation. The implementation of technologies should not be seen as an end in itself, but rather should become part and a natural tool of an integrated corporate digital transformation strategy. This will require dynamic capabilities, continuous learning, interdisciplinary collaboration, and adaptive leadership (traditional models rarely take these areas into account). For example, if an organization updates its management system but does not adjust production processes and personnel skills accordingly, the transformation will stop. It is necessary to move from a fragmented approach to a holistic model, to form a new culture (Verhoef et al., 2021) and ensure the effective integration of technologies into the organizational structure.

Limitations of management structures. Traditional top-down management structures are not compatible with the interdisciplinary, collaborative nature of DT. It is advisable to form a distributed management network that goes beyond traditional hierarchical chains, covering all regions of activity and divisions of the organization. Granting autonomy to target groups will provide flexibility in adapting to a new level of technological complexity, which will increase the effectiveness of DT implementation.

New Methods of Scaling Digital Technologies

One of the previously mentioned tools that ensure effective digital transformation are *dynamic capabilities,* the bearers of which are able to increase the potential for mastering emerging opportunities, quickly redistribute resources (Teece, 2007), and increase the strategic flexibility and adaptability of management systems. It is important to view DT not as an internal project, but as an open platform that closely interacts with the external *ecosystem.* Such an approach will allow us to take full advantage of platform models, open innovations and external partnerships, and will make it possible to complete DT with minimal costs. For example, the Minimum Viable Transformation method ensures the rapid launch of pilot versions of innovative business models, their testing and adjustment.[2]

Examples of Successful Large-Scale Transformations

Microsoft has transformed itself from a manufacturer of operating systems for local devices into a provider of cloud services. The key drivers of the transformation were: moving away from a fragmented business process model, appointing leaders capable of organizing such a transition, a culture of continuous learning and growth, and establishing collaboration in the format of interdisciplinary working groups (Ali, Begum, 2024). The combination of these factors gave rise to the Azure cloud ecosystem, thanks to which Microsoft was able to significantly increase its market capitalization, becoming one of the leaders in innovation in the field of AI and cloud computing. **Siemens,** having made large-scale investments in attracting digital transformation specialists, was able to smoothly move from a production to a platform model based on the Industrial Internet of Things and digital twins.[3] **DBS** has reshaped its business model and corporate culture, using immersive employee training methods and engaging executives in customer experience transformation projects.[4]

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[2] https://www2.deloitte.com/us/en/insights/focus/business-trends/2015/minimum-viable-business-model-transformation-business-trends.html, accessed 04.03.2025.

[3] https://www.powermag.com/long-form-stories/digitalization-how-siemens-is-leading-the-transformation-of-the-energy-industry/, accessed 11.04.2025.

[4] https://www.mckinsey.com/capabilities/mckinsey-digital/how-we-help-clients/rewired-in-action/dbs-transforming-a-banking-leader-into-a-technology-leader, accessed 18.04.2025.

All of these initiatives, despite having differences in priorities and methods, have contributed to expanding the knowledge base on the "recipes" for successful DT.

Conclusion

Digital transformation allows one to integrate into a new technological world offering higher-level capabilities only under certain conditions, which for most organizations can be perceived as insurmountable barriers. This is especially true for large enterprises that have been successful and competitive for a long time. If the average failure rate of digital transformation for companies of different sizes is 80%, then for large players it can reach up to 90% (Ramesh, Delen, 2021). This state of affairs is mainly explained by the lack of dynamic capabilities as a key component of transformation potential. Many organizations enter this process unprepared, without fully understanding the hidden complexity of this phenomenon. To overcome this trend, a shift in the strategic paradigm and significant efforts to update the competence of personnel are required. The large-scale and rapid development of digital ecosystems based on AI necessitates a fundamental change in the composition of competencies and types of management models to adapt organizations to an increasingly complex context. We are talking about higher-order capabilities, from the point of view of which managing complex technological transitions, leading companies through different cycles of renewal in many dimensions, looks like a natural practice.

This study analyzes the impact of digital competencies of managers on the effectiveness of digital transformation in organizations, focusing on the reasons why most such initiatives do not achieve their goals. The key components of digital transformation are analyzed, including technological competencies, transformation potential, strategic flexibility, and the management of cooperation networks. It is found that the optimal balance of transformational, strategic, and technological competencies stimulates innovation and ensures a competitive advantage. One of the most difficult cognitive options to master is synthesizing seemingly incompatible aspects, keeping multidirectional processes in focus, and seeing the unity of opposites. In other words, before starting digital transformation at an organization, it is necessary to revise the competency portfolio and corporate culture. The staff must undergo a radical update of established ideas about development in the era of constant change and accept more complex work patterns. All this requires going beyond the established models of thinking and behavior that previously guaranteed successful development dynamics, but stopped working in the new context. To better understand the specifics of digital transformation processes, it is necessary to conduct longitudinal studies of cases of such transformations in different national and industry contexts. It is advisable to create dynamic roadmaps that allow for adjusting the movement toward a given goal as technological innovations develop in different countries. Particular attention should be paid to the principles of ethical management concerning the retraining of personnel, ensuring data confidentiality, and minimizing the "bias" of algorithms.

Digitally competent executives implement complex transformation processes, determine the optimal trajectory, and coordinate business strategies. However, their impact on the functionality and structure of the organization, the specific effects for specific industries and organizations of different sizes remain understudied. Theoretical foundations are given more attention than empirical data, which limits the diversity of studies. Geographical bias (developed countries are primarily analyzed) creates gaps in understanding the role of digital competencies of executives in the digital transformation of organizations in developing countries. In addition, the main focus is on large enterprises, while SMEs are ignored. It should be noted that there are no standard tools for assessing the effect of digital competencies of executives. In an era when digital transformation covers an increasing number of industries, the digital competencies of personnel are becoming the most important factor in the effectiveness of this process. Organizations that invest sufficient funds in their development increase the likelihood of their success in the modern digital world.

References

Al Maazmi A., Piya S., Araci Z.C. (2024) Exploring the Critical Success Factors Influencing the Outcome of Digital Transformation Initiatives in Government Organizations. *Systems*, 12(12), 524. https://doi.org/10.3390/systems12120524

Aldoseri A., Al-Khalifa K.N., Hamouda A.M. (2024) AI-powered innovation in digital transformation: Key pillars and industry impact. *Sustainability*, 16(5), 1790. https://doi.org/10.3390/su16051790

Ali M.M., Begum S. (2024) Case Study: Satya Nadella's Leadership at Microsoft. *IOSR Journal of Business and Management (IOSR-JBM),* 26(12), 74–79.

AlNuaimi B.K., Singh S.K., Ren S., Budhwar P., Vorobyev D. (2022) Mastering digital transformation: The nexus between leadership, agility, and digital strategy. *Journal of Business Research*, 145, 636–648. https://doi.org/10.1016/j.jbusres.2022.03.038

Bharadwaj A., El-Sawy O.A., Pavlou P.A., Venkatraman N. (2013) Digital business strategy: Toward a next generation of insights. *MIS Quarterly*, 37, 471–482. https://doi.org/10.25300/MISQ/2013/37:2.3

Bresciani S., Huarng K.H., Malhotra A., Ferraris A. (2021) Digital transformation as a springboard for product, process and business model innovation. *Journal of Business Research*, 128, 204–210. https://doi.org/10.1016/j.jbusres.2021.02.003

Carroll N., Conboy K., Wang X. (2023) From transformation to normalisation: An exploratory study of a large-scale agile transformation. *Journal of Information Technology*, 38(3), 267–303. https://doi.org/10.1177/02683962231164428

Correani A., De-Massia A., Frattini F., Petruzzelli A.M., Natalicchio A. (2020) Implementing a digital strategy: Learning from the experience of three digital transformation projects. *California Management Review*, 62, 37–56. https://doi.org/10.1177/0008125620934864

Espina-Romero L., Norono-Sanchez J.G., Rojas-Cangahuala G., Palacios Garay J., Parra D.R., Rio Corredoira J. (2023) Digital Leadership in an Ever-Changing World: A Bibliometric Analysis of Trends and Challenges. *Sustainability*, 15(17), 13129. https://doi.org/10.3390/su151713129

Feliciano M.M., Ameen N., Kotabe M., Paul J., Signoret M. (2023) Is digital transformation threatened? A systematic literature review of the factors influencing firms' digital transformation and internationalization. *Journal of Business Research*, 157, 113546. https://doi.org/10.1016/j.jbusres.2022.113546

Gao J., Zhang W., Guan T., Feng Q., Mardanic A. (2022) The effect of manufacturing agent heterogeneity on enterprise innovation performance and competitive advantage in the era of digital transformation. *Journal of Business Research*, 155, 113387. https://doi.org/10.1016/j.jbusres.2022.113387

Haskamp T., Dremel C., Marx C., Uebernickel F. (2021) *Understanding Inertia in Digital Transformation: A Literature Review and Multilevel Research Framework*. Paper presented at the 42th International Conference on Information Systems (ICIS), December 2021, Austin, USA.

Heredia J., Castillo V.M., Geldes C., Carbajal F.M.G. (2022) How do digital capabilities affect firm performance? The mediating role of technological capabilities in the "new normal". *Journal of Innovation & Knowledge*, 7(2), 100171. https://doi.org/10.1016/j.jik.2022.100171

Hinings B., Gegenhuber T., Greenwood R. (2018) Digital innovation and transformation: An institutional perspective. *Information and Organization*, 28, 52–61. https://doi.org/10.1016/j.infoandorg.2018.02.004

Hussein H., Albadry O.M., Mathew V., Al-Romeedy B.S., Alsetoohy O., Abou Kamar M., Khairy H.A. (2024) Digital leadership and sustainable competitive advantage: Leveraging green absorptive capability and eco-innovation in tourism and hospitality businesses. *Sustainability,* 16(13), 5371. https://doi.org/10.3390/su16135371

Jöhnk J., Oesterle S., Ollig P., Riedel L.N. (2020) The Complexity of Digital Transformation – Conceptualizing Multiple Concurrent Initiatives. In: *WI2020 Zentrale Tracks* (eds. C.M. König, N. Guhr, J. Svetachova, M.H. Breitner), Berlin: GITO, pp. 1051–1066. https://doi.org/10.30844/wi_2020_j8-joehnk

Karakose T., Kocabas I., Yirci R., Papadakis S., Ozdemir T.Y., Demirkol M. (2022) The development and evolution of digital leadership: A bibliometric mapping approach-based study. *Sustainability,* 14(23), 16171. https://doi.org/10.3390/su142316171

Karakose T., Tülübaş T. (2023) Digital leadership and sustainable school improvement — A conceptual analysis and implications for future research. *Educational Process: International Journal,* 12(1), 7–18. https://doi.org/10.22521/edupij.2023.121.1

Karippur N.A., Balaramachandran P.R. (2022) Antecedents of Effective Digital Leadership of Enterprises in Asia Pacific. *Australasian Journal of Information Systems*, 26, 2525. http://dx.doi.org/10.3127/ajis.v26i0.2525

Kirti N., Rakesh D.R., Vinay S.Y., Pragati P., Balkrishna E.N. (2022) The impact of sustainable development strategy on sustainable supply chain firm performance in the digital transformation era. *Business Strategy and the Environment*, 31(3), 845–859. https://doi.org/10.1002/bse.2921

Klos C., Spieth P., Clauss T., Klusmann C. (2021) Digital Transformation of Incumbent Firms: A Business Model Innovation Perspective. *IEEE Transactions on Engineering Management*, 99, 3075502. https://doi.org/10.1109/TEM.2021.3075502

Kotter J.P. (1995) Leading change: Why transformation efforts fail. *Harvard Business Review*, May-June 1995. https://hbr.org/1995/05/leading-change-why-transformation-efforts-fail-2, accessed 11.12.2024.

Kraus S., Durst S., Ferreira J.J., Veiga P., Kailer N., Weinmann A. (2022) Digital transformation in business and management research: An overview of the current status quo. *International Journal of Information Management*, 63, 102466. https://doi.org/10.1016/j.ijinfomgt.2021.102466

Mergel I., Edelmann N., Haug N. (2019) Defining digital transformation: Results from expert interviews. *Government Information Quarterly*, 36(4), 101385. https://doi.org/10.1016/j.giq.2019.06.002

Mollah M.A., Amin M.B., Debnath G.C., Hosain M.S., Rahaman M.A., Abdullah M. (2024) Nexus among digital leadership, digital transformation, and digital innovation for sustainable financial performance: Revealing the influence of environmental dynamism. *Sustainability*, 16(18), 8023. https://doi.org/10.3390/su16188023

Mrugalska B., Ahmed J. (2021) Organizational Agility in Industry 4.0: A Systematic Literature Review. *Sustainability*, 13(15), 8272. https://doi.org/10.3390/su13158272

Nambisan S., Wright M., Feldman M. (2019) The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy*, 48(8), 103772. https://doi.org/10.1016/j.respol.2019.03.018

O'Brien J., Singh M., Whelan A., Manning E., Jayes F., Murphy J., Brosnan A. (2023) *Unpacking Digital Transformation Risk: A Systematic Review On Why Digital Transformations Often Fail To Deliver Value*. Paper presented at the 2023 European Academy of Management Conference, March 2023, Dublin, Ireland.

Oludapo S., Carroll N., Helfert M. (2024) Why do so many digital transformations fail? A bibliometric analysis and future research agenda. *Journal of Business Research*, 174, 114528. https://doi.org/10.1016/j.jbusres.2024.114528

Pagani M. (2013) Digital business strategy and value creation: Framing the dynamic cycle of control points. *MIS Quarterly*, 37, 617–632. https://doi.org/10.25300/MISQ/2013/37.2.13

Peng Y., Alias B.S., Mansor A.N., Ismail M.J. (2024) Charting the evolving landscape of digital leadership in education: A systematic literature review. *Journal of Infrastructure, Policy and Development*, 8(8), 5925. https://doi.org/10.24294/jipd.v8i8.5925

Piepponen A., Ritala P., Keränen J., Maijanena P. (2022) Digital transformation of the value proposition: A single case study in the media industry. *Journal of Business Research*, 150, 311–325. https://doi.org/10.1016/j.jbusres.2022.05.017

Plekhanov D., Franke H., Netland T.H. (2023) Digital transformation: A review and research agenda. *European Management Journal,* 41(6), 821–844. https://doi.org/10.1016/j.emj.2022.09.007

Qiao G., Li Y., Hong A. (2024) The strategic role of digital transformation: Leveraging digital leadership to enhance employee performance and organizational commitment in the digital era. *Systems,* 12(11), 457. https://doi.org/10.3390/systems12110457

Qiao W., Ju Y., Dong P., Tiong R.L.K. (2024) How to realize value creation of digital transformation? A system dynamics model. *Expert Systems with Applications*, 244, 122667. https://doi.org/10.1016/j.eswa.2023.122667

Ramesh N., Delen D. (2021) Digital Transformation: How to Beat the 90% Failure Rate? *IEEE Engineering Management Review*, 49(3), 22–25. https://doi.org/10.1109/EMR.2021.3070139

Schiuma G., Santarsiero F., Carlucci D., Jarrar Y. (2024) Transformative leadership competencies for organizational digital transformation. *Business Horizons*, 67(4), 425–437. https://doi.org/10.1016/j.bushor.2024.04.004

Teece D.J. (2007) Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal,* 28(13), 1319–1350. https://doi.org/10.1002/smj.640

Trenerry B., Chng S., Wang Y., Suhaila Z.S., Lim S.S., Lu H.Y., Oh P.H. (2021) Preparing Workplaces for Digital Transformation: An Integrative Review and Framework of Multi-Level Factors. *Frontiers in Psychology*, 12, 620766. https://doi.org/10.3389/fpsyg.2021.620766

Trischler J., Trischler W.J. (2022) Design for experience – A public service design approach in the age of digitalization. *Public Management Review*, 24(8), 1251–1270. https://doi.org/10.1080/14719037.2021.1899272

UNCTAD (2019) *Digital Economy Report 2019*, Geneva: United Nations.

Veeraya S., Raman M., Gopinathan S., Singh J. (2024) Digital Business Transformation of Malaysian Small and Medium-Sized Enterprises: A Review on Digital Leadership and Digital Culture. *International Journal of Organizational Leadership*, 13(4), 703–721. https://doi.org/10.33844/ijol.2024.60439

Verhoef P.C., Broekhuizen T., Bart Y., Bhattacharya A., Dong J.Q., Fabian N., Haenlein M. (2021) Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Wang L., Jin X., Yoo J.J. (2024) The process of visionary leadership increases innovative performance among IT industry 4.0 for SMEs for organizational sustainability: Testing the moderated mediation model. *Sustainability,* 16(19), 8690. https://doi.org/10.3390/su16198690

Zhang H., Ding H., Xiao J. (2023) How organizational agility promotes digital transformation: An empirical study. *Sustainability*, 15(14), 11304. https://doi.org/10.3390/su151411304

Zhu X., Ge S., Wang N. (2021) Digital transformation: A systematic literature review. *Computers & Industrial Engineering*, 162, 107774, 10.1016/j.cie.2021.107774

Patent Trends Analysis as a Basis for Innovation Strategies

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Abstract

The analysis of patent trends reveals significant patterns that have the potential to drive technological advancements in specific domains, particularly by identifying emerging areas and research gaps. This study examines how the economic appropriation of research and development outcomes mirrors the dynamics of the innovation process and informs strategic planning, policy formulation, and innovation management. By conducting a detailed analysis of the economic appropriations made by public science and technology institutions within Brazil's aerospace and defense sectors, we identify how these trends can inform proactive approaches to technological innovation. The institutions studied exhibit research and development and innovation dynamics that are finely tuned to the specific needs and trends of their technological fields, illustrating the increasing diversity of research and development interests and the complexity of the innovation ecosystems in which they operate. Ultimately, the success of innovation policies and strategies hinges on the ability to anticipate technological trends, strategically invest in high-potential areas, and efficiently transfer technologies to the productive sector. This ensures that institutions are well-positioned to respond quickly and effectively to technological changes and market opportunities, fostering sustainable development and technological progress.

Keywords: innovation development; innovation management; patenting; R&D management; R&D&I policies; technological change; Brazil

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Introduction and Contextualization

The intersection of technological innovation, Research, Development and Innovation (R&D&I) policies, and development strategies has become increasingly critical in the global landscape. As economies and societies face complex challenges, from economic sustainability to industrial competitiveness, the need for an integrated and strategic approach to innovation and technological development becomes imperative (Fagerberg et al., 2009; Mazzucato, 2013; Etzkowitz, Zhou, 2018). The distinction between R&D Management and R&D&I Policies is essential for understanding how innovation is managed and promoted at different levels. While R&D management focuses on the internal organization of projects and the operational efficiency of research and development within institutions, R&D&I policies encompass the regulatory and strategic instruments formulated to promote and guide innovation in key sectors. The interdependence between these two levels is evident: R&D managers operate within a normative ecosystem established by public policies, and these policies, in turn, are shaped by the needs and challenges identified in management practices. This differentiation allows for a more structured approach to analyzing innovation strategies, preventing conceptual misunderstandings between the roles of organizational managers and institutional policymakers.

This focus seems to be relevant as it addresses critical aspects of R&D management and technological innovation management in public Scientific and Technological Institutions (STIs), which are oriented toward expanding the technological capabilities of strategic sectors such as aerospace and defense, with the development of technologies that have the potential to be utilized by a wide range of industries. The complex innovation ecosystem encompasses the intricate interactions between patenting trends, institutional research activities, and national innovation policies. In the context of this study, it refers to how technological development is influenced by the interplay of scientific research, intellectual property management, and strategic policy-making. The aeronautics institutes analyzed operate within this ecosystem, where patenting is not just a measure of scientific output but also a reflection of broader strategic priorities in research and development. Understanding this complexity is essential for aligning innovation policies with institutional capabilities and market opportunities.

This work aims to offer critical insights for R&D&I policymakers, R&D managers, researchers, and innovation strategists, highlighting the importance of well-founded innovation policies and strategies that promote R&D in emerging and strategic areas. We will examine how focusing on specific technologies, such as microstructures and nanotechnology, semiconductors, and electrical engineering, as well as the commitment to R&D&I in fundamental technological domains, reflects global needs and demands for sustainability-conscious solutions. Furthermore, we will discuss how identifying strategic areas for investment and exploring opportunities for technology transfer can serve as catalysts for technological advancement and Brazilian economic development.

The statistics and dynamics of patenting is considered to be one of the key indicators of innovation activity. In this context, this article explores how patenting activities reflect the dynamics of the innovation process and how this information can guide strategic planning in Research and Development (R&D), as well as the formulation of R&D&I policies and strategies for innovation management. Thus, this article interprets these trends and identifies opportunities to align R&D strategies, R&D&I policies, and technology transfer strategies for the Brazilian productive sector.

Over the past two decades, the analysis of patenting trends at leading research institutions, such as those of the Department of Aerospace Science and Technology (DCTA), has revealed significant patterns of innovation potential. These patterns not only indicate technological domains with the capacity to drive significant advances in technological development but also highlight emerging research areas and existing gaps. Through a meticulous analysis of patenting and innovation activities within the STIs of the DCTA (Institute of Aeronautics and Space - IAE, Institute for Advanced Studies - IEAv, and Aeronautics Institute of Technology - ITA), we explore how these trends can reveal insights and guide efforts toward a proactive role in the technological innovation process.

Materials and Methods

The methodology employed in the present study reflects a comprehensive and meticulous effort to capture and analyze how the economic appropriability of R&D outcomes generated by the STIs IAE, IEAv, and ITA can produce economically relevant results, thereby feeding back into the R&D&I process. This effort also aims to provide insights for the formulation of strategic planning in R&D, as well as the development of R&D&I policies and innovation management strategies.

We applied an exploratory and descriptive research methodology (Gil, 2010; Prodanov, Freitas, 2013; Matias-Pereira, 2019; Creswell, Creswell, 2009) to establish associations among various variables based on data collected from multiple sources. We adopted an integrated approach, combining data collection methods, bibliographic analysis, and data analysis to ensure the robustness and validity of the findings. This holistic and integrated methodology ensured the generation of valuable insights for the formulation of effective innovation strategies and public policies in response to patenting trends.

Initially, the selection of sources formed the cornerstone of our research strategy, involving a case study in public STIs that are recognized as highly relevant in the research and development of technologies for strategic technological sectors essential for Brazilian economic and social development.

The PatSeer® IP research and intelligence application, developed by GridLogics, was used as the primary data collection tool from patent databases, including those filed with the National Institute of Industrial Property (INPI) and similar agencies abroad. The International Patent Classification (IPC) system was used to categorize the presented technological domains and subdomains.

The literature analysis involved a careful review and the use The literature analysis involved a careful review and the use of established literature to support our data analysis. Our approach to data analysis was primarily qualitative, aiming to identify significant trends in relation to the adopted theoretical framework.

We opted for a qualitative representation of the obtained results, prioritizing the identification of patterns and trends over exact quantifications in order to capture the essence of the observed R&D and innovation processes.

Finally, the study can be classified as a clear example of applied research, given its intent to generate practical knowledge for solving specific problems, as the driving force behind technological innovation management studies is practice (Dodgson et al., 2014).

The validation of findings was achieved through data triangulation, a methodological strategy that involved comparing results obtained from different sources. This process strengthened the credibility and reliability of our conclusions.

Results and Discussion

The innovation dynamic requires both the formulation of R&D&I policies, which define incentives, regulations, and strategic priorities, and R&D management, which implements and operationalizes research and development strategies within institutions and companies. The relationship between these dimensions is not exclusive but complementary: policies establish broad directions and structure favorable environments for innovation, while R&D management translates these directions into concrete practices, projects, and applicable technologies. Ignoring this distinction would lead to a limited approach to innovation since the governance of research and development demands both political orientation and managerial competence.

Furthermore, while R&D management involves decision-making at the organizational and microeconomic levels, R&D&I policies operate on a broader scale, creating the institutional foundations necessary for innovation to thrive. The analytical separation of these dimensions enables a more refined study of innovation strategies, highlighting the interactions between the agents who formulate guidelines and those who execute innovative projects.

Innovation does not occur in isolation. It is embedded in a complex ecosystem where scientific research, patenting activities, institutional strategies, and policy frameworks interact dynamically. The aeronautics institutes analyzed in this study (IAE, IEAv, and ITA) contribute to this ecosystem through their specialized research domains, while their patenting efforts indicate areas of technological progress. At the same time, external factors such as government policies, funding mechanisms, and industry collaborations shape the direction of innovation, reinforcing the interconnected nature of technological advancement.

Recognizing this complexity allows for a more strategic approach to R&D&I, where technological foresight, institutional research capabilities, and economic appropriability must be considered together. By analyzing patenting trends and institutional roles within this ecosystem, we provide insights into how innovation strategies can be optimized to foster technological progress and economic impact.

The strategic management of R&D&I is a dynamic process that continuously evolves in response to technological advancements, policy interventions, and market demands. The institutions analyzed in this study operate within an adaptive framework where research priorities, collaboration models, and innovation strategies undergo constant refinement to maximize impact and relevance.

A key transformation in R&D management is the increasing integration of foresight methodologies, allowing institutions to anticipate emerging technological domains and strategically allocate resources toward high-potential research areas. This shift is evident in the evolution of research portfolios, where interdisciplinary approaches — combining materials science, nanotechnology, and electrical engineering — have gained prominence in recent years.

Similarly, innovation management has undergone significant transformation, moving from a closed model of internal development to a networked approach that emphasizes technology transfer, open innovation, and industry-academia partnerships. The increasing engagement with external stakeholders, including private-sector collaborators and international research networks, has facilitated a more agile and responsive innovation ecosystem.

Moreover, policy-driven shifts in STI governance have played a pivotal role in reshaping R&D&I strategies. The emphasis on sustainability, digital transformation, and dual-use technologies (civilian and defense applications) has led to new funding models, regulatory incentives, and collaborative platforms that encourage institutions to align their research agendas with broader economic and societal priorities.

These transformations illustrate that R&D management and innovation management are not static disciplines but rather evolving strategic systems that continuously adapt to internal and external drivers. A purely quantitative assessment of patenting trends, while valuable, does not fully capture the complexity of these strategic shifts. By incorporating these qualitative insights, we highlight how institutional governance, strategic foresight, and policy frameworks collectively shape the trajectory of research and innovation.

The relationship between R&D, innovation, and patenting is not linear but interactive, meaning that research outputs do not simply lead to patents—instead, patenting trends influence research directions and innovation policies in a continuous feedback loop. This interaction is evident in the patenting dynamics presented in Tables 1 and 2, which reveal:

- Sustained patenting activity in core technological domains such as materials and metallurgy, indicating strong institutional focus and long-term research investment in these areas. These domains benefit from continuous advancements, incremental improvements, and direct alignment with industry needs.
- More intermittent patenting activity in areas such as semiconductors and telecommunications, which suggests a higher dependence on policy incentives, funding availability, and interdisciplinary collaboration.
- Cross-sector influence, where advancements in one technological domain (e.g., optics) lead to spillover effects in other areas (e.g., instrumentation and measurement technologies). This demonstrates the systemic nature of innovation, where breakthroughs in fundamental research often trigger secondary waves of innovation across multiple disciplines.

The analysis of technological trends through patents is an effective and strategic mechanism for use in institutional S&T policies and for guiding innovation process strategies, including R&D management, economic appropriability, and technology transfer to the productive sector. (Campbell, 1983; Kaminishi et al., 2014; Niemann et al., 2017; Kim, Bae, 2017).

IIn public technology-based STIs such as IAE, IEAv, and ITA, R&D&I activities must be oriented toward meeting the demands of an innovation ecosystem that regularly faces the need to incorporate new technologies into its portfolio to remain competitive and active on a complex market, characterized by engineering-intensive, high-performance products with high cost and added value, as well as a high spin-off potential (Becz et al., 2010).

It is important to emphasize that the primary discussion on the strategic management of technological innovation in public STIs goes far beyond merely protecting inventions, as Intellectual Property (IP) should not be viewed as an end in itself but rather as part of the strategic management of the outcomes obtained in R&D&I. In this process of managing technological innovation, it is necessary to keep in mind that innovation depends on the particularities of technology and the market (Tidd et al., 2001).

Another key point is that R&D&I management is not an isolated activity with the sole purpose of managing projects and delivering research results; on the contrary, research and development management must be understood and approached from a systemic and interactive perspective (Rothwell, 1994; PMI, 2021).

This study adopts a systematic and interactive approach to analyzing research, development, and innovation trends. The systematic component involves a structured assessment of patent data, identifying key technological domains, patenting intensity over time, and potential areas for technology transfer. This approach allows us to map the evolution of innovation activities and their alignment with institutional and national priorities.

Simultaneously, the interactive component considers the bidirectional influence between patenting, research management, and innovation strategies. Instead of viewing patenting as merely an outcome of R&D, we analyze how patent trends feed back into research prioritization and innovation management frameworks. Through an extensive search of the patent databases of the STIs in focus, both from the National Institute of Industrial Property (INPI) and similar agencies abroad, extracted using the PatSeer® application and meticulously compiled into tables, we explore the evolution and impact of the conducted research, reflecting on the significant role that the DCTA STIs play in promoting technological innovation. This analysis aims not only to recognize the contribution of these entities to science and technology but also to understand how they shape technological trends and open avenues for new opportunities in technology transfer and industrial development.

The decision was made to separate the technological domains developed by IAE and IEAv from those of ITA. This separation is due to institutional characteristics. IAE is responsible for developing R&D projects and activities in aeronautics, space access, and defense, while IEAv is responsible for applied research and experimental development aimed at future applications in aerospace technologies and systems. ITA, on the other hand, is a higher education institution specializing in engineering education and research related to aerospace activities.

Thus, ITA's IP portfolio contains technologies in diverse fields of knowledge, many of which originate from teaching and research activities requested by companies seeking to train human resources in stricto sensu graduate programs, a trend that does not occur in the other STIs analyzed.

Tables 1 and 2 provide consolidated matrices of annual publications by technological domain for active patents associated with both DCTA's STIs (IAE and IEAv) and ITA, detailing patenting activity across different areas of technology over time. Some insights are extremely relevant regarding the potential for technology transfer, innovation, and its impact on the industry and the generation of profitable businesses.

The data consolidated in Table 1 (IAE and IEAv) allows for a detailed analysis of the trends in technological advances in the domains of "Materials" and "Metallurgy," highlighting a consistent pattern of patenting activities extending from 2006 to 2023. This continuity in patenting suggests a sustained commitment to research and development (R&D) in these fields, indicating several important trends in technologies with the potential to generate innovations.

Considering R&D in Materials, it is evident that this is crucial for the advancement of various technologies and industries, including electronics, automotive, aerospace, and healthcare. Advanced materials, such as nanomaterials, biomaterials, and new polymers, are at the forefront of research and development, offering enhanced properties like increased strength, lightweight, and specific functionalities, such as self-healing and stimulus responsiveness.

In the case of nanomaterials and composites, global research has been intense, focusing on the development of materials with unique properties for use in electronics, catalysts, and construction materials, which may indicate a prioritization wave for DCTA's STIs, leveraging their acquired expertise and established competence. The manipulation of materials on a nanometric scale enables the creation of structures with innovative physical, chemical, and biological properties. Similarly, this established competence can be leveraged to focus on sustainable materials, as sustainability has become a growing area of global focus, with research directed towards developing eco-friendly, recyclable, or biodegradable materials, as well as manufacturing processes that reduce waste and energy consumption. For this, government and private funding and incentives abound, which can favor the R&D sector of the DCTA.

Likewise, delving into another area highlighted in Table 1 of the STIs IAE and IEAv, patentability in Metallurgy emerges as a vital field for innovation, especially with the growing demand for materials that withstand extreme conditions and are produced more sustainably.

The development of Advanced Alloys, capable of operating at high temperatures and resisting corrosion, is fundamental for applications in extreme environments, such as aviation, hypersonics, and energy. Similarly, exploring what is known as Powder Metallurgy is essential, allowing for the production of materials with specific properties unattainable by conventional casting methods, crucial for manufacturing complex components used in various industries.

Finally, when it comes to recycling and sustainability, metallurgical processes can also include more efficient and environmentally friendly aspects. Thus, patenting in the areas of Materials and Metallurgy reflects a continuous pursuit of R&D&I that not only advances the state of the art in terms of material properties and functionalities but also addresses global challenges such as sustainability and energy efficiency, following current trends. These trends underline the importance of a multidisciplinary approach to research and development, integrating knowledge from chemistry, physics, biology, and engineering to tackle current and future challenges.

On the other hand, Table 2, which refers to ITA, clearly highlights technological domains such as "Instruments," "Mechanical Engineering," "Chemistry," and "Electrical Engineering," among others. This diversity of fields reflects a multifaceted approach to research and development, with Mechanical Engineering and Instruments showing the highest number of activities over the years, indicating a strong area of expertise and ongoing R&D&I.

The consistent presence of activities in these areas over the years demonstrates not only ITA's ability to maintain vigorous and relevant research but also its ability to adapt to new trends and demands on the technological market. This strategic focus on key areas such as Mechanical Engineering and

Table 1. **Status of Active Intellectual Properties of DCTA's STIs (IAE and IEAv)**

Tech Sub Domain	Total	Publication year																	
		2002	2006	2007	2008	2009	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Materials	20		X	X	X	X		X	X			X	X	X	X		X	X	X
Metallurgy	20		X	X	X	X		X	X			X	X	X	X		X	X	X
Measurement	9				X	X	X				X	X		X	X	X			
Coating	6		X				X						X	X		X			
Surface technology	6		X				X						X	X		X			
Other special machines	4	X						X		X						X			
Engines	3										X					X	X		
Optics	3														X			X	X
Pumps	3										X					X	X		
Turbines	3										X					X	X		
Audio-visual technology	2	X										X							
Machine tools	2														X				X
Macromolecular chemistry	2												X				X		
Micro-structural and nano-technology	2								X								X		
Polymers	2												X				X		
Semiconductors	2												X			X			
Telecommunications	2	X										X							
Textile and paper machines	1					X													

*Note: The totals may include multiple technological domains classified according to the International Patent Classification (IPC).

Source: authors.

Table 2. **Status of Active Intellectual Properties of DCTA / ITA**

Tech Sub Domain	Total	Publication year													
		2008	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Instruments	25	X	X	X		X		X	X	X	X	X	X	X	X	X
Mechanical engineering	18	X			X	X		X	X	X		X	X	X	X	
Chemistry	12		X		X	X			X			X	X		X	
Electrical engineering	5		X									X		X		X
Other fields	5		X		X		X					X	X			

*Note: The totals may include multiple technological domains classified according to the International Patent Classification (IPC).

Source: authors.

Instruments suggests a solid foundation for industrial collaboration and technology transfer, positioning ITA among the leaders in research and development in these areas. The diversification of technological domains also indicates a comprehensive approach to tackling complex global challenges, preparing ITA to significantly contribute to the technological innovation processes on the global stage.

Regarding Mechanical Engineering and Instruments specifically, the emphasis on these areas reveals robust expertise and continuous contributions to technological advancement. Mechanical Engineering, with its vast applicability - from the development of complex systems to the optimization of manufacturing processes - serves as a fundamental pillar for progress in various industrial sectors. R&D&I in this domain often translates into significant improvements in the efficiency, durability, and performance of machines and equipment, directly impacting industrial competitiveness.

On the other hand, the "Instruments" area reflects advances in measurement and control technologies, fundamental for scientific research, the manufacturing industry, and the service sector. The ability to measure accurately and control processes is vital for executing activities in areas such as aerospace, defense, healthcare, and energy, areas where ITA increasingly aims to establish itself as a reference for Brazil and the world. ITA's continued focus in this domain suggests proficiency in developing technologies that not only elevate the standard of experimental research but also strengthen the technological infrastructure necessary for R&D&I. Moreover, both Chemistry and Electrical Engineering are also highlighted in Table 2, revealing a diversification strategy aimed at addressing interdisciplinary challenges and exploring new scientific frontiers. Chemistry, especially in the era of green technologies and advanced materials, is a field rich in potential for innovations that promote sustainability and new material functionalities. Electrical Engineering, in turn, with its central role in the development of electronic systems, telecommunications, and information technologies, is fundamental for digitization and connectivity.

Finally, ITA's excellence in Industrial Collaboration and Technology Transfer not only ensures its leadership position in research and development but also establishes a solid foundation for proactive action and technology transfer. The ability to generate technologies applicable across multiple sectors positions ITA as a valuable partner for companies seeking advanced technological solutions, promoting economic development and responding to the demands of an increasingly technology-driven global market.

Continuing the analysis of Tables 1 and 2, we turn to another relevant trend that can be observed, namely the "Periods of High Patenting Activity" and consequently the "R&D&I Cycles."

In a more detailed analysis of the "Periods of High Patenting Activity," Table 1 (IAE and IEAv) shows a diverse distribution of patenting activities over the years across various technological areas, such as Materials, Metallurgy, and Measurement, among others. On the other hand, areas like Coating and Surface Technology show concentrated patenting activity between 2012 and 2023, indicating a significant focus on R&D&I related to these fields in the recent period. This may reflect an increased demand for new materials and surface technologies with enhanced properties for various industrial applications. Meanwhile, technologies such as Optics and Semiconductors also demonstrate consistency in patenting activity, suggesting ongoing development and interest in these sectors.

Considering Table 2 (ITA), one observes patenting activity in broader technological domains, such as Instruments, Mechanical Engineering, and Electrical Engineering, with consistent patenting activity in Instruments and Mechanical Engineering throughout the covered period, with peaks of activity in certain years. This suggests continuous investment in seeking innovations in these areas, possibly driven by technological advances and the need for more efficient and precise solutions. The area of Electrical Engineering shows a growing trend in patenting activity, especially notable from 2010 onward, reflecting the expansion of electrical and electronic innovations in response to the increasing demand for more advanced and sustainable technology.

Innovation and patenting activity do not occur in a linear progression; instead, they follow distinct R&D&I cycles, characterized by fluctuating periods of high and low innovation intensity. These cycles are influenced by a combination of technological maturity, institutional priorities, funding structures, and market readiness.

From the patenting trends observed in Tables 1 and 2, we identify three key factors shaping these cycles:

- Sustained research fields (e.g., materials and metallurgy) exhibit longer, more stable cycles, where innovation is driven by incremental advancements and steady funding.
- Disruptive and policy-sensitive fields (e.g., semiconductors, telecommunications, and optics) demonstrate shorter, high-intensity cycles, often triggered by regulatory incentives, breakthrough discoveries, or shifts in industrial demand.
- Cross-disciplinary fields (e.g., instrumentation and mechanical engineering) show intermittent cycles, where patenting surges occur when interdisciplinary innovations create new technological applications.

Understanding these cyclical dynamics is critical for strategic R&D&I management, as it enables institutions to anticipate and leverage periods of high innovation activity, aligning investments and research efforts with emerging technological opportunities. On this basis, they identify optimal timing for technology transfer and commercialization, ensuring that patented innovations reach the market at peak relevance. Finally, there are emerging opportunities to adapt institutional strategies based on cycle length and intensity, balancing investments between long-term foundational research and short-term disruptive innovation.

By integrating these insights into strategic innovation management, organizations can proactively navigate technology life cycles, enhance resource allocation, and strengthen institutional competitiveness in an evolving R&D ecosystem.

On the other hand, through a more detailed analysis of the "R&D&I Cycles," Table 1 (DCTA) presents continuous innovation and persistent interest in areas such as Semiconductors and Telecommunications, reflecting rapid innovation cycles where technology constantly evolves to meet new market demands. In contrast, areas with less patenting activity, such as Engines and Pumps, may indicate longer innovation cycles or a period of technological maturation, where disruptive innovations are less frequent but potentially more impactful when they occur.

Still in the "R&D&I Cycles", Table 2 (ITA) shows consistent activity in fields like Instruments and Mechanical Engineering, suggesting relatively stable R&D&I cycles, with incremental improvements being regularly introduced. This stability can be attributed to the fundamental nature of these technologies in a wide range of industrial and commercial applications. In contrast, the observed increase in patenting activity in Electrical Engineering may indicate a period of accelerated innovation in this field, possibly in response to advances in related technologies, such as renewable energy, consumer electronics, and communication systems, which are increasingly prominent on the global stage.

Moving on to some additional points that Tables 1 and 2 present in a very relevant way, we can clearly address "Research Gaps" and "Areas of Growing Interest".

In "Research Gaps", Table 1 (DCTA) suggests that some technological areas, such as Engines, Pumps, and Textile and Paper Machines, have relatively low or sporadic patenting activity over the years. This could indicate research gaps or opportunities for innovation and development in these areas.

The lack of recent patents in these categories suggests that there may be unresolved challenges or potential for new discoveries. The limited patenting activity in Audiovisual Technology also highlights a possible research gap, suggesting an opportunity for disruptive innovations that could transform this industry.

On the other hand, when looking at Table 2 (ITA), although it shows a broader distribution of patenting activities across technological domains, areas like Chemistry and Other Fields show lower patenting activity. This may indicate potential research gaps or areas that could benefit from renewed focus, especially considering the fundamental role of chemistry in emerging technologies and sustainability.

The lower number of patents in specific years for Electrical Engineering and Mechanical Engineering also suggests that there may be opportunities for exploration and additional R&D&I projects, especially in subdomains that have not been widely explored.

Once the "Research Gaps" are understood, the next important step is to analyze those "Areas of Growing Interest", which, based on Table 1 (IAE and IEAv), suggest that Coating and Surface Technology, along with Micro-Structural and Nano-Technology, show a significant increase in patenting activity, reflecting a growing interest in these areas. This indicates a focus on the research and development of new materials and technologies with advanced properties, potentially driven by demands for better performance and sustainability. Meanwhile, Semiconductors and Telecommunications maintain steady patenting activity, suggesting ongoing interest and investments in R&D&I in these critical areas for technological advancement and global connectivity.

Looking at Table 2 (ITA), we see that Instruments and Mechanical Engineering exhibit robust and consistent patenting activity, indicating sustained interest in these areas. This reflects the enduring importance of R&D&I in mechanics and precise instruments across various applications. The growing activity in Electrical Engineering is particularly notable in the later years of the table, signaling increasing interest in electrical and electronic technologies. This may be driven by trends such as vehicle electrification, renewable energy, and the need for more efficient power systems. Starting with "Strategic Areas for Investment," Table 1 (IAE and IEAv) specifically shows that in the area of Micro-Structural and Nano-Technology, consistent patenting activity indicates that this is a growing area of importance, with the potential to generate disruptive innovations in a wide range of applications, from advanced materials to electronics and medicine. Investing in research and development in this area could position an organization at the forefront of technology. Similarly, Semiconductors and Telecommunications continue to be crucial for technological advancement, driving innovations in communication, computing, and electronics; strategic investments in these sectors could boost the development of new technologies and products that meet the global demand for improved connectivity and performance.

Likewise, Table 2 (ITA) shows that Electrical Engineering has a growing patenting activity reflecting the importance of this area, particularly concerning sustainable technologies and energy efficiency. Investments here could pave the way for innovative developments in renewable energy, energy storage, and transportation electrification. Meanwhile, Instruments, with strong patenting activity, suggest that R&D&I in instrumentation is critical for advances in research and development across various fields; investing in precise and advanced measurement technologies could enhance innovation capabilities in sectors like manufacturing, life sciences, and environmental research.

Similarly, if we consider "Opportunities for Technology Transfer", Table 1 (IAE and IEAv) shows that the increase in patenting activity in Coating and Surface Technology suggests significant advances that could be applied in industries such as automotive, aerospace, and construction, offering opportunities for patent licensing or development partnerships. In the area of Optics, based on the observed patenting activity, there are opportunities to transfer optical technology solutions to sectors such as healthcare for medical equipment, or to communication and imaging systems, where improvements in these optical technologies could offer significant advantages.

On the other hand, Table 2 (ITA) shows strong consistency in Mechanical Engineering patenting activity, indicating that there are solid advances that could be applied in the industrial, automotive, and manufacturing sectors, suggesting opportunities for industrial partnerships or the commercialization of new innovations. Additionally, Chemistry, although showing less patenting activity, suggests that potential innovations in this area could impact sectors such as sustainable materials, biochemistry, and pharmaceuticals, which are currently in high demand globally.

Investing in technology transfer here could lead to innovative solutions that meet the emerging demand for greener products and production processes.

Conclusions

Based on the analyses presented above, it is clear that the patenting routine of the DCTA STIs over the past 19 years reveals a series of trends that should be observed and serve as a basis for strategic planning in the R&D sector, strategic innovation management, and the formulation of S&T&I policy for the STIs.

These analyses reveal the distinct dynamics of R&D and innovation, adapted to the trends and needs of their specific technological fields. IAE and IEAv stand out for their focus on specific technologies, such as advanced materials and communications, identifying areas with growth potential and research gaps that offer significant opportunities for innovation. In contrast, ITA demonstrates a consistent commitment to fundamental technological domains, evidencing a continuous interest in innovations in mechanical areas. These institutions recognize the importance of strategic areas for investment, especially in advanced technologies that are crucial to maintaining competitiveness and leading opportunities for innovation. The exploration of technology transfer opportunities, particularly in fields such as Coating, Surface Technology, Optics, Electrical Engineering, and Instruments, is highlighted as a means of expanding the impact of innovations across various sectors, promoting technological advancement and sustainable development.

This strategic approach not only underscores the complexity and multifaceted nature of the technological innovation process but also reinforces the need for S&T&I policies and innovation strategies that support research and development in these emerging and strategic areas. By identifying research gaps and focusing on areas of growing interest, institutions can direct efforts to maximize the impact of R&D&I, significantly contributing to technological progress and addressing global needs for sustainability and efficiency.

The evident diversity in patenting activities and areas of growing interest highlights the complexity of the innovation ecosystem in which these STIs operate (Aerospace and Defense), where opportunities and challenges coexist. This critical analysis focuses on the implications for research and development, as well as the impact on S&T&I policy and innovation strategy, derived from observations on periods of high patenting activity, innovation cycles, research gaps, and strategic areas for investment and technology transfer.

A proper identification of areas of intense patenting activity and growing interest provides a compass for directing research and development efforts. Strategic investments in domains such as Micro-Structural and Nano-Technology, Semiconductors, and Electrical Engineering are essential to maintaining technological leadership and responding to market demands. Simultaneously, identifying research gaps points to untapped potential in areas such as Engines, Pumps, and Chemistry, where renewed efforts could unlock disruptive innovations. Therefore, balancing the exploration of new territories and expanding known frontiers is crucial for a healthy and dynamic innovation ecosystem.

Regarding the impact of R&D&I policy and strategic innovation management, the former plays a vital role in shaping the environment for effective innovation. The conclusions drawn highlight the need for policies that foster research and development in areas identified as strategic, as well as facilitating technology transfer to maximize the social and economic impact of innovations. This includes investments in education and research infrastructure, tax incentives for R&D&I, and support for intellectual property. Additionally, an effective innovation strategy should include managerial mechanisms for the rapid adoption of emerging technologies in the public and private sectors, leveraging innovation to address global challenges such as sustainability, health, and security.

When examining the entire scope presented, the patenting activities of the DCTA STIs reveal a vibrant R&D&I landscape, with clear focus areas and potential for significant advancement. However, a successful strategy requires not only identifying these areas but also overcoming the inherent challenges in developing and implementing innovations. This includes addressing regulatory barriers, ensuring adequate funding, and promoting collaboration between industry, academia, and the government. Moreover, rapid technological evolution demands agility in R&D&I policies and innovation strategies, ensuring that they can adapt and respond to changes in the technological environment.

From a strategic innovation management perspective, the study highlights several key takeaways. Innovation is not a linear process; rather, it follows distinct cycles influenced by technological maturity, institutional priorities, and market demand. Recognizing these cycles enables better resource allocation, optimized technology transfer, and enhanced long-term research planning. Patent activity serves as both an outcome and a driver of innovation, shaping future research directions by signaling technological opportunities and guiding funding decisions. Institutions should leverage patent analytics not just for intellectual property protection but as a tool for strategic foresight and investment planning. Interdisciplinary and cross-sectoral innovation is critical for sustaining long-term competitiveness. The observed spillover effects between technological domains (e.g., materials science and optics, telecommunications and instrumentation) demonstrate the importance of collaborative research frameworks and open innovation models.

For policymakers and R&D&I leaders, these findings emphasize the need for flexible and adaptive innovation policies that:

- Encourage long-term research investment in foundational technologies while maintaining mechanisms to support high-impact, short-cycle innovation bursts.
- Strengthen industry-academia partnerships to maximize the economic and societal impact of innovation, ensuring that patenting efforts translate into technological applications.
- Leverage data-driven foresight mechanisms to anticipate technological shifts, aligning national and institutional research agendas with emerging global trends.

By integrating these strategic insights, organizations and policymakers can enhance their ability to anticipate, manage, and capitalize on the evolving R&D&I landscape, ensuring sustained technological progress and economic growth.

In conclusion, success in research and development, as well as in R&D&I policy and innovation strategy, depends on the ability to anticipate technological trends, strategically invest in promising areas, and facilitate the technology transfer process. A holistic and adaptive approach that considers both opportunities and challenges is essential to maximizing the impact of R&D&I and potential innovation, promoting sustainable development and technological progress.

The findings of this study reinforce the complexity and dynamic nature of the innovation ecosystem, where research, development, and patenting are interconnected through cyclical patterns of activity. The analysis of patenting trends within the three aeronautics institutes (IAE, IEAv, and ITA) provides critical insights into how technological priorities shift over time, how institutional research strategies evolve, and how external policy incentives shape innovation trajectories.

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References

Becz S., Pinto A., Zeidner L.E., Banaszuk A., Khire R., Reeve H.M. (2010) *Design System for Managing Complexity in Aerospace Systems*. Paper presented at the 13th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Fort Worth, TX AIAA, AIAA-2010-9223. https://doi.org/10.2514/6.2010-9223

Campbell R.S. (1983) Patent Trends as a Technological Forecasting Tool. *World Patent Information*, 5(3), 137–143. https://doi.org/10.1016/0172-2190(83)90134-5

Creswell J.W., Creswell J. D. (2009) *Research design: Qualitative, quantitative, and mixed methods approaches* (3rd. ed.), Thousand Oaks, CA: Sage.

Dodgson M., Gann D.M., Phillips N. (eds.) (2014) *The Oxford Handbook of Innovation Management*, Oxford: Oxford University Press.

Etzkowitz H., Zhou C. (2018) *The Triple Helix: University – Industry – Government Innovation and Entrepreneurship* (2nd ed.), New York: Routledge.

Fagerberg J., Srholec M., Verspagen B. (2009) *Innovation and economic development* (UNUMERIT Working Papers No. 032), Maastricht: UNU-MERIT.

Gil A.C. (2010) *How to Develop Projects of Research* (5th ed.), Sao Paulo: Atlas Press.

Kaminishi K., Muhamad A.K.B., Kyontani T., Miyake K., Kimura T., Haruyama S. (2014) A study of technology trends analysis using patent search systems. *Journal of Technology Innovation and Sustainability*, 5(2), 18–35.

Kim G., Bae J. (2017) A novel approach to forecast promising technology through patent analysis. *Technological Forecasting & Social Change*. 117, 228–237. https://doi.org/10.1016/j.techfore.2016.11.023

Matias-Pereira J. (2019) *Manual de metodologia da pesquisa científica* (4th ed.), Sao Paulo: Atlas Press.

Mazzucato M. (2013) *The Entrepreneurial State: Debunking Public vs. Private Sector Myths*, London; New York: Anthem Press.

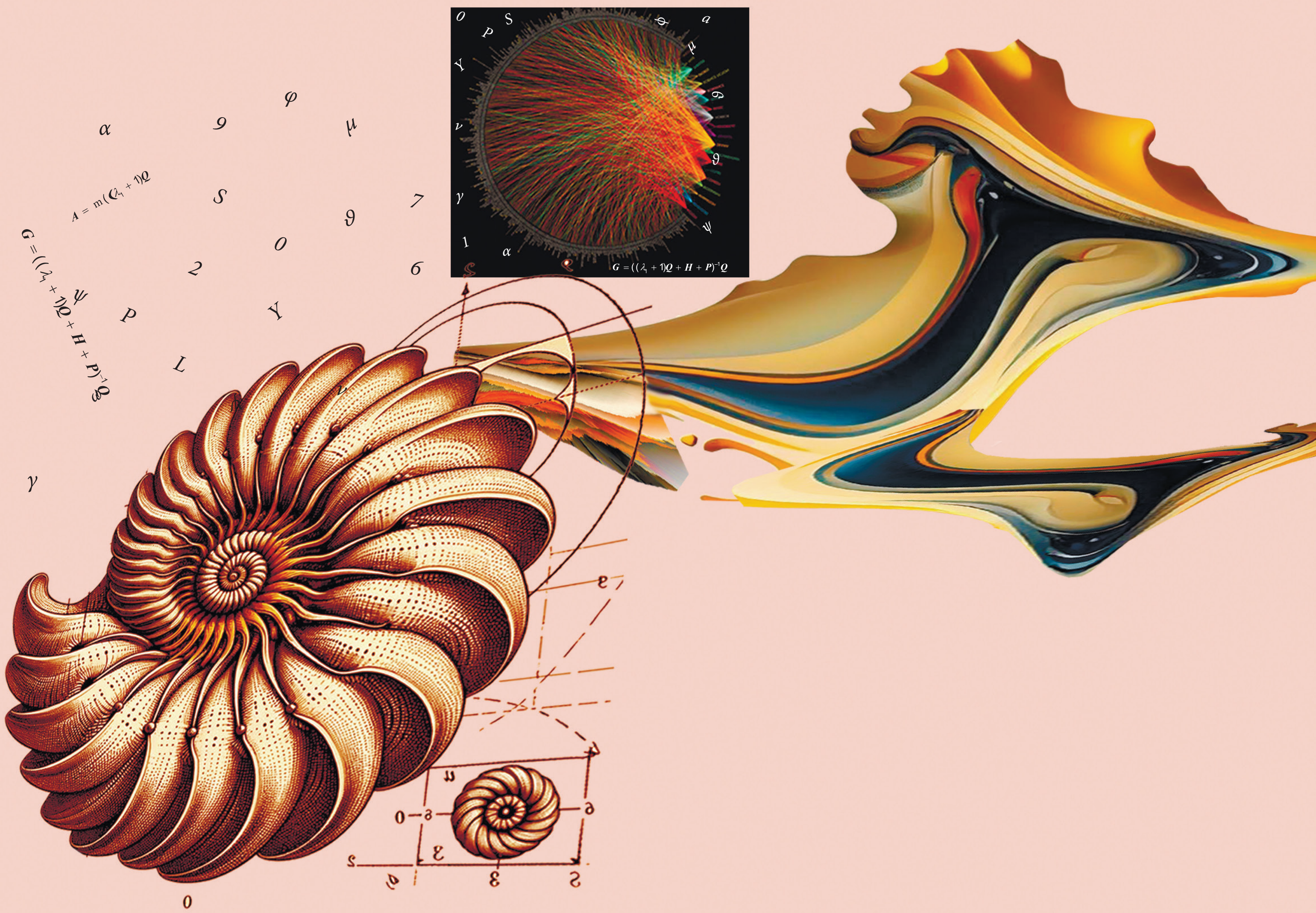
Niemann H., Moehrle M.G., Frischikorn J. (2017) Use of a new patent text-mining and visualization method for identifying patenting patterns over time: Concept, method and test application. *Technological Forecasting & Social Change*, 115, 210–220. https://doi.org/10.1016/j.techfore.2016.10.004

Prodanov C.C., Freitas E.C. (2013) *Methodology of Scientific Work: Methods and Techniques of Research and Academic Work* (2nd ed.), Novo Hamburgo, RS: Feevale.

PMI (2021) *A Guide to the Project Management Body of Knowledge (PMBOK)* (7th ed.), Newtown Square, PA: Project Management Institute.

Rothwell R. (1994) Towards the fifth-generation innovation process. *International Marketing Review*, 11(1), 7–31. https://doi.org/10.1108/02651339410057491

Tidd J., Bessant J., Pavitt K. (2001) *Managing innovation: Integrating technological market and organizational change*, Chicester: Wiley.



$G = ((\lambda_1 + 1)Q + H + P)^{-1}Q$
$A = m(Q_1 + 1)Q$

Dynamic Capabilities: Toward an Assessment of Futures Literacy Competency

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Abstract

In recent years, the topic of dynamic capabilities has acquired new content. As higher-order competencies, they allow one to constantly update oneself with new knowledge, flexibly recombine resources, and adapt to a rapidly changing environment. A key part of dynamic capabilities is working with the future, starting with basic skills - futures literacy (FL). Since this competence is key to the human resources of organizations, its development seems important, starting with university programs. For a long time, there were no objective tools for measuring the degree of their mastery. The authors of this article attempt to fill this problem by offering an innovative approach to identifying and standardizing the assessment of FL competence. Six theoretical dimensions of FL are proposed as a basis for grouping assessment criteria and compiling final assessments and their interpretation. The corresponding dimensions, such as FL sub-competencies that include foresight, the assessment of future scenarios, and decision-making under uncertainty, can be assessed independently of each other. The ability to measure the initial level of FL will allow for the development of more effective educational programs for the development of this competence.

Keywords: dynamic capabilities; futures literacy (FL); skills evaluation; strategic thinking; futures studies; innovative thinking; Foresight; scenario planning.

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Introduction

In today's turbulent, rapidly changing environment, organizations need to develop dynamic capabilities to maintain strategic sustainability. This refers to building up the organization's potential to synthesize internal and external competencies, build them up, and recombine them in order to adapt. They reflect the ability to achieve innovative forms of advantage. This concept was first proposed in the mid-1990s in (Teece et al., 1997). In recent years, the number of publications on this topic has been growing dramatically. It is one of the most relevant topics in the expert discourse concerning development strategies in conditions of turbulence, complexity, and ambiguity. According to Google trends, at the turn of 2024 and 2025, the number of queries on this topic reached its highest value in the entire history of the concept. It is addressed by the world's leading universities, including Harvard, MIT, and Oxford, and journals on economics and business (such as Journal of Business Research, Strategic Management Journal, Research Policy, etc.). Dynamic abilities are considered a complementary addition to «ordinary» abilities. Both categories of abilities are used in different contexts.

Attempts are being made to build different lists and classifications of dynamic capabilities. These often include skills for working with multiple futures (futures literacy, FL), which involve a deep study and correct interpretation of socioeconomic challenges and prospects for their development as a basis for decision-making. Teaching this complex competence to support its implementation and the subsequent analysis of the results involves the integration of more methodological elements. This concerns the development of a reliable, valid, and objective data collection instrument for assessing the level of FL in line with the methodological foundations of the UNESCO concept (Miller, 2018; Bergheim, 2024). At the core of the academic tradition of FL training is the need to develop the individual capacity to imagine and use the future, while in a broader context the main interest is focused on the future of nature, communities and organizations.

Since developing skills in any area involves strengthening the ability to solve problems, it cannot just "arise" within people, but must be nurtured through learning, becoming a continuous process in which learning is measured at different levels of competence. This leads to the need to evaluate something tangible using certain criteria, procedures, and instruments. The study of characteristics and formation of conceptual bases for FL is desperately needed, but the process is not yet complete. This raises the question of whether FL can be codified and evaluated to consider it more than a simple scientific term.

At the most basic level, FL is related to strategic thinking. However, there are certain problems with the formation of this competence – both in the educational system and at business schools. Although our article focuses on the university environment, we look further into the corporate world, which is also investing in the formation of competences for working with the future, in the development of strategists capable of solving complex problems in a changing context. Today, even many companies are experiencing problems with the formation of these particularly sought-after competences.

Thus, billions of dollars (Moules, 2020) and hundreds of millions of hours are invested annually in training strategists (Doh, Stumpf, 2007). However, most of these investments do not pay off, since the competencies acquired during such training programs cannot be applied by the strategist in his/her workplace. Therefore, the question remains relevant: how can these programs produce a new result in the form of better quality work with the future. A significant gap has been identified between the content of knowledge about the corporate world taught at universities and its practical applicability. It would seem that university programs transmit "scientifically sound" knowledge, and they are taught in accordance with strict academic standards. However, when it comes to practice, this knowledge turns out to be inoperative, since it is based on outdated concepts that, although they were effective in the past (in previous conditions of stability and predictability), they have lost their relevance in the new turbulent, rapidly changing environment (Birkinshaw et al., 2016; Costigan, Brink, 2015). An effective way to overcome this gap is to learn to reformulate the existing problem, to look at it from a different angle, to go deeper, to pose the question in such a way as to arrive at a new question: to identify the next, deeper problem behind the known problem. "Digging to the roots" fundamentally changes the perception of the situation, a new space for tools for its solution opens up (Ramirez et al., 2021).

Business schools today are facing increasing pressure. They continue to train strategists focused on a narrow set of end goals, mainly aimed at increasing shareholder returns and short-term planning horizons. Meanwhile, external pressure and the number of stakeholders is increasing, requiring companies to train specialists in working with the future so that the strategies they develop can cope with complex, multidirectional processes. Thus, there is a growing demand for a new generation of strategists who are able to manage increased complexity and remain resilient no matter the volatility (Spanjol et al., 2023). The problem is that business schools are not doing a good job of teaching students how to work with the future; the methods used to teach this work are outdated. At the same time, FL has a lot of untapped potential. In other words, rethinking the possibilities of FL can radically change the situation. In order for FL training to be more effective, it is necessary to improve the tools for teaching the relevant skills, introduce more relevant methods, and combine them in accordance with the specifics of the learning context, starting at the university level. A prerequisite for improving the educational methodology is the formation of a system of criteria by which the degree of assimilation of the taught FL skills by students is assessed. One way or another, the task is to prepare specialists with the relevant competencies, starting from the university bench. During the learning process, students are at a decisive stage of personal and professional development where their career track has not yet been determined, and they retain great potential for flexibility in the development of strategic behavior. With developed FL, students are better prepared for complex, turbulent processes throughout their careers (Miller, 2007). Various initiatives aimed at developing competencies for working with the future are already being implemented in different countries. However, this direction has not yet acquired a systemic basis, it has not become an integral part of broader educational programs and uniform standards for teaching such competencies have not yet been developed. In addition, a review of known publications on this topic shows the absence of special tools for objectively assessing the degree of assimilation of FL skills by students.

In an attempt to fill this gap, this article presents the author's tools for assessing the degree of students' acquisition of FL skills.

The article is structured as follows. First, we provide a brief history of futures science and the formation of the FL concept. Then the latest trends that make up the discourse in this area are described, examples of projects for the development of FL in the educational system and business are given. The remaining sections describe the methodology for compiling the questionnaire, the basis of the proposed toolkit for measuring the initial level of FL in students, the obtained results are then discussed, and conclusions are provided.

Literature Review

The FL concept describes an educational process aimed at developing people's abilities to think about the future, to view the current context through the lens of realistic future scenarios. On this basis, decisions are made and development strategies are formed to avoid undesirable tracks and implement preferred ones (Poli, 2021). Strategies are developed both at the individual level and at the collective, organizational level, including defining long-term development goals for a company or country and forming innovation policies (Miller, 2007, 2018; Karlsen, 2021). Let us consider approaches to the development of FL in the private sector and education.

FL, as a science of working with the future, has its own history. The idea of developing skills for dealing with the future as a basic competence "for the masses" (such as financial, digital, etc.) was first proposed in the 1970s (Toffler, 1970, Polak, 1973; Vygotskii, Cole, 1978). However, for several decades it remained outside the broader discourse. The situation changed in 2012, when UNESCO, represented by the head of the Foresight Research department, Riel Miller, began to create networks of special training laboratories for the development of these competencies in many countries (Miller, 2012). By that time, this concept had acquired a different meaning, becoming a synthesis of complexity theory and anticipation theory (Rosen, 1991; Louie, 2010; Nadi, 2012). The most significant role in the development of the FL concept and its translation into practice was played by the work (Miller, 2018). Thus, the science of the future entered a new historical stage of development. Different development institutions use their own terminology to describe it. Thus, in Germany (Stifterverband) and other countries they use the English names "Future Skills" or "Next Skills". The University of Dublin (Ireland) operates with the concept of "Transversal Skills". International organizations consider FL part of broader "21st century skills" (OECD, 2018, 2023), "Key Competences for Lifelong Learning" (European Commission, 2019). As part of "Next Skills", FL is closely related to "working with ambiguity", "ethical competence", "meaning-making", and "reflexivity" (Ehlers, 2024). In turn, the study (Lalot et al., 2020) operates with the concept of "Futures Consciousness", focusing on aspects such as "openness to alternatives." Regardless of the terminology, it is believed that skills for working with the future can be trained, developed, or strengthened in a variety of ways.

FL is considered through the prism of the classical definition of competence – as a set of knowledge, practical skills, and psychological attitude. Six of its components are distinguished (Table 1), which are interconnected, complementary, and upon one another.

From the point of view of FL leveling, four levels are distinguished (Bergheim, 2024):

Basic: Generally common to all people who imagine different futures and are somewhat open to new ideas and activities.

Intermediate: It is typical for people with heightened awareness, who are able to more deeply "draw" different versions of the future, comprehend them, and build their plans on this basis.

Table 1. **Components of FL**

Subcompetence	Description
1) "Complexity & Uncertainty Competence"	The future is viewed through the lens of complex adaptive systems (CAS), which are characterized by emergence, ambiguity, high unpredictability, etc.
2) "Multiple Futures Competence"	The diversity of possible paths is an integral characteristic of the CAS and these options can have different connotations in terms of perception (probable, desirable, etc.). The ability to work with such blocks as planning, self-organization, and optimization. Identify restraining factors such as "blind spots" and question the content of various data.
3) "Imagination & Assumptions Competence"	The future exists only in the imagination, so being aware of its images present in one's own consciousness and the consciousness of others, as well as the roots from which they arise, helps shape narratives.
4) "Reframe & Experiment Competence"	It is revealed through experiments, cognitive stretching, openness to the unknown, narrative practices, role-playing games, and living out individual scenarios.
5) "Novelty & Emergence Competence"	The ability to feel the difference between images of different versions of the future, to raise new, important questions that can open doors to new quests, to develop and accept unfamiliar situations, to explore new spaces and phenomena.
6) "Agency & Action Competence"	Knowledge of the connections between expectations, future images, and present action. Understanding the possibilities as well as the limitations of agency in the CAS. Identify strategies for different future images and develop roadmaps.

Source: authors, based on (Bergheim, 2024).

Advanced: Characteristic of those with strategic thinking who regularly update their knowledge of complexity theory, anticipation, foresight, and take part in strategic sessions.

Specialized: A small group of experts generating knowledge in the field of complexity science, anticipation, and foresight. They create new ways and methods of interacting with advanced systems and processes.

FL presented above has a logical connection with the multi-layer structure of the process of research into a multi-variant future (futures studies, FS) (Poli, 2021), reflected in Table 2. Each of the levels (layers) involves working with “known” and “unknown” aspects of the future. Thus, using these categories, one can explain the fundamental difference between forecasting and foresight. Forecasting is an attempt to “guess” the future, often based on the assumption that the future is a linear continuation of the present. In turn, the task of foresight is to outline different possible realistic options for the future, which forms the information basis for decision-making and strategy development, allowing one to avoid unwanted options and take steps toward the implementation of preferred options (Miller, 2018; Poli, 2017, 2019). Another key dimension that comes to the fore is the distinction between complex systems and CASs (Poli, 2013, 2017). The strategic environment of the 21st century is fundamentally different from the strategic environment of the 20th century, such that a truly complex organization requires a truly flexible structure to be resilient (McChrystal, 2019). This cannot be achieved without the majority of its members possessing FL.

When synthesizing these “contradictory” dimensions, a strategy of anticipation is developed, responsible for converting the accumulated knowledge base about the future into a roadmap of steps to implement preferred scenarios. In moving from the first layer to the fourth, and from known dimensions to unknown ones, the FL level is improved.

According to the works (Poli, 2021; Inayatullah, 2020), the development of FL as a competence is associated with the transition from less advanced to more advanced ways of using knowledge about the future. In this regard, the degree of aspiration to go beyond one’s current environment to new horizons and heights, to get rid of the rut trap, and transform the life track is of key importance. This ability is distributed very unevenly across spaces and cultural contexts and has few areas of concentration. The ways in which knowledge about the future is used (or not used) serve as the basis for its development. Knowledge about the future as a tool embedded in actions that thus take the form of a strategy has a fundamentally different value compared to simple abstract reflection (Shutz, 1967). In the most general terms, one can contrast “passive” and “active” orientation to the future.

In relation to the field of education, this means that a passive orientation is expressed in the persistent widespread motivation to receive an education only for the sake of knowledge, without setting a specific life or career goal. With this attitude, the future remains unarticulated, appears as an implicit background for the educational process and does not have the potential to become a resource for proactive use (Miller, 2015). In contrast to a passive approach, there are types of active orientation, where knowledge about the future is built into the educational process. Most often, an active orientation to the future is expressed in optimizing efforts to achieve goals, taking into account the environment and relationships with other people (Facer, 2016). Contextual optimization is based on an understanding of what to expect and how to use resources in accordance with the priorities. The future is seen as a background for making rational decisions, but the optimality of the choice can be judged, provided that the same set of criteria exists for evaluating all options. Optimization as a competitive advantage involves the acquisition of higher-order skills. However, various versions of "optimization" are becoming less and less viable options in today's turbulent world (Archer, 2013).

An effective alternative seems to be the development of educational programs based on work with contrasting scenarios and modeling immersion in unfamiliar experiences. Such conditions favor the development of innovative thinking and skills for recognizing new opportunities (Bloch, 1995; Poli, 2017). For this, safe learning spaces for experimenting with scenarios that have not yet been lived seem to be the optimal solution.

An additional factor of complexity in the process of FL formation is introduced by the diversity of intellectual traditions and practices of futures studies (Mangnus et al., 2021). Reflection on different modes of engagement with the future and an understanding of what these different approaches can offer for future-oriented action is recognized as fundamental to the development of FL. Different intellectual traditions and practices of futures studies make epistemologically different claims about the future and its manifestations in the present. Four main approaches were identified.

The first approach assumes that the future is at least partially known. The accompanying tools and methods consist of planning mechanisms and models to determine the probabilities of certain future events, including low-probability events with large-scale effects (wild cards), in order to mitigate risks.

The second approach starts from fundamental uncertainty about the future, favoring the conceptualization of several plausible forecast scenarios in order to test adaptive capabilities in these contexts. Methods such as quantitative modeling, scenario development, and horizon scanning are used.

The third way of engaging with the future aims to open alternative future paths through collective imagination using design, games, and other experimental and experiential interventions aimed at co-creating narratives.

The fourth, critical deconstruction, questions engagement with the "future". It asks how visions and ideas about the future are formed and how their political implications are assessed.

The approaches listed represent fundamentally different attitudes toward what it means to meaningfully engage with the future. Due to this diversity of attitudes toward the future and the different possible ways of engaging with it, the task of shaping FL turns out to be more difficult than it might seem at first glance. For example, confidence in the future is crucial for perceiving life as meaningful (Myllyniemi, 2017). The lack of a positive vision of the future can manifest itself, for example, in the choice of a suboptimal educational or career tracks, the growth of public fears, and other negative outlooks.

Thus, having FL depends on reflexivity regarding the different ways of interacting with the future and their effects. The interpretation of this concept always depends on the types of interventions currently carried out and on which pictures of the future are drawn (individually and collectively) and the ways of achieving them . Different practical results follow from this and there are grounds to speak about different levels of FL. The aforementioned four approaches to the future operate with different tools and practices, uniting people around specific images of the future and, accordingly, have different social functions. Some approaches open up more space for action, while others narrow this range (Stirling, 2008). Reflexive FL can contribute to raising awareness of different possible scenarios and

Table 2. **Multi-Layered Matrix of Futures Studies**

FS Levels	Futures Work Dimensions		Key Messages
	Known	Unknown	
Layer 4. Dance (Working with complex systems)	Studying complicated systems	Working with complex living adaptive systems	Learning to "dance" with complex adaptive systems
Layer 3. Ignorance (Working with incomplete data)	Risk assessment (events with a known probability of occurrence)	Delving into uncertainty (exploring possible events with an unknown probability of occurrence)	Ignorance is more relevant than knowledge (What we do not know is much more important than what we do know)
Layer 2. Deed (Focus on current activities)	Focus on mainstream trends (megatrends)	Exploration and identification of emerging processes, weak signals, potential jokers, and windows of opportunity	The future grows or shrinks according to our deeds (The chances of any scenario, whether desirable or undesirable, coming to fruition depend largely on our knowledge of them and the nature of the actions or inactions we take)
Layer 1. Action (Scanning the Future)	Forecasting	Foresight	Translation into action (The future is not predetermined, different scenarios for its implementation are possible)

Note: The layers are arranged in the matrix according to their hierarchy in relation to each other.
Source: authors, based on (Poli, 2021).

ways of realizing them. Reflexive forms of FL, regardless of approach, can deliberately and subtly guide future visions into a space of expanded possibilities. It is also possible to achieve an organic synthesis of different future regimes – "open" and "closed" – through interdisciplinary and transdisciplinary collaboration, especially if reflexivity takes on an institutional form.

The paper (Pouru-Mikkola, Wilenius, 2021) proposes the concept of transformative FL as a new paradigmatic framework for educational institutions, synthesizing the theories of transformative learning and FL. Transformative learning, based on a holistic approach, involves changing the frames of reference that determine the nature of people's interactions with the future. The goal is to develop a person's cognitive, motivational, and action-oriented abilities to interact with the future. "Frames of reference" describe the structures of assumptions through which life experience is understood: associations, concepts, values, feelings, and conditioned reactions (Mezirow, 1991). They shape and limit expectations, perception, cognition, and feelings. In the process of transformation, critical reflection on established interpretations and beliefs occurs.

FL development is based on the multidimensionality of human nature. For example, in the article (Ahvenainen et al., 2015), learning to work with the future is defined as a process that involves both rational and non-rational aspects of thinking, such as emotions and intuition. According to Gidley and Hampson (2005), FL training places excessive emphasis on the role of the cognitive dimension and the development of individual abilities. In turn, non-cognitive dimensions (empathic, creative, communicative, etc.) and collective learning are underrepresented, despite the fact that they also open up space for learning. The works (Rogers, Taff, 1996; Rogers, 1998) present a five-stage FL learning cycle, which was later used as an example of transformative learning (e.g. Siirilä et al., 2018; Sterling, 2010):

1. Cognitive: New knowledge acquisition, new ways of thinking, new perspectives.

2. Affective: Emotional responses to the newly gained knowledge, ranging from sorrow, despair, and anger to hope, acceptance, and courage.

3. Existential: Existential questioning of one's life, values and lifestyles caused by the two preceding phases.

4. Empowerment: Sense of personal empowerment and new clarity as one begins to consider how one can contribute to the future on a personal level.

5. Action: The sense of empowerment finds concrete manifestation in personal choices and social action for the building of a better future.

Thus, the combination of FL and transformative learning theories places a significant role in the learning experience of critically analyzing personal assumptions and emotions about the future, understanding new roles and perspectives, and finding ways to act upon new ideas.

FL Training – General Theoretical and Practical Considerations

FL labs are part of a limited portfolio of methods for working with "social complexity" (Aaltonen, 2009). They help people learn to engage creatively with the future and allow for ambiguity and self-organization (Bergheim, 2022). A large number of methods, grouped under the name "engineering approaches", rely on the ability of managers, experts, or researchers to understand, design, and control a system from the outside and to define clear rules. These include: environmental scanning, forecasting, text mining, roadmaps, scenarios and the "wheel of the future" (Aaltonen, 2009). Different methods used for different reasons in different situations require different methods of evaluation.

The educational process in most laboratories consists of four sequential stages (Bergheim, 2022), the overall goal of which is to make explicit and experiment with predictive models and assumptions.

Stage 1: "Reveal" (Phantom scenario). First, the student is asked to outline his *vision* of the future (phantom scenario). Then the reasons that made him assume such a course of events are revealed.

Stage 2: Reframe (Realistic Scenario): Students imagine the future through a lens that is fundamentally different from the phantom scenario, experimenting with a different set of assumptions.

Stage 3: "Rethink". The current context is viewed through the lens of the scenarios developed in the previous stages. New issues that were not previously recognized emerge.

Stage 4: "Action". The rehearsal of the action options developed in the three previous stages. Learning through action is carried out.

During the learning process, the necessary competencies are developed (the ability to work in teams, to form collective intelligence, to move through complexity and uncertainty in a state of certain stability, etc.) (Burns, 2015).

The second principle of the labs is to create collective intelligence, which allows students to experience different forms of perception and understanding, to better understand what they know and what they do not know, and to discover common patterns in complex processes. Rethinking transforms the mental-cognitive block. Different tools are used in this process. In some labs, educational sessions can be limited to a few hours, in others they stretch out over several days. Some labs work with a small number of participants, while others involve hundreds. Some labs prioritize Phase 2, which promotes increased creativity, while others touch on it only briefly. Some labs focus on identifying and developing new ways of doing things in Phase 4, while others deliberately conclude the learning process with Phase 3 and rely on the energy of the participants to continue working independently with the new ideas identified after the lab session.

FL training is the training of teachers with the relevant competencies. The work (Kazemeir et al., 2021) presents a case study of the implementation of such an educational program. An assessment was made of the extent to which participants acquired three FL qualities that the program aimed to develop: improved perception of the future, acceptance of complexity, and a new sense of agency. The perceived value of the instructional strategies and program design was examined by the participants. All participants reported developing one or more FL qualities and noted the supporting role of the instructional strategies and program design. The need for additional research was identified to determine the content of the skills that make up FL and their assessment, taking into account the importance of such factors as students' personality traits, and their previous experience with the future.

Improving perceptions about the future is linked to the problem of people getting stuck in their "normalized" ways of thinking and acting, which are often taken for granted. A blind spot arises in relation to these factors that influence the nature of judgments and limit internal potential (Wals, Peters, 2017). People generally have difficulty expanding their imaginations toward emergent possibilities and transcending the limitations of ingrained assumptions about what is possible and probable now and in the future (Bell, 2002). The idea of the future is also influenced by subjective emotions and experiences, and by the views, values, and opinions shared in society (Rubin, 1998). The ability to think about the future is manifested in action: images and assumptions about the future influence actions in the present, which in turn contribute greatly to the shape that the future begins to take.

The development of FL seems to be one possible way out of this impasse. By abandoning the focus on forecasting and planning and instead diversifying the ways of seeing the world, it is possible to overcome anxiety about change and accept uncertainty and novelty as resources for development (Larsen et al., 2020; Nelson, 2019). FL thus allows one to embrace complexity, act in new and improved ways, and move beyond one's comfort zone (Damhof et al., 2020). Thus, in order to modernize the educational program on FL, one of the FL laboratories in Hansa (Germany) implemented a three-module teacher development program called Mastering Futures Literacy (MFL) in 2019. Each module addressed the task of developing one of the three FL qualities outlined above – improving the perception of the future, accepting complexity and gaining a new sense of subjectivity (from the performing approach to the transformative one). The idea was based on the idea of the gradual development of FL: the process begins with an improved perception of the vision of the future and the other two learning effects follow from this and can be intertwined. When the perception of the world changes, complexity and uncertainty cease to be a challenge. The design of the program was built in such a way that the participants felt like a community sharing common meanings. In this way, they gained the potential for integration into a wider network of FL training organizers (Kazemier et al., 2021). Following the training, university teachers expressed a commitment to creating spaces for experimenting with different futures in different contexts and building FL capacity in the wider community. Such initiatives are intended to contribute to the transformation of the established higher education system, as FL training goes beyond the incremental innovation processes and external quantitative assessment measures that dominate it. This increases the potential of the higher education sector to respond to large-scale and complex societal challenges.

Collaboration between Companies and Universities in the Formation of FL

There are expanding dynamics of cooperation between companies and universities in the development of FL. Companies from different sectors, mastering FL together with universities, create a knowledge spillover effect that enhances the educational potential of the latter and expands opportunities for experimental learning. One of the tools actively used in the corporate educational environment is scenario planning. Of interest is the teaching practice at Oxford University (UK) (Ramirez et al., 2021). The training takes place on "live" cases related to real strategic problems faced by one of the participant learning groups. Live cases are flexible learning tools for exploring the future through scenario planning. One of the skills acquired here is the ability to identify the real deep roots of a persistent problem. Through a collaborative search, the members of the study group discover the "question behind the question," which leads to a breakthrough solution.

The work (Toivonen et al., 2021) is also worth attention, since it assesses how the use of different teaching methods affects FL proficiency in the context of Finland and Sweden. Four student test groups (373 participants) took part in special training programs on work-

Table 3. **Description of Thematic Categories for the Distribution of FL Assessment Criteria**

Component	Functions for working with images of the future
Forecasting	Focus on generalized forecasts of imaginary futures based on extrapolations from the past.
Fate	Specific and unique imaginary futures based on fatalistic stories or entrenched myths.
Creative reform	Use of imaginary futures to solve known problems in innovative ways.
Self-improvement	Imaginary futures oriented toward the appreciation of process and ephemerality, with endogenous creativity.
Strategic thinking	Imaginary futures to perceive and make sense of the emergence of phenomena in the present, focused on repetitive phenomena.
Tao-being wisdom	Imaginary futures to make sense of the emergence of phenomena in the present, focused on unique and locally specific attributes.

Source: authors, based on (Miller, 2018).

ing with the future. Two groups tested the "wheels of the future" method, the third — the development of scenarios, while the fourth limited itself to listening to theoretical material. The task was to achieve three levels of FL "awareness – discovery – choice" (Miller, 2007, 2012), the result of which is the growth of the potential of transformative subjectivity. The testing of acquired knowledge and skills showed different levels of effectiveness for the different methods. As a rule, achievement of higher levels of FL was declared by those who were involved in more practice-oriented methods. At the same time, additional difficulties and limitations were noted in the implementation of the methods of "scenario planning" and the "wheel of the future" in decision-making practice. The following were noted: the high complexity of working with the future, deep involvement, and a weak understanding of how to operate the results. The findings of this study are equally useful for university teachers and companies seeking to establish more constructive interactions with local communities.

The literature review demonstrates existing proposals and approaches for the use of FL. However, before embarking on educational projects in this direction, the contextual features of the initial attitude of prospective students toward the future should be carefully studied. The development of FL is seen as a guarantee that company and university projects will have social significance and comply with the principles of sustainable development. The need to assess the initial level of FL in students is emphasized so that training programs can be planned more effectively, taking into account many aspects (Mangnus, 2021). Although the cases presented in the aforementioned works (Kazemier et al., 2021) and others demonstrate sufficient signs of development of the target competencies, the research tools used by their authors are not able to provide an objective assessment of the degree of acquisition of FL skills, since all the conclusions made are based on the opinions of the respondents themselves. The need to develop an objective multi-criteria tool for assessing the acquisition of FL skills by students to improve the effectiveness of educational programs is the purpose of our study.

Methodology

The main objective of the study is to contribute to standardizing the measurement of the starting level of FL in students, with which work will be carried out to increase it. Such a tool will be relevant for anyone engaged in futures research and especially those who implement educational projects in this direction. For this purpose, a questionnaire was circulated, the questions of which were grouped according to the six components of FL identified in the work (Miller, 2018) (Table 3). UNESCO's developments in the creation of educational laboratories in this area were used (Miller, 2018; Bergheim, 2024a). The questionnaire was validated by nine academic experts in the field of futures studies. The results were analyzed using Aiken statistics (Aiken, 1985). On this basis, adjustments were made to the questions.

It was pilot tested on a sample of students from a state university in Mexico. The survey involved 256 students over the age of 17 years old as shown in Table 4. Of the total number of respondents, more than two thirds (173 people) were women, which indicates their increased interest in the proposed questionnaire.

The questions were distributed into six FL categories and are presented in Table 5. Respondents were asked to choose one of five answer options to assess the probability – an indicator of the degree of their confidence in the answer: maximum, high, medium, low, and minimum. A five-point Likert scale was used to measure the answers. The questionnaire was carried out with using the Microsoft Forms web application.

Results

The next research stage consisted of the assessment of the statistical reliability of the answers obtained using exploratory factor analysis (Hair et al., 2019), KMO tests (Kaiser, 1974) and Bartlett (1954) and Cronbach's alpha coefficient calculations. Data processing was carried out using the statistical software package SPSS. To describe the results of the analysis, a set of factor and structural matrices was constructed.

Table 4. **Frequencies - Age and Gender of the Respondents**

a) Age

Valid	Frequency	Percentage	Valid Percentage	Cumulative Percentage
	3	1.2	1.2	1.2
17	20	7.8	7.8	9.0
18	61	23.8	23.8	32.8
19	44	17.2	17.2	50.0
20	38	14.8	14.8	64.8
21	38	14.8	14.8	79.7
More than 21 years	52	20.3	20.3	100.0
Total	256	100.0	100.0	

b) Gender

Valid	Frequency	Percentage	Valid Percentage	Cumulative Percentage
	3	1.2	1.2	1.2
Man	79	30.9	30.9	32.0
Woman	173	67.6	67.6	99.6
Not specified	1	0.4	0.4	100.0
Total	256	100.0	100.0	

Source: authors.

In total, six main factors were analyzed, in which group elements related to different sub-competencies. FL (the ability evaluate future scenarios, make decisions under conditions of uncertainty, "play ahead", etc.).

Trends in the responses of the surveyed students were identified using descriptive statistics. The values of the Cronbach's alpha coefficient in all cases were greater than 0.8, which reflects the high reliability of the selection of aspects characterizing competence and FL. They can be considered a guarantee that the wording of questions in each group describing the corresponding FL component correlates, measuring similar constructs.

Exploratory factor analysis (EFA) was conducted using maximum likelihood with Oblimin oblique rotation and Kaiser normalization. Results are reflected in Table 6.

The structural matrix presented in Table 7 demonstrates the general correlations between the items and their underlying factors. Its components reflect a significant correlation with the expected factors, confirm-

Table 5. **Survey Questions and their Distribution by FL Categories**

Forecast
R1. Do you use statistical, historical, or context information to evaluate options before making important decisions related to your career? R2. Do you keep up to date with information or the latest trends and advances in your field of study? R3. Do you know how to identify trends that could impact your future career? R4. Do you know how to identify early alerts/signals about significant changes in your field of study?
Destiny
R5. Do you believe that there is a single future in which people's events or actions are predetermined? R6. Do you believe that there is an order and destiny of things that cannot be changed? R7. Do you think that no matter what is done, the conclusion of the world will be the same?
Creative Reform
R8. Are you capable of planning projects in the present considering their results in the medium or long term (10 or more years in the future)? R9. Do you conceptualize futuristic ideas and express them through models, prototypes, or other creative means to facilitate their understanding in the present and their results in the future? R10. Do you use scenarios to transform your ideas about the future into actions that help solve current problems?
Self-Improvement
R11. Are you willing to take on additional responsibilities to advance your goals? R12. Do you strive to set ambitious and meaningful goals in your academic and professional life? R13. Do you take the initiative to address situations before they become problems? R14. Do you actively seek opportunities in your field of study or work rather than waiting for them to rise? R15. Do you think of innovative solutions to problems in your academic or professional life?
Strategic Thinking
R16. Do you use short, medium, and long-term goals for your professional and personal future? R17. Do you use strategies to identify and take advantage of future opportunities in your field of study? R18. Do you anticipate possible problems and take preventive measures in your studies or work? R19. Do you consider the medium and long-term consequences of your current actions and decisions in relation to your career? R20. Do you have contingency plans in case you have to face unexpected changes in your academic or professional life?
Wisdom-Tao-Being
R21. Are you able to identify possible challenges or changes in your academic or professional environment before they occur? R22. How perceptive are you of emerging events in your environment to associate them with future events that could impact your field of study or work? R23. Do you believe you are prepared to face local challenges with global awareness in a proactive way in your area of study or work?
Source: authors.

Table 6. **KMO and Bartlett's Test**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.903
Bartlett›s Test of Sphericity	Approx. Chi-Square	1950.695
	df	253
	Sig.	0.000

Source: authors.

ing the validity of the proposed tool structures. The items with the highest correlation are related to questions R19–21, which showed a strong positive correlation with Factor 1 (loadings of 0.776, 0.639 and 0.625 respectively). There is reason to believe that these items reliably reflect the theoretical dimension represented by the mentioned factor.

On the contrary, some items also present negative loadings (e.g., R21 with Factor 3, loading of -0.439), which indicates inverse relationships between some items and non-dominant factors.

At the same time, the pattern matrix (See Table 8) was key to understanding the pure loadings between items and factors, excluding indirect influences from other factors. This matrix made it possible to clearly identify which items are more strongly related to each factor, disregarding possible cross-influences from other factors. For example, item R6 showed a strong loading on Factor 2 (0.824), confirming its direct association with it. In contrast, some items such as R12 presented more complex factor loadings, showing both a strong negative relationship with Factor 3 (-0.772) and a moderate positive one with other factors, which may suggest the need to revise this item or its interpretation in further studies.

Each factor is composed of items that correlate coherently, which confirms the validity of the structure initially proposed in the theory. However, some items presented minor cross-loadings with more than one factor, suggesting the need for further revisions or the refinement of the questionnaire in future studies.

The variables are grouped into three factors that according to the proposed literature review can be named as follows: F1 (specific knowledge), F2 (scalable knowledge), and F3 (awareness of the future).

Discussion and Conclusions

Previous studies in the FL area, for example (Kazemier et al., 2021; Pouru-Mikkola, Wilenius, 2021), emphasized the need to develop educational tools that promote long-term thinking in university contexts. In response to this need, our study proposes an innovative approach to identifying and standardizing the assessment of students' FL competence. Statistical computing confirms the reliability of the questionnaire we developed to measure the level of FL in students, since

Table 7. **Structure Matrix**

	Factors					
	1	**2**	**3**	**4**	**5**	**6**
R21	0.776	0.312	–0.439	0.517	0.236	
R19	0.639		–0.447	0.385	0.229	0.443
R20	0.625		–0.36	0.292		0.159
R18	0.623	0.212	–0.497	0.455	0.219	0.383
R22	0.6	0.217	–0.399	0.523	0.221	
R23	0.504	0.2	–0.386	0.501	0.224	
R6	0.13	0.824		0.134	–0.12	0.114
R7		0.631			0.399	–0.162
R5	0.178	0.595		0.192	0.161	
R12	0.394		–0.772	0.388	0.176	0.329
R11	0.346		–0.763	0.371	0.19	0.326
R13	0.47	0.132	–0.654	0.445		0.108
R17	0.541	0.178	–0.614	0.439	0.531	0.336
R14	0.516	0.168	–0.602	0.406	0.308	0.109
R15	0.566	0.222	–0.583	0.472	0.183	0.252
R16	0.462	0.127	–0.527	0.369	0.484	0.414
R4	0.372	0.212	–0.433	0.694	0.271	0.124
R3	0.383		–0.427	0.643	0.177	0.141
R9	0.44	0.331	–0.348	0.571	0.281	0.192
R1	0.295		–0.273	0.567	–0.174	0.183
R2	0.301		–0.301	0.522		0.109
R8	0.47	0.174	–0.359	0.482	0.311	0.154
R10	0.38	0.119	–0.536	0.395	0.134	0.586

Extraction Method: Maximum Likelihood. Rotation Method: Oblimin with Kaiser Normalization.
Source: authors.

Table 8. **Pattern Matriax**

	Factors					
	1	**2**	**3**	**4**	**5**	**6**
R21	0.681	0.124		0.141		–0.158
R20	0.655					
R19	0.551	–0.108				0.314
R18	0.426		–0.112	0.102		0.247
R22	0.420			0.277		
R6		0.890			–0.281	0.173
R7		0.597		–0.176	0.311	–0.115
R5		0.566				
R11			–0.775			
R12			–0.763			
R13	0.155		–0.605		–0.196	–0.125
R14	0.223		–0.451		0.144	
R15	0.285	0.110	–0.335	0.114		
R4				0.660	0.180	
R3			–0.112	0.586		
R1				0.571	–0.243	
R2				0.488		
R9	0.114	0.204		0.456	0.168	0.103
R8	0.232			0.317	0.210	
R23	0.283			0.306		–0.139
R17	0.188		–0.318		0.394	0.166
R16	0.155		–0.228		0.377	0.284
R10			–0.285	0.122		0.465

Extraction Method: Maximum Likelihood. Rotation Method: Oblimin with Kaiser Normalization.
Source: authors.

it ensures the high accuracy of coverage of the competence in question. Exploratory factor analysis (EFA) and reliability calculations using Cronbach's alpha testify to the high consistency of the components of the proposed assessment tool.

In particular, the results of the factor analysis confirm that the proposed six theoretical dimensions of FL are a relevant basis for the design of corresponding university programs. It is shown that working with images of the future is not just an abstract ability, but a competence subject to assessment through a rigorous approach (Miller et al., 2018; Karlsen, 2021).

Through the EFA, clear groupings of the elements of FL across six main factors indicate that sub-competencies ("foresight", "evaluation of future scenarios", and "decision making under uncertainty", etc.) can be assessed independently of one another. The high correlations between the items and their corresponding factors, reflected in the structural matrix, confirm the structural validity of the proposed instrument. However, some items show minor cross - loadings with more than one factor, indicating the need for further revision to improve content clarity and theoretical coherence. Items with negative loadings on non-dominant factors, such as item 21 in Factor 3, require in-depth consideration to determine whether they need to be reformulated or excluded from the questionnaire.

To further validate the structure we have identified, it is advisable as part of further research to conduct confirmatory factor analysis (CFA). Thus, the assessment of the potential for reproducibility of the proposed theoretical factors in the different samples of respondents will become more substantiated, due to which the generalizability of the instrument will be demonstrated.

Developing and testing the submitted questionnaire contributes not only to the field of futures studies, but also offers a new assessment tool for universities. The ability to measure the initial level of FL in students will allow for the development of more effective educational programs to develop this increasingly in-demand skill.

References

Aaltonen M. (2009) Evaluation and Organization of Futures Research Methodology — Version 3.0. In: *Futures Research Methodology — V3.0* (eds. J.C. Glenn, T.J. Gordon), Washington, D.C.: The Millennium Project.

Ahvenainen M., Jokinen L., Korento K., Ollila J. (2015) Learning for the future - thinking ahead. *Futura,* 46–53, 2/2015 (in Finnish).

Aiken L.R. (1985) Three coefficients for analyzing the reliability and validity of ratings. *Educational and Psychological Measurement*, 45(1), 131–142. https://doi.org/10.1177/0013164485451012

Archer M.S. (2013) *The reflexive imperative in late modernity,* Cambridge: Cambridge University Press.

Bartlett M.S. (1954) A Note on the Multiplying Factors for Various χ2 Approximations. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 16(2), 296–298. Available at: https://doi.org/10.1111/j.2517-6161.1954.tb00174.x

Bell W. (2002) Foreword. In: *Lessons for the future: The missing dimension in education* (ed. D. Hicks), London: Routledge-Falmer, pp. 11–16.

Bergheim S. (2022) *On the Evaluation of Futures Literacy Laboratories*, Frankfurt am Main: Center for Societal Progress.

Bergheim S. (2024) *On the Competence of Futures Literacy*, Frankfurt am Main: Center for Societal Progress.

Birkinshaw J., Lecuona R., Barwise P. (2016) The relevance gap in business school research: Which academic papers are cited in managerial bridge journals? *Academy of Management Learning and Education*, 15 (4), 686–702. https://doi.org/10.5465/amle.2015.0282

Bloch E. (1995) *The principle of hope* (3 vols.), Cambridge, MA: The MIT Press.

Burns A. (2015) Action Research. In: *Handbook of Research in Second Language Teaching and Learning* (ed. E. Hinkel), New York: Routledge, pp. 187–204.

Costigan R.D., Brink K.E. (2015) Another perspective on MBA program alignment: An investigation of learning goals. *Academy of Management Learning and Education,* 14(2), 260–276. http://dx.doi.org/10.5465/amle.2013.0315

Damhof L., Kazemier E., Gulmans J., Cremers P., Doornbos A., Beenen P. (2020) Anticipation for emergence: Defining, designing and refining futures literacy in higher education. In: *Humanistic futures of learning: Perspectives from UNESCO Chairs and UNITWIN Networks* (ed. S. Joseph), Paris: UNESCO, pp. 168–171.

Doh J.P., Stumpf S.A. (2007) Executive education: A view from the top. *Academy of Management Learning and Education*, 6(3), 388–400. http://dx.doi.org/10.5465/AMLE.2007.26361628

Ehlers U.D. (2020) *Future Skills — Future Learning and Future Higher Education*, Heidelberg, Dordrecht, London, New York: Springer.

European Commission (2019) *Key competences for lifelong learning,* Brussels: European Commission.

Facer K. (2016) Using the future in education: Creating space for openness, hope and creativity. In: *The Palgrave international handbook of alternative education* (eds. H. Lees, N. Noddings), London: Palgrave McMillan, pp. 63–78.

Gidley J.M., Hampson G.P. (2005) The evolution of futures in school education. *Futures*, 37(4), 255–271. https://doi.org/10.1016/j.futures.2004.07.005

Hair J.F., Babin B.J., Anderson R.E., Black W.C. (2019) *Multivariate Data Analysis* (8th ed.), England: Pearson Prentice.

Inayatullah S. (2020) A castle surrounded by hungry wolves: Toward a stage theory of the uses of the future. *World Futures Review*, 12(1), 40–54.

Kaiser H.F. (1974) An index of factorial simplicity. *Psychometrika,* 39(1), 31–36. https://doi.org/10.1007/BF02291575

Karlsen J.E. (2021) Futures literacy in the loop. *European Journal of Futures Research*, 9(1), 17. https://doi.org/10.1186/s40309-021-00187-y

Kazemier E.M., Damhof L., Gulmans J., Cremers P.H.M. (2021) Mastering futures literacy in higher education: An evaluation of learning outcomes and instructional design of a faculty development program. *Futures,* 132, 102814. https://doi.org/10.1016/j.futures.2021.102814

Lalot F., Ahvenharju S., Minkkinen M., Wensing E. (2020) Aware of the Future?: Development and Validation of the Futures Consciousness Scale. *European Journal of Psychological Assessment*, 36(5), 874–888. http://dx.doi.org/10.1027/1015-5759/a000565

Larsen N., Mortensen K.J., Miller R. (2020) *What is Futures Literacy and why is it important?*. https://medium.com/copenhageninstitute-for-futures-studies/what-is-futures-literacy-and-why-is-it-important-a27f24b983d8, accessed 19.11.2024

Louie A. (2010) Robert Rosen's Anticipatory Systems. *Foresight*, 12(3), 18–29. https://doi.org/10.1108/14636681011049848

Mangnus A.C., Oomen J., Vervoort J.M., Hajer M.A. (2021) Futures literacy and the diversity of the future. *Futures,* 132, 102793. Available at: https://doi.org/10.1016/j.futures.2021.102793

McChrystal S. (2019) *Team of teams*, New York: Penguin.

Mezirow J. (1991) *Transformative dimensions of adult learning*, San Francisco: Jossey-Bass.

Miller R. (2018) *Transforming the Future. Anticipation in the 21st Century,* London: Routledge.

Miller R. (2007) Futures Literacy: A Hybrid Strategic Scenario Method. *Futures,* 39, 341–362. https://doi.org/10.1016/j.futures.2006.12.001

Miller R. (2012) Anticipation: The discipline of uncertainty. In: *The future of futures*, Washington, D.C.: Association of Professional Futurists, pp. 39–43.

Miller R. (2015) Learning, the future, and complexity. An essay on the emergence of futures literacy. *European Journal of Education*, 50 (4), 513–523. https://doi.org/10.1111/ejed.12157

Moules J. (2020) FT Executive Education Rankings 2020: Analysis amid the Pandemic. *Financial Times,* 10.05.2020. https://www.ft.com/content/1c3f4b42-8172-11ea-b6e9-a94cffd1d9bf, accessed 10.12.2024

Myllyniemi S. (2017) *Youth Barometer 2016,* Helsinki: Ministry of Education and Culture.

Nadin M. (2012) Prolegomena — What Speaks in Favor of an Inquiry into Anticipatory Processes? In: *Anticipatory systems: Philosophical, mathematical and methodological foundations* (ed. R. Rosen), Heidelberg, Dordrecht, London, New York: Springer, pp. 19–60.

Nelson C. (2019) Interview with Riel Miller by Clair Nelson. In: *Human futures* (ed. E. Overland), Washington, D.C.: World Futures Studies Federation, pp. 37–44.

OECD (2018) *The OECD Survey of Adult Skills is the jewel in the crown of its Programme for the International Assessment of Adult Competencies (PIAAC)*, Paris: OECD.

OECD (2023) *21st Century competencies,* Paris: OECD.

Polak F. (1973) *The Image of the Future,* London: Elsevier.

Poli R. (2013) A note on the difference between complicated and complex social systems. *Cadmus,* 2(1), 142–147.

Poli R. (2017) Social time as a multidimensional category. *World Futures Review,* 9(1), 19–25.

Poli R. (2019) *Working with the future,* Milan: Bocconi University Press.

Poli R. (2021) The challenges of futures literacy. *Futures,* 132, 102800. https://doi.org/10.1016/j.futures.2021.102800

Pouru-Mikkola L., Wilenius M. (2021) Building individual futures capacity through transformative futures learning. *Futures,* 132, 102804. https://doi.org/10.1016/j.futures.2021.102804

Ramírez R., Rowland N.J., Spaniol M.J., White A. (2021) Avoiding the valley of death in educating strategists. *Long Range Planning,* 54(3), 102000. https://doi.org/10.1016/j.lrp.2020.102000

Rogers M. (1998) Student responses to learning about futures. In: *Futures education. World yearbook of education 1998* (eds. D. Hicks, R. Slaughter), London: Kogan Page, pp. 203–216.

Rogers M., Tough A. (1996) Facing the future is not for wimps. *Futures,* 28(5), 491–496. https://doi.org/10.1016/0016-3287(96)00021-3

Rosen R. (1991) *Life itself: A comprehensive inquiry into the nature, origin, and fabrication of life*, New York: Columbia University Press.

Rubin A. (1998) *The images of the future of young Finnish people,* Turku: Publications of the Turku School of Economics and Business Administration.

Schütz A. (1967) *The Phenomenology of the Social World,* Evanston, IL: Northwestern University Press.

Siirila J., Laininen E., Tikkanen J., Salonen A.O., Pantsar T. (2018) Transformative learning in the Anthropocene era. *Journal of Professional Education*, 20(5), 39–56 (in Finnish).

Spanjol J., Rosa A., Schirrmeister E., Dahl P., Domnik D., Lindner M., de la Cruz M., Kuhlmann J.F. (2023) The potential of futures literacy for impact-oriented business schools. *Futures,* 146. Available at: https://doi.org/10.1016/j.futures.2022.103084

Sterling S. (2010) Transformative Learning and Sustainability: Sketching the Conceptual Ground. *Learning and Teaching in Higher Education*, 5, 17–33.

Toffler A. (1970) *The Future Shock,* New York: Random House.

Toivonen S., Rashidfarokhi A., Kyrö R. (2021) Empowering upcoming city developers with futures literacy. *Futures,* 129, 102734. https://doi.org/10.1016/j.futures.2021.102734

Vygotsky L.S., Cole M., Jolm-Steiner V., Scribner S., Souberman E. (1978) *Mind in Society: Development of Higher Psychological Processes*, Cambridge, MA: Harvard University Press.

Wals A.E.J., Peters M.A. (2017) Flowers of resistance: Citizen science, ecological democracy and the transgressive education paradigm. In: *Sustainability Science* (1st ed.), New York: Routledge, pp. 29–52.

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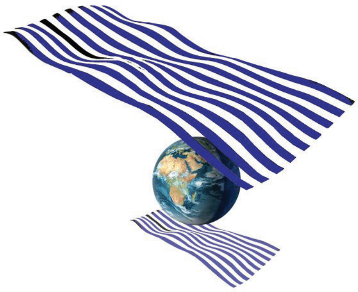

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