# Enhancing Strategy Planning Using AI

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## Abstract

A productive approach to integrating strategic Foresight and machine learning is the Generalized Strategic Foresight Model embedding MLOps (GSF(M)²), a unified governance architecture that combines the interpretive depth of long-term scenario-based Foresight with the adaptivity of real-time machine learning pipelines. The model addresses structural deficiencies in existing decision-making systems, where Foresight methods generate anticipatory insights but lack operationalization mechanisms, while machine learning algorithms automate processes but ignore strategic and participatory context as well as socio-organizational specificity. A systematic literature review following PRISMA methodology (16 publications in each block—Foresight and machine learning lifecycle) identified methodological gaps in both fields when compared against reference architectures. GSF(M)² synthesizes the strengths of both approaches by embedding Foresight logic into adaptive machine learning processes and integrating automated feedback loops into scenario planning. The result is a continuously learning ecosystem that recalibrates scenarios, model parameters, and strategic options in real time. The synthesis of anticipatory analytics, continuous horizon scanning, and data-driven prioritization enhances policymaking effectiveness and institutional agility under conditions of international and technological uncertainty. GSF(M)² represents the first dual-core framework for the co-evolution of strategic Foresight and adaptive algorithms within a unified reflexive governance architecture.

**Keywords:** strategic foresight; scenario planning; MLOps; governance models; anticipatory systems; continuous learning; adaptive decision-making; automation pipelines; uncertainty analysis; policy intelligence.

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## Introduction

Contemporary governance systems operate in an environment shaped simultaneously by accelerating technological innovation, deep geopolitical restructuring, and increasingly complex socio-economic interdependencies. Public and private decision-makers face conditions of volatility, uncertainty, and rapid change that continuously erode the relevance of static planning frameworks. As strategic horizons shrink and information ecosystems expand, institutions struggle to anticipate emerging disruptions while remaining responsive to real-time developments. This tension has exposed the limitations of traditional foresight practices on one side and data-driven algorithmic systems on the other.

Strategic foresight — rooted in systemic inquiry, actor analysis, and scenario construction—provides powerful cognitive and organizational tools for navigating uncertainty. Yet despite its conceptual richness, it remains predominantly qualitative and episodic, lacking a sustained mechanism for bridging long-term anticipatory insights with continuous operational adaptation. Conversely, the rise of Machine Learning Operations (MLOps) has transformed predictive modeling through automation, traceability, and continuous retraining. MLOps enables agile, data-centric decision support, but typically functions without strategic framing, participatory grounding, or interpretive depth. These two fields evolve in parallel, each demonstrating maturity where the other shows structural limitations, but they rarely intersect.

This article addresses this gap by proposing the Generalized Strategic Foresight Model embedding MLOps — GSF(M)$^2$, a hybrid, dual-core architecture that fuses foresight's proactive orientation with the pre-active adaptivity of MLOps. Using a PRISMA-based systematic literature review, the study identifies the methodological discontinuities within both fields and demonstrates that their complementarities form the basis for an integrated, continuously learning governance framework. GSF(M)$^2$ transforms foresight into a dynamic, data-responsive system and, reciprocally, endows MLOps pipelines with strategic coherence, ethical framing, and contextual intelligence.

Building on this foundation, the article develops a structured model consisting of two layers:

1. a nine-step foresight architecture inheriting the systemic rigor of the French prospective school (figure 1)
2. a technical implementation pipeline leveraging the $A_1$–$D_2$ MLOps lifecycle (Figure 2).

Together, these layers create a closed-loop decision system capable of scenario generation, automated learning, continuous monitoring, strategic recalibration, and action planning.

The objective of the study is therefore twofold:

- to conceptualize a hybrid governance architecture uniting human interpretive intelligence and machine-driven adaptivity, and
- to demonstrate how this integration resolves the structural misalignment between long-term strategic anticipation and real-time operational responsiveness.

The following sections present the literature review, the methodological approach, the structural modeling of GSF(M)$^2$, and finally, its innovative contributions, limitations, and prospective avenues for comparative global application.

## Literature review

### *Strategic Foresight Stream*

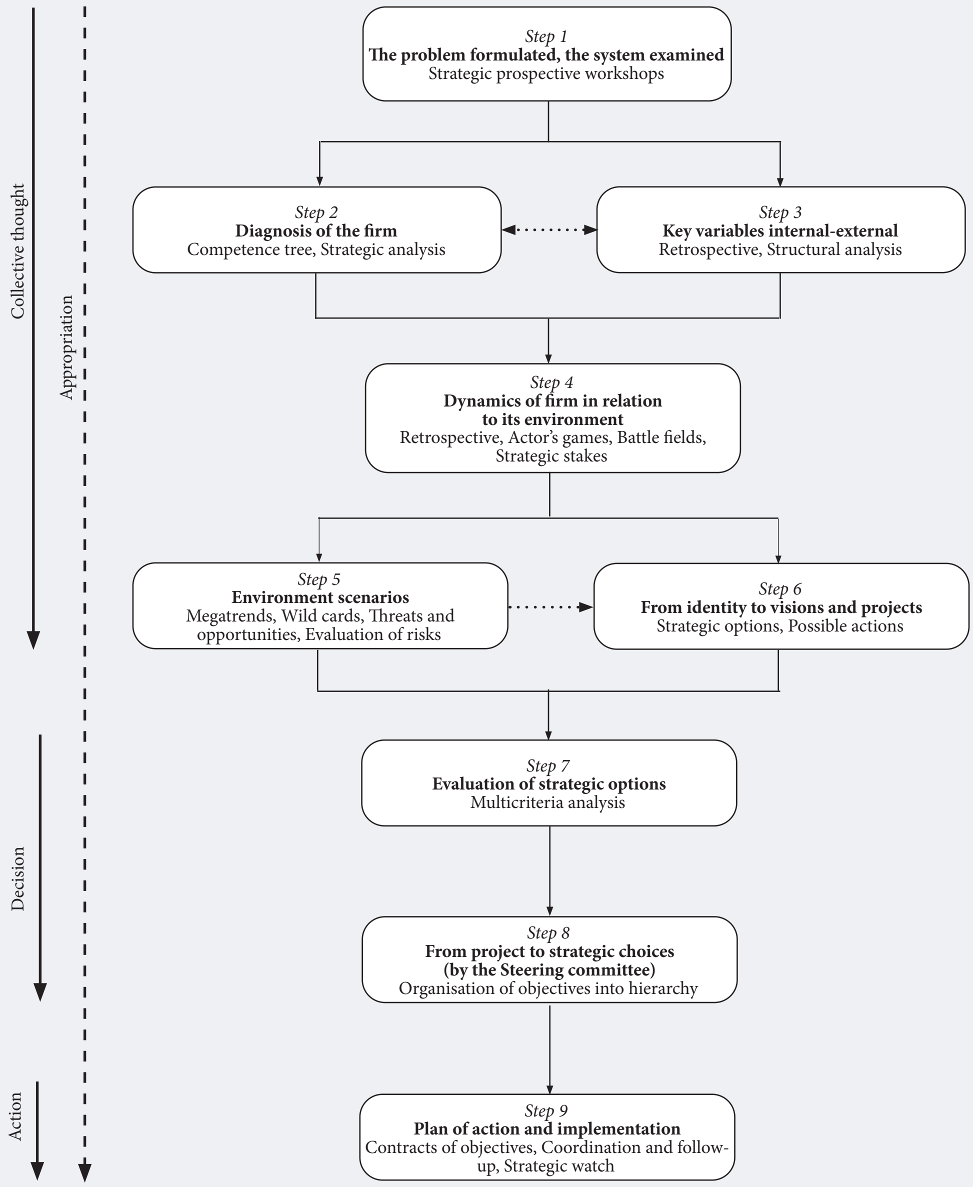
The foresight literature reviewed through the PRISMA 2020 methodology, comprising sixteen validated studies, forms a structured corpus that converges around the French "prospective" school and scenario planning approaches. The foundational layer of this corpus originates from seminal works (Godet, 2001; Godet, Durance, 2011; Durance, Godet, 2010), which define the epistemology of prospective thinking and emphasize systemic structuring, variable analysis, and stakeholder mapping. These studies collectively establish scenario planning as a disciplined and rule-based method for reducing uncertainty and designing long-term strategic options.

A second layer of methodological expansion emerges in later systematic reviews and theoretical developments (Amer et al., 2013; Varum, Melo, 2010; Ramírez et al., 2017; Burt, Nair, 2020; Cordova-Pozo, Rouwette, 2023; Kobes, Loy, 2020; MacKay, Stoyanova, 2017; Chermack, 2018), which diversify scenario typologies, integrate sociological insights, and assess the validity of existing foresight approaches. These contributions converge on the notion that scenario planning must balance conceptual creativity with methodological consistency, thereby reinforcing prospective analysis as a strategic learning device. They also introduce concerns regarding scenario quality, cognitive biases, and organizational embedding — elements crucial to the operational relevance of foresight.

A final subset of studies (Vecchiato, 2012; Ramírez, Wilkinson, 2016; Sossa et al., 2021; Abuzaid, 2018; von der Gracht, 2023) tests foresight concepts empirically, providing evidence that scenario-based methods enhance organizational resilience, strategic agility, and reframing capacities. These works illustrate how scenarios function not only as anticipatory tools but as mechanisms for collective sensemaking and decision structuring. However, despite this empirical grounding, the literature tends to remain descriptive in its treatment of later foresight phases, particularly those related to decision-making, strategic choice, and implementation.

Across the sixteen studies, alignment with PRISMA items (3–20) shows consistent methodological transparency, although the corpus exhibits a clear imbalance: conceptual and exploratory steps (problem framing, structural analysis, scenario generation) are richly documented, while downstream operational steps (evaluation, decision, action, monitoring) are sparsely addressed. This gap indicates that foresight research excels in generating insight but lacks frameworks for embedding those insights into dynamic, iterative governance mechanisms. The approach of (Godet, Durance, 2011) remains the most complete methodological anchor, providing a structured nine-step prospective model that integrates diagnostic and projective elements. This model constitutes the proactive cognitive nucleus upon which GSF(M)$^2$ builds its anticipatory dimension.

Figure 1. **Strategic Planning using Scenarios: An Integrated Approach (Godet, Durance, 2011)**



*Source*: (Godet, Durance, 2011).

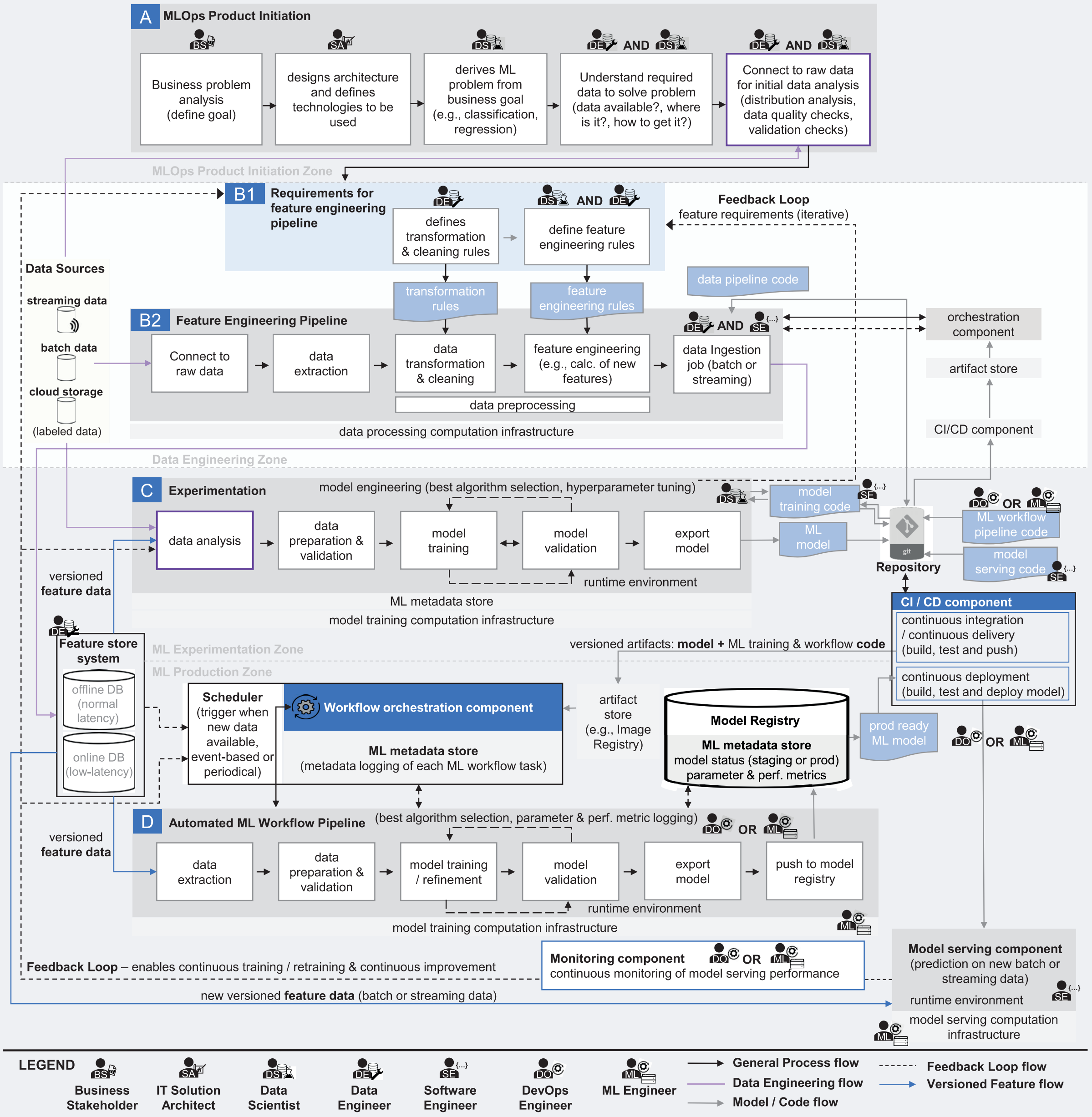
### *MLOps Stream*

The sixteen studies forming the MLOps literature review depict the evolution of the field from conceptual definitions to robust engineering frameworks. The foundational cluster (Kreuzberger et al., 2023; Najafabadi et al., 2024; Eken et al., 2024; Symeonidis et al., 2022) clarifies the architecture, tool taxonomy, and end-to-end lifecycle structure of MLOps systems, offering blueprints that integrate data pipelines, experimentation workflows, and deployment processes. These works collectively propose a unified architecture that supports full automation of the machine-learning lifecycle and aligns technical design with reliability, traceability, and reproducibility.

A second group of contributions focuses on maturity models, organizational factors, and governance (Lima et al., 2022; Zarour et al., 2025; Stone et al., 2025; Mehmood et al., 2024). These studies highlight the increasing recognition of MLOps as a managerial and socio-technical discipline, moving beyond pipelines to incorporate quality assurance, risk management, and lifecycle oversight. They observe that successful MLOps adoption depends not only on tools but on organizational culture, process standardization, and cross-functional collaboration.

A third set of works (Berberi et al., 2025; Faubel, Schmid, 2024; Hanchuk, Semerikov, 2024; Reich, 2024; Subramanyam, 2022; John et al., 2025; Araujo et al., 2024) addresses operationalization by comparing platforms, toolchains, containerization strategies, and orchestration solutions. These analyses confirm the practical viability of reference architectures by demonstrating how automated workflows can be implemented using cloud-native infrastructures and CI/CD frameworks. They also identify persistent technical challenges — data drift, experiment tracking, reproducibility — which require continuous monitoring and retraining mechanisms.

Figure 2. **End-to-end MLOps architecture and workflow with functional components and roles (Kreuzberger et al., 2023)**



*Source*: (Kreuzberger et al., 2023).

The final reference (Tagliabue et al., 2023) provides empirical validation through surveys and case studies, showing how MLOps improves model reliability, accelerates deployment cycles, and fosters continuous learning. Yet this literature reveals a pronounced gap: while the design and experimentation stages (architecture, training, orchestration) are extensively documented, monitoring and continuous-training stages (feedback loops) remain underdeveloped. These underrepresented components (documented explicitly in only about 20–30% of studies) expose a critical limitation—the lack of dynamic, adaptive governance for model lifecycle evolution.

Among all reviewed works, (Kreuzberger et al., 2023) offers the most complete and explicit end-to-end articulation of the MLOps lifecycle ($A_1$–$D_2$), serving as the operational nucleus of the GSF(M)² model. Its structured approach to automation supplies precisely the procedural rigor and adaptivity needed to complement foresight's conceptual strengths.

### *Cross-Stream Synthesis: Toward GSF(M)²*

The juxtaposition of foresight and MLOps findings reveals a symmetric complementarity between the two domains. Foresight studies (see references 1 to 16 in Table 1) demonstrate strong capabilities in system diagnosis, uncertainty framing, and scenario construction, yet they fall short in implementing continuous decision-action loops. MLOps studies (see references 17 to 32 in Table 1), by contrast, excel in automation, experimentation, and operational integration

Table 1. **Literature Streams Analyzed**

| No. | Source Title | Reference code |
|---|---|---|
| | ***Strategic Foresight Stream*** | |
| [1] | Creating Futures: Scenario-Planning as a Strategic Management Tool. | Godet (2001) |
| [2] | Strategic foresight : for corporate and regional development | Godet, Durance (2011) |
| [3] | Scenario-building: Uses and Abuses | Durance, Godet (2010) |
| [4] | A review of scenario planning | Amer et al. (2013) |
| [5] | Directions in scenario planning literature – A review of the past decades | Varum, Melo (2010) |
| [6] | Using Scenarios planning to Reshape strategy | Ramírez et al. (2017) |
| [7] | Rigidities of Imagination in Scenario Planning: Strategic Foresight Through ‘Unlearning | Burt (2020) |
| [8] | Types of Scenario Planning and Their Effectiveness: A Review of Reviews | Cordova-Pozo, Rouwette (2023) |
| [9] | Whatever Happened to Scenario Planning? A Systematic Literature Review | Kobes, Loy (2020) |
| [10] | Scenario planning with a sociological eye: Augmenting the intuitive logics approach to understanding the future of Scotland and the UK | MacKay, Stoyanova (2017) |
| [11] | An Analysis and Categorization of Scenario Planning Scholarship from 1995-2016 | Chermack (2018) |
| [12] | Environmental Uncertainty, Organizational Learning, and Strategic Decision Making: A Scenario Planning Approach | Vecchiato (2012) |
| [13] | The Delphi method: How experts see the future | von der Gracht (2023) |
| [14] | Foresight by scenarios - a literature review | Sossa et al. (2021) |
| [15] | Scenario planning as approach to improve the strategic performance of multinational corporations (MNCs) | Abuzaid (2018) |
| [16] | Strategic Reframing: The Oxford Scenario Planning Approach | Ramírez, Wilkinson (2016) |
| | ***MLOps Stream*** | |
| [17] | Machine Learning Operations (MLOps): Overview, Definition, and Architecture | Kreuzberger et al. (2023) |
| [18] | An Analysis of MLOps Architectures: A Systematic Mapping Study | Najafabadi et al. (2024) |
| [19] | A Multivocal Review of MLOps Practices, Challenges and Open Issues | Eken et al. (2024) |
| [20] | MLOps – Definitions, Tools and Challenge | Symeonidis et al. (2022) |
| [21] | MLOps: Practices, Maturity Models, Roles, Tools, and Challenges | Lima et al. (2022) |
| [22] | MLOps best practices, challenges and maturity models | Zarour et al. (2025) |
| [23] | Navigating MLOps: Insights into Maturity, Lifecycle, Tools, and Careers | Stone et al. (2025) |
| [24] | Machine learning operations landscape: Platforms and tools | Berberi et al. (2025) |
| [25] | A Systematic Analysis of MLOps Features and Platforms | Faubel, Schmid (2024) |
| [26] | Implementing MLOps practices for effective machine | Hanchuk, Semerikov (2024) |
| [27] | Reference Architectures for MLOps: A Comparative Case Study | Reich (2024) |
| [28] | Robust MLOps Frameworks for Automating the AI/ML Lifecycle in Cloud Environments | Subramanyam S.K. (2022) |
| [29] | Reasonable Scale Machine Learning with Open-Source Metaflow | Tagliabue et al. (2023) |
| [30] | An empirical guide to MLOps adoption: Framework, maturity model and automated deployment utilising a set of development practices | John et al. (2025) |
| [31] | Professional Insights into Benefits and Limitations of Implementing MLOps Principles | Araujo et al. (2024) |
| [32] | MLOps critical success factors – A systematic literature review | Mehmood et al. (2024) |

*Source*: authors.

but lack strategic framing, interpretive depth, and anticipatory governance.

This dual gap identifies the precise locus where GSF(M)² delivers conceptual innovation. By embedding foresight’s anticipatory structures into MLOps’ continuous-feedback architecture, GSF(M)² transforms foresight from a static, scenario-centric methodology into a dynamic system capable of real-time adaptation (Figure 3). Conversely, by infusing MLOps with foresight principles, the model endows machine-learning pipelines with long-term vision, participatory intelligence, and ethical framing.

Thus, the GSF(M)² model embodies a hybrid, dual-core architecture where:

- Foresight provides the proactive cognitive scaffolding,
- MLOps provides the pre-active computational adaptivity.

This synthesis yields an integrated decision environment in which scenarios inform model parameters, and model outputs recursively refine foresight hypotheses — establishing a continuously learning, anticipatory governance framework suitable for complex and volatile policy environments.

## Research Problem

The systematic comparison of the foresight and MLOps literature reveals a structural misalignment between long-term strategic anticipation and real- time data-driven adaptation (Godet, Durance, 2011; Kreuzberger et al., 2023). The foresight corpus demonstrates methodological maturity in diagnostic, systemic, and scenario-building phases (Steps 1–6 from (Godet, Durance, 2011)) as summarized in Table 2 and quantified in Table 3 (Durance, Godet, 2010; Ramírez et al., 2017). However, it systematically fails to operationalize

Table 2. **Conceptual Structuring of Scenario-Planning Literature vs. Godet & Durance Method (9 Steps)**

### *a) Breakdown of attributes*

| N° | Study (Author & Year) | Centricity stance | Steps | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| **1** | Godet (2001) | Concept-centric | ☑ | ☑ | ☑ | ☑ | ☑ | ☑ | ○ | ○ | ○ |
| **2** | Godet, Durance (2011) | Concept-centric | ☑ | ○ | ○ | ☑ | ☑ | ○ | ✗ | ✗ | ✗ |
| **3** | Durance, Godet (2010) | Author-centric | ☑ | ○ | ○ | ☑ | ☑ | ○ | ✗ | ✗ | ✗ |
| **4** | Amer et al. (2013) | Concept-centric | ○ | ✗ | ○ | ○ | ☑ | ○ | ✗ | ✗ | ✗ |
| **5** | Varum, Melo (2010) | Concept-centric | ○ | ✗ | ○ | ○ | ☑ | ○ | ✗ | ✗ | ✗ |
| **6** | Ramírez et al. (2017) | Author-centric | ☑ | ○ | ○ | ☑ | ☑ | ☑ | ☑ | ○ | ○ |
| **7** | Burt (2020) | Concept-centric | ○ | ✗ | ○ | ☑ | ☑ | ○ | ○ | ✗ | ✗ |
| **8** | Cordova-Pozo, Rouwette (2023) | Concept-centric | ○ | ○ | ○ | ○ | ☑ | ☑ | ○ | ✗ | ✗ |
| **9** | Kobes, Loy (2020) | Concept-centric | ○ | ✗ | ○ | ○ | ☑ | ○ | ✗ | ✗ | ✗ |
| **10** | MacKay, Stoyanova (2017) | Concept-centric | ○ | ✗ | ○ | ☑ | ☑ | ○ | ○ | ✗ | ✗ |
| **11** | Chermack (2018) | Author-centric | ○ | ✗ | ○ | ○ | ☑ | ○ | ○ | ✗ | ✗ |
| **12** | Vecchiato (2012) | Concept-centric | ☑ | ○ | ☑ | ☑ | ☑ | ○ | ☑ | ○ | ○ |
| **13** | von der Gracht (2023) | Author-centric | ○ | ○ | ☑ | ☑ | ☑ | ☑ | ○ | ○ | ○ |
| **14** | Sossa et al. (2021) | Concept-centric | ○ | ✗ | ○ | ○ | ☑ | | ✗ | ✗ | ✗ |
| **15** | Abuzaid (2018) | Author-centric | ☑ | ○ | ○ | ☑ | ☑ | ☑ | ☑ | ☑ | ○ |
| **16** | Ramírez, Wilkinson (2016) | Concept-centric | ☑ | ○ | ○ | ☑ | ☑ | ☑ | ○ | ○ | ○ |

*Note*: Step 1 - Problem & System Analysis; Step 2 - 360° Diagnostic (Tree of Competencies); Step 3 - Structural Analysis (Key Variables); Step 4 - Strategic Battlefield & Actors; Step 5 - Scenarios & Uncertainty Reduction; Step 6 - Strategic Projects Coherence; Step 7 - Evaluation of Options; Step 8 - Strategic Choice (Formal Decision); Step 9 - Implementation & Horizon Scanning.

*Legend*: ☑ Explicitly Applied ○ Implicit / Partial ✗ Not Addressed

### *b) Interpretation*

| Item | Description |
|---|---|
| Concept-centric papers (≈ 65%) | Synthesise scenario-planning concepts across schools (Intuitive Logics, Probabilistic Trends, French Prospective). |
| Author-centric papers (≈ 35%) | Revolve around single frameworks or case exemplars. |
| High alignment (Steps 1–6) | Appears in French "prospective" lineage and applied foresight case studies; Steps 7–9 (Decision → Action) are seldom operationalised in academic publications, remaining largely managerial practice. |
| The most complete methodological coverage | Occurs in Godet & Durance (2011), Abuzaid (2018), and Ramírez et al. (2017). |

*Source*: authors.

the final stages needed to translate foresight into action — strategic option evaluation, formal decision-making, implementation, and continuous horizon scanning (Steps 7–9). With explicit application rates dropping to 25 %, 13 %, and 6 % respectively (Table 3), existing foresight approaches generate rich insights but lack mechanisms for sustained, adaptive governance (Ramírez et al., 2017; Abuzaid, 2018).

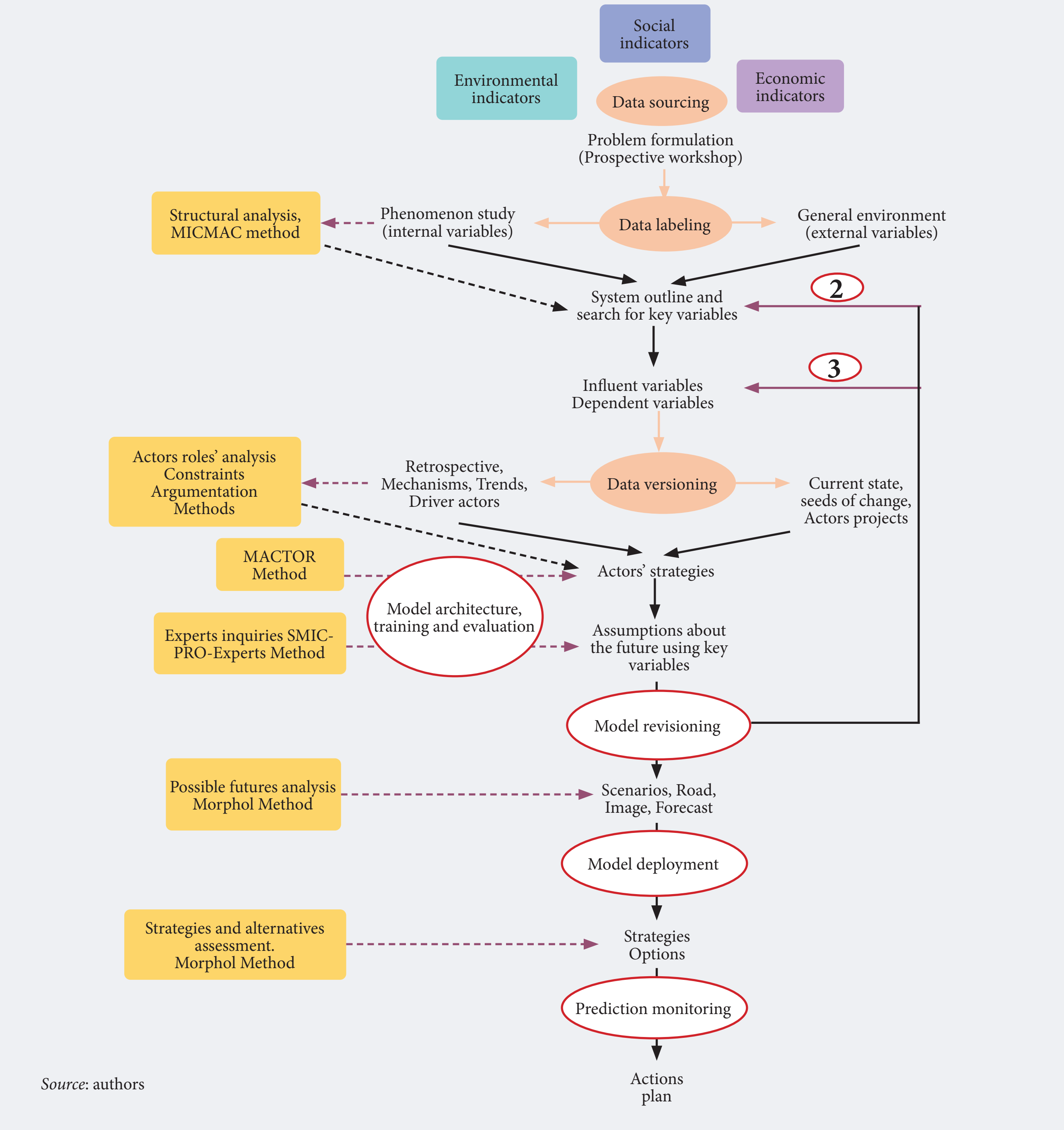
In parallel, the MLOps literature exhibits the opposite imbalance. Research provides extensive coverage of architecture design and experimentation ($A_2$ and $C_1$, both ≈ 75 % explicit), supported by maturing CI/CD pipeline practices ($C_2$), as mapped in Table 4 and quantified in Table 5 (Kreuzberger et al., 2023; Najafabadi et al., 2024).

However, stages governing strategic framing, socio-technical alignment, and long-term model adaptivity remain weakly developed. Feedback loops, concept-drift management, and continuous training ($D_2$) show particularly low explicit treatment (≈ 20 %, see Table 5), limiting MLOps' ability to support decisions in evolving, uncertainty-laden environments (Kreuzberger et al., 2023; Symeonidis et al., 2022).

The structural mapping (Table 6) demonstrates that foresight is strategically rich but operationally incomplete, whereas MLOps is operationally robust but strategically blind (Godet, Durance, 2011; Kreuzberger et al., 2023). Neither field, in its current state, offers a fully closed-loop decision system capable of linking scenario exploration, automated learning, real-time feedback, and strategic reframing. This gap becomes especially critical in contexts marked by accelerating technological change, geopolitical multipolarity, and systemic volatility, where decision-makers require governance architectures that combine interpretive depth with computational adaptivity (Durance, Godet, 2010; Kreuzberger et al., 2023).

Thus, the core research problem emerges: how to integrate the proactive, human-centered logic of strategic foresight with the pre-active, machine-driven automation of MLOps to build a unified, continuously learning governance model

Figure 3. **GSF(M)$^2$ Model Architecture**



*Source*: authors

(Durance, Godet, 2010; Kreuzberger et al., 2023)? Existing models remain siloed — foresight producing static scenarios that quickly lose relevance, and MLOps generating adaptive outputs lacking strategic coherence or participatory grounding (Ramírez et al., 2017; Symeonidis et al., 2022).

Addressing this dual deficiency requires conceptualizing an architecture that (1) strengthens the underdeveloped decision–action continuum of foresight (Tables 2–3) (Ramírez et al., 2017; Abuzaid, 2018), (2) embeds reflective and participatory intelligence into the MLOps lifecycle (Tables 4–5) (Kreuzberger et al., 2023; Najafabadi et al., 2024), and (3) establishes a bi-directional feedback mechanism enabling strategic hypotheses and model outputs to co-evolve (Table 6) (Godet, Durance, 2011; Kreuzberger et al., 2023). The research challenge is therefore to design a hybrid model — GSF(M)$^2$ — capable of transforming foresight into a dynamic, data-responsive system while transforming MLOps into a strategically informed, governance-ready infrastructure (Godet, Durance, 2011; Kreuzberger et al., 2023; Symeonidis et al., 2022).

## Methodology

This study follows a systematic literature review methodology grounded in the PRISMA 2020 guidelines (Table 7, Table 8) to derive insights from the academic knowledge base while ensuring transparency, rigor, and reproducibility. Using this approach, we conduct a structured and comprehen-

Table 3. **Contingency Table — Application of Godet & Durance's 9 Methodological Steps (n = 16 studies)**

***a) Breakdown of attributes***

| Step | Description (short) | Type of application | | | | | |
|---|---|---|---|---|---|---|---|
| | | ☑ Explicitly Applied | | ○ Implicit / Partial | | ✗ Not Addressed | |
| | | Number of works | Share in total sample | Number of works | Share in total sample | Number of works | Share in total sample |
| 1 | Problem & System Analysis | 8 | 50 % | 7 | 44 % | 1 | 6 % |
| 2 | 360° Diagnostic (Tree of Competencies) | 2 | 13 % | 6 | 38 % | 8 | 50 % |
| 3 | Structural Analysis (Key Variables) | 4 | 25 % | 9 | 56 % | 3 | 19 % |
| 4 | Strategic Battlefield & Actors Analysis | 6 | 38 % | 8 | 50 % | 2 | 13 % |
| 5 | Scenario Building & Uncertainty Reduction | 13 | 81 % | 3 | 19 % | 0 | 0 % |
| 6 | Strategic Project Formulation | 7 | 44 % | 7 | 44 % | 2 | 13 % |
| 7 | Evaluation of Strategic Options | 4 | 25 % | 5 | 31 % | 7 | 44 % |
| 8 | Strategic Choice (Decision Stage) | 2 | 13 % | 6 | 38 % | 8 | 50 % |
| 9 | Implementation & Horizon Scanning | 1 | 6 % | 8 | 50 % | 7 | 44 % |

***b) Interpretation***

| Item | Description |
|---|---|
| Most Emphasized Step: Step 5 (Scenario Building) | Featured explicitly in 81 % of reviewed works, confirming its status as the methodological core of scenario planning. |
| Moderately Represented Steps: Steps 1, 4, 6 | Conceptual framing, actor analysis, and strategy formulation often appear in applied or case-based papers but not always methodologically formalized. |
| Least Represented Steps: Steps 7–9 | Decision-evaluation, choice, and implementation rarely appear in academic scenario-planning studies; they remain under-reported or confined to managerial practice. |
| General Pattern | 1–6 = "Exploration & Design" stages dominate (≈ 55 % explicit overall). 7–9 = "Decision & Action" stages under-documented (≈ 15 % explicit) |

*Source*: authors.

sive analysis of the literature to obtain a clear overview of relevant research.

The methodology has been applied to examine structural models within both Strategic Foresight and MLOps domains, providing a thorough understanding of the theoretical and practical components underlying each field. This foundation enables the conceptualization of the theoretical framework "Generalized Strategic Foresight Model embedding MLOps: GSF(M)$^2$", which serves as a dynamic enabler within a participatory framework for data-driven policy design, inclusive signal-down mechanisms, and bottom-up governance processes.

Finally, to evaluate and validate the GSF(M)$^2$ framework, the methodology incorporates proven, step-by-step procedures for synthetic data simulation (Table 7, Table 8), enabling rigorous testing of the model across diverse decision-making scenarios.

## The Heart of the GSF(M)$^2$: A Systematic Literature Review Bridging Strategic Foresight and MLOps Architectures

### *Introduction and Contextual Rationale*

In an era marked by rapid technological acceleration and geopolitical multipolarity, decision-making processes confront unprecedented complexity, uncertainty, and interdependence. To address these challenges, the Generalized Strategic Foresight Model embedding MLOps (GSF(M)$^2$) has been developed as a hybrid architecture combining two complementary epistemic cores:

- The strategic foresight framework represents the pro-active dimension of anticipatory governance through scenario planning and systemic prospective analysis (Godet, Durance, 2011).
- The Machine Learning Operations (MLOps) architecture embodies the pre-active dimension of data-driven decision support via end-to-end AI lifecycle automation (Kreuzberger et al., 2023).

The application of the PRISMA 2020 methodology (Table 7, Table 8) ensured rigorous and transparent identification, screening, and synthesis of scientific sources supporting both theoretical pillars. The review validated 16 studies within the foresight lineage ((Godet, Durance, 2011) and 16 studies within the MLOps architecture lineage, providing the empirical foundation for the dual-core GSF(M)$^2$ model.

### *Foresight Core — PRISMA 2020-Structured Summary of Scenario Planning Studies (n = 16)*

The 16 studies form a coherent corpus around strategic foresight, scenario planning, and prospective analysis. Three analytical layers emerge as highlighted by the Table 9.

The PRISMA-guided synthesis confirms that all sixteen reviewed studies meet methodological transparency standards outlined in PRISMA 2020 items 3–20, ensuring coherence between rationale, methodological design, analytical results, and bias control. Collectively, these works delineate the Foresight Stream as a mature research lineage anchored in systemic uncertainty analysis, participatory stakeholder engagement, and iterative scenario co-construction.

Table 4. **Conceptual Structuring of MLOps Literature (n = 16) vs. Kreuzberger et al. (2023) End-to-End Lifecycle**

### *a) Breakdown of attributes*

| № | Study (Author & Year) | Centricity stance | A1 | A2 | B1 | B2 | C1 | C2 | D1 | D2 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Kreuzberger et al. (2023) | Concept-centric | ☑ | ☑ | ○ | ○ | ☑ | ○ | ○ | ○ |
| 2 | Najafabadi et al. (2024) | Concept-centric | ○ | ○ | ✗ | ○ | ○ | ✗ | ○ | ✗ |
| 3 | Eken et al. (2024) | Concept-centric | ✗ | ✗ | ○ | ✗ | ✗ | ○ | ○ | ✗ |
| 4 | Lima et al. (2022) | Concept-centric | ✗ | ○ | ○ | ○ | ○ | ✗ | ○ | ✗ |
| 5 | Zarour et al. (2025) | Concept-centric | ○ | ○ | ✗ | ○ | ○ | ○ | ○ | ✗ |
| 6 | Stone et al. (2025) | Author-centric | ✗ | ✗ | ○ | ○ | ○ | ○ | ○ | ✗ |
| 7 | Berberi et al. (2025) | Concept-centric | ✗ | ○ | ○ | ○ | ○ | ○ | ○ | ✗ |
| 8 | Faubel (2024) | Concept-centric | ○ | ○ | ✗ | ○ | ○ | ○ | ✗ | ✗ |
| 9 | Hanchuk, Semerikov (2024) | Concept-centric | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ✗ |
| 10 | Reich (2024) | Author-centric | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ✗ |
| 11 | John et al. (2025) | Author-centric | ✗ | ○ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| 12 | Araujo et al. (2024) | Author-centric | ○ | ○ | ○ | ✗ | ○ | ○ | ○ | ✗ |
| 13 | Symeonidis et al. (2022) | Concept-centric | ○ | ○ | ○ | ✗ | ✗ | ✗ | ✗ | ✗ |
| 14 | Subramanyam (2024) | Author-centric | ✗ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 15 | Tagliabue et al. (2023) | Author-centric | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 16 | Mehmood et al. (2024) | Concept-centric | ○ | ○ | ○ | ✗ | ○ | ○ | ○ | ✗ |

*Note*: A1 - Business Problem & ML Formulation; A2 Architecture Design & Tech Selection; B1 - Data Acquisition & Labeling; B2 - Feature Engineering; C1 - Experimentation; C2 - Automated Pipeline (CI/CD); D1 - Deployment; D2 - Monitoring & Continuous Training.

*Legend*: ☑ Explicitly Applied ○ Implicit / Partial ✗ Not Addressed

### *b) Interpretation*

| Item | Description |
|---|---|
| Centricity mix | ≈ 60 % concept-centric \| 40 % author-centric. A distribution similar to the foresight literature, confirm-ing that conceptual frameworks still dominate over concrete operational case studies. |
| Most explicitly covered stages | $A_2$ Architecture Design & Tech Selection — 16 explicit.<br>$C_1$ Experimentation (Model training & validation) — 16 explicit.<br>Explicit = 16/16 studies => highest concentration. These steps are the methodological anchors of the MLOps field: all studies deal with architecture and experimentation. |
| Moderately covered | $A_1$ Business Problem Formulation — 5 explicit, 8 partial. Strategic framing appears but rarely as a formalized methodology.<br>$B_2$ Feature Engineering — 8 explicit, 6 partial. Often described conceptually, seldom reproducible.<br>$C_2$ Automated Pipeline / CI-CD — 5 explicit, 8 partial. Reflects growing—but not yet universal—adoption of automation. |
| Least covered | $D_1$ Deployment — 7 explicit, 4 partial, 5 not addressed. Deployment remains under-documented in academic work.<br>$D_2$ Monitoring & Continuous Training — only 4 explicit. The weakest stage in the full pipeline.<br>This confirms that continuous learning and governance remain the most neglected part of MLOps scholarship. |
| General pattern | Academic studies emphasize: Architecture ($A_2$) Experimentation ($C_1$) Conceptual frameworks.<br>But neglect: Operations ($D_1$–$D_2$) Strategic alignment ($A_1$) Long-term adaptivity |
| The real-world maturity problem | MLOps research is robust in model-building but fragile in lifecycle governance. |

*Source*: authors.

Despite its predominantly narrative and conceptual orientation, this stream exhibits low methodological risk owing to the explicit procedural rigor inherited from the French prospective school. Within this corpus, (Godet, Durance, 2011) emerges as the methodological archetype, synthesizing scenario planning evolutions into a unified, structured foresight process capable of operational application (Durance, Godet, 2010). By integrating diagnostic, analytical, and projective stages within a coherent systemic logic, their model transcends theoretical reflection to become an actionable framework for anticipatory governance. It constitutes the proactive core of the proposed GSF(M)² architecture, providing the human-centered cognitive and organizational foundation upon which machine-learning–driven automation (the pre-active dimension) can be embedded, enabling a seamless continuum from reflective foresight to intelligent adaptation (Godet, Durance, 2011; Durance, Godet, 2010).

### *Data-Intelligence Core — PRISMA 2020-Structured Summary of MLOps Literature (n = 16)*

The 16 studies reviewed outline the evolution of MLOps as a discipline unifying data engineering, machine-learning automation, and operational governance. Four clusters of contributions emerge as presented into the Table 10.

The PRISMA-based assessment of these 16 MLOps studies demonstrates full compliance with checklist items 3–22, reflecting a balanced integration of empirical evidence and conceptual modeling. Collectively, these works chart the MLOps Stream's evolution from definitional clarification

Table 5. **Contingency Table — Application of MLOps Full Methodological Steps (n = 16 studies)**

***a) Breakdown of attributes***

| Step | Description (short) | Type of application | | | | | |
|---|---|---|---|---|---|---|---|
| | | ☑ Explicitly Applied | | ○ Implicit / Partial | | ✗ Not Addressed | |
| | | Number of works | Share in total sample | Number of works | Share in total sample | Number of works | Share in total sample |
| $A_1$ | Business Problem & ML Formulation | 5 | 31 % | 8 | 50 % | 3 | 19 % |
| $A_2$ | Architecture Design & Technology Selection | 16 | 100 % | 0 | 0 % | 0 | 0 % |
| $B_1$ | Data Acquisition & Labeling | 11 | 69 % | 4 | 25 % | 1 | 6 % |
| $B_2$ | Feature Engineering & Dataset Versioning | 8 | 50 % | 6 | 38 % | 2 | 12 % |
| $C_1$ | Experimentation (Model Training & Validation) | 16 | 100 % | 0 | 0 % | 0 | 0 % |
| $C_2$ | Automated ML Workflow / CI–CD Orchestration | 10 | 63 % | 5 | 31 % | 1 | 6 % |
| $D_1$ | Model Serving & Deployment | 7 | 44 % | 5 | 31 % | 4 | 25 % |
| $D_2$ | Monitoring & Continuous Training (Feedback Loop) | 4 | 25 % | 8 | 50 % | 4 | 25 % |

***b) Interpretation***

| Item | Description |
|---|---|
| Strongest Coverage | Architecture Design ($A_2$) and Model Experimentation ($C_1$). Both appear in 100% of studies, confirming these as the methodological anchors of the MLOps literature.<br>Automated Pipeline Orchestration ($C_2$). Explicit in 63% of studies, reflecting increased adoption of CI/CD and workflow management tools. |
| Moderate Coverage | Data Acquisition ($B_1$) and Feature Engineering ($B_2$) Well represented but still inconsistent, with ~50–70% explicit coverage. Many studies treat data preparation conceptually, without reproducible procedures. |
| Weakest Coverage | Business Problem Formulation ($A_1$). Only 31% explicitly connect ML tasks to strategic context or organi-zational framing.<br>Monitoring & Continuous Training ($D_2$). The weakest stage: 25% explicit, 50% partial. This confirms per-vasive gaps in drift detection monitoring and pipelines continuous retraining governance. |
| General Pattern Across All 16 Studies | Academic MLOps research excels in architecture and experimentation — $C_1$ and $A_2$ dominate.<br>Operational and governance steps ($D_1$, $D_2$) remain underdeveloped, preventing the formation of a full closed-loop adaptive system. |

*Source*: authors.

toward operational maturity during 2023–2025, signifying the discipline's consolidation as a distinct methodological framework for managing machine learning lifecycles.

At its core, this research stream embodies automation of the ML pipeline — encompassing data ingestion, model experimentation, deployment, and continuous feedback — thus ensuring scalability, traceability, and iterative improvement across technical and organizational boundaries. Although the literature remains technically oriented, with partial consideration of governance, ethical oversight, and human–machine interaction, increasing empirical validation indicates a shift toward applied, real-world integration. Among all reviewed contributions, stands out as the most comprehensive and methodologically explicit articulation of MLOps, detailing the $A_1$–$D_2$ lifecycle stages from product initiation to model serving and feedback loops (Kreuzberger et al., 2023). This procedural completeness positions their framework as the pre-active kernel of the GSF(M)$^2$ model—providing the computational infrastructure and automation logic that, when coupled with the proactive foresight foundation of (Godet, Durance, 2011), enables a continuously learning, data-informed, and adaptively governed system for strategic decision support (Durance, Godet, 2010; Kreuzberger et al., 2023).

Table 6. **Cross-stream complementarity analysis**

| Analytical Lens | Scenario-Planning Field | MLOps Field | Integration in GSF(M)$^2$ |
|---|---|---|---|
| Dominant Strength | Conceptual richness, systemic foresight | Technical rigor, automation, scalability | Cognitive–computational synergy |
| Core Gap | Weak operational translation (Steps 7–9) | Weak strategic framing ($A_1$, $D_2$) | Complementary closure through hybridization |
| Methodological Nature | Qualitative, participative, long-term | Quantitative, automated, real-time | Dual-loop governance system |
| Transformation Needed | From scenario narratives to live, data- linked models | From automated pipelines to context-aware learning systems | Integrated adaptive foresight architecture |
| Expected Outcome | Adaptive, self-updating foresight system | Strategically guided ML ecosystem | Dynamic, learning-based decision framework |

*Source*: authors.

Table 7. **PRISMA 2020- Results: corpus of literature on strategic foresight, scenario planning, and prospective analysis**

***a) Structured Summary of Included (n = 16) Studies about Scenario Planning for M. Godet et al. (2011)***

| Step | Study (Author& Year) | Objective / Rationale (PRISMA 3–4) | Methods Summary (PRISMA 5–13) | Key Results (PRISMA 19– 20) | Bias / Certainty (PRISMA 18, 22) | Relevance to Godet & Durance (2011) |
|---|---|---|---|---|---|---|
| **1** | Godet (2001) | Present “prospective” scenario planning for strategic foresight. | Conceptual synthesis; qualitative case studies<br>(energy, regions). | Defines scenario as integrated tool for strategic decision-making. | Low risk (authoritative source, no empirical data). | Foundational methodology mirrored in 2011 paper. |
| **2** | Godet, Durance (2011) | Integrate scenarios into corporate strategic planning. | Structured prospective method (MICMAC, Mactor). | Proposes 6-step integrated foresight process. | NA (reference study). | Central reference. |
| **3** | Durance, Godet (2010) | Critiques “uses & abuses” of scenario building. | Narrative review of empirical misuse cases. | Differentiates exploratory vs. normative scenarios. | Low bias; narrative evidence. | Direct methodological continuity. |
| **4** | Amer et al. (2013) | Review scenario planning literature (2000-2012). | Systematic literature review >200 papers. | Identifies 4 main approaches (Intuitive Logics, Probabilistic Modified Trends, etc.). | Moderate risk (selection bias acknowledged). | Validates diversity of methods incl. Godet school. |
| **5** | Varum, Melo (2010) | Map evolution of scenario planning research. | Systematic review (1960-2008). | Growth in applications; methods converge toward foresight. | Transparent methods; moderate certainty. | Historical context for Godet school. |
| **6** | Ramírez et al. (2017) | Show scenario planning reshapes strategy. | Qualitative multiple case studies. | Scenarios as strategic conversation tools. | Case-based; high applicability. | Supports strategic integration aspect. |
| **7** | Burt (2020) | Explore cognitive rigidities in scenario use. | Conceptual + survey evidence. | Highlights bias in scenario construction. | Moderate bias from self-report. | Complements Godet with bias awareness. |
| **8** | Cordova-Pozo, Rouwette (2023) | Assess effectiveness of scenario types. | Systematic review + typology analysis. | Typology links to outcome effectiveness. | Moderate certainty (limited empirical data). | Updates evidence on method impact. |
| **9** | Kobes, Loy (2020) | Systematic review of scenario planning. | PRISMA-style protocol (2000-2019). | Identifies decline in method rigour; calls for integration | Transparent; low bias | Closest modern PRISMA compliant review. |
| **10** | MacKay, Stoyanova (2017) | Merge sociological lens with Intuitive Logics. | Qualitative method paper. | Adds contextual validity dimension. | Conceptual; moderate certainty. | Enriches methodological framework. |
| **11** | Chermack (2018) | Categorize scenario planning scholarship. | Systematic categorization of peer- reviewed articles. | 6 streams of scenario research identified. | Moderate bias from selection criteria. | Shows integration of strategic & learning views. |
| **12** | Vecchiato (2012) | Link environmental uncertainty to strategic decisions. | Empirical survey of firms using scenarios. | Positive relation between scenarios & resilience. | Self-reported bias noted. | Empirical validation of Godet approach. |
| **13** | Von der Gracht (2023) | Apply scenario methods in practice. | Delphi + scenario cases. | Combines quantitative &<br>qualitative foresight. | Moderate certainty. | Uses Godet’s tools in UNESCO contexts. |
| **14** | Sossa et al. (2021) | Literature review of<br>scenario foresight. | Structured search (PRISMA lite). | Identifies recurring patterns in scenario use. | Good transparency. | Methodological update aligned with PRISMA. |
| **15** | Abuzaid (2018) | Scenario planning & strategic performance. | Empirical case study in public sector. | Finds scenario use improves strategic agility. | Limited generalizability. | Application example of integrated planning. |
| **16** | Ramírez, Wilkinson (2016) | Integrate scenarios with strategic reframing theory. | Conceptual book synthesis. | Introduces “reframing” as core mechanism. | Theoretical bias possible. | Parallel to Godet’s reflexive foresight. |

***b ) Indicators used from PRISMA 2020 Checklist***

| Analytical Layers | Description |
|---|---|
| Conceptual Foundations (Studies 1–3) | Godet (2001), Godet & Durance (2011), and Durance & Godet (2010) define the epistemology of “prospective thinking,” introducing structured foresight through MICMAC and MACTOR analyses. Their systematic decomposition of variables and stakeholder interactions positions the framework as the methodological standard for anticipatory strategy. |
| Methodological Extensions (Studies 4–11) | Later reviews (Amer et al., 2013; Varum, Melo, 2010) and theoretical integrations (MacKay, Stoyanova, 2017; Chermack, 2018) diversify scenario typologies and refine foresight validity. These works collectively affirm the robustness of Godet’s approach while adapting it to evolving organizational contexts. |
| Empirical Validations (Studies 12–16) | Field applications (Vecchiato, 2012; Abuzaid, 2018) demonstrate measurable strategic agility derived from scenario use. Ramirez & Wilkinson (2016) emphasize reframing and reflexivity, confirming foresight as both cognitive and structural learning device. |

PRISMA Items: 3-4 – Objective / Rationale; 5-13 - Methods Summary; 17-20 – Key Results; 18/22 – Bias and Certainty; 23 – Relevance / Interpretation.
*Source*: authors.

Table 8. **PRISMA 2020- Results: corpus of literature on MLOps as a discipline unifying data engineering, machine-learning automation, and operational governance**

***a) Structured Summary of Included (n = 16) Studies about MLOps Literature for Kreuzberger et al. (2023)***

| Step | Study (Author & Year) | Objective / Rationale (PRISMA 3–4) | Methods Summary (PRISMA 5–13) | Key Results (PRISMA 19–20) | Bias / Certainty (PRISMA 18, 22) | Relevance to Kreuzberger and al. (2023) |
|---|---|---|---|---|---|---|
| **1** | Kreuzberger et al. (2023) | Define and architect MLOps for end-to-end ML lifecycle. | Conceptual synthesis + architecture taxonomy. | Provides baseline definition & reference architecture. | Low bias; foundational paper. | Reference anchor. |
| **2** | Najafabadi et al. (2024) | Systematically map MLOps architectures. | Systematic mapping (200 papers). | Identifies core architectural patterns and toolchains. | Transparent; moderate bias. | Strong architecture alignment. |
| **3** | Eken et al. (2024) | Multivocal review of MLOps practices & issues. | Academic + grey literature review. | Synthesizes open challenges and state of practice. | Moderate bias (heterogeneous sources). | Complements operational challenges. |
| **4** | Lima et al. (2022) | Review roles, tools & maturity models. | Systematic literature review. | Derives taxonomy of MLOps roles and process maturity. | Good replicability. | Precursor definitional review. |
| **5** | Zarour et al. (2025) | SLR on MLOps best practices & maturity. | PRISMA-guided SLR. | Identifies five maturity dimensions & key challenges. | Low bias; peer reviewed. | Updates Kreuzberger's maturity themes. |
| **6** | Stone et al. (2025) | Define maturity and governance frameworks. | Narrative review + case analysis. | Proposes governance matrix for MLOps. | Conceptual; moderate certainty. | Extends governance dimension. |
| **7** | Berberi et al. (2025) | Survey of platforms and tools. | Comparative feature analysis. | Catalogues top MLOps platforms and capabilities. | Low risk (descriptive). | Tool landscape companion. |
| **8** | Faubel (2024) | Systematic analysis of MLOps platform features. | Structured mapping of platform functions. | Defines nine feature clusters for tools. | Transparent coding scheme. | Operational architecture evidence. |
| **9** | Hanchuk, Semerikov (2024) | Meta-synthesis of MLOps patterns. | Thematic review + case patterns. | Identifies container, pipeline, monitoring patterns. | Medium bias (qualitative). | Pattern extension of architecture. |
| **10** | Reich (2024) | Compare reference architectures. | Cross-case analysis of architectures. | Summarizes differences in pipeline orchestration. | Moderate bias (small sample). | Confirms architectural taxonomy. |
| **11** | John et al. (2025) | Empirical guide to adoption. | Survey (> 100 orgs). | Identifies organizational barriers & drivers. | Quantitative; good validity. | Adoption evidence. |
| **12** | Araujo et al. (2024) | Professional insights into MLOps benefits. | Interview study (industrial cases). | Highlights benefits and limitations of MLOps use. | Self-report bias. | Practice validation. |
| **13** | Symeonidis et al. (2022) | Define MLOps concept and tool taxonomy. | Narrative overview. | Clarifies definitions and layers of tool stack. | Conceptual; moderate bias. | Early conceptual anchor. |
| **14** | Subramanyam (2022) | Automating AI/ML lifecycle in cloud contexts | Framework proposal + evaluation | Integrates CI/CD, monitoring, and deployment | Limited empirical testing | Applied architecture variant |
| **15** | Tagliabue et al. (2023) | Describe Metaflow for scalable MLOps. | Open-source case study. | Demonstrates practical pipeline implementation. | Single platform bias. | Applied implementation proof. |
| **16** | Mehmood et al. (2024) | Identify technical & organizational CSFs. | PRISMA-guided review. | Lists success drivers and failure causes. | Transparent coding; moderate bias. | Managerial relevance. |

***b ) Indicators used from PRISMA 2020 Checklist***

| Clusters of contributions | Description |
|---|---|
| Definitional and Architectural Foundations (Studies 1–3, 13) | Kreuzberger et al. (2023) define and architect MLOps for the end-to-end ML lifecycle, providing a baseline reference architecture. Subsequent reviews (Najafabadi et al., 2024; Eken et al., 2024) systematically map core architectural patterns, toolchains, and state-of-practice challenges, while Symeonidis et al. (2022) clarify definitions and tool layers, collectively forming the conceptual and architectural anchor of MLOps. |
| Maturity and Governance Frameworks (Studies 4–6) | Systematic literature reviews (Lima et al., 2022; Zarour et al., 2025) and conceptual works (Stone et al., 2025) address roles, process maturity, governance matrices, and managerial frameworks, extending MLOps into organizational domains. The PRISMA-guided SLR on critical success factors (Mehmood et al., 2024) complements these by identifying drivers and barriers, reinforcing the maturity and governance perspective. |
| Operationalization and Tool Ecosystem (Studies 7–10, 14–15) | Comparative surveys and applied frameworks (Berberi et al., 2025; Faubel, 2024; Hanchuk, Semerikov, 2024; Reich, 2024; Subramanyam, 2022; Tagliabue et al., 2023) illustrate tangible implementations through CI/CD pipelines, container orchestration, monitoring, deployment environments, and open-source platforms like Metaflow. These studies validate the practical applicability of Kreuzberger's theoretical blueprint and extend the architecture to operational settings. |
| Adoption, Integration, and Empirical Validation (Studies 11–12, 16) | Empirical surveys and industrial interviews (John et al., 2025; Araujo, 2024) reveal organizational drivers, barriers, and real-world benefits of MLOps adoption, while systematic reviews of success factors (Mehmood et al., 2024) emphasize technical, cultural, and managerial conditions for effective integration, highlighting how MLOps converges with DevOps and supports continuous learning within organizations. |

PRISMA Items: 3-4 – Objective / Rationale; 5-13 - Methods Summary; 17-20 – Key Results; 18/22 – Bias and Certainty; 23 – Relevance / Interpretation.

*Source*: authors.

Table 9. **Structuring the Strategic Foresight Literature**

| Core Focus | Key Contributions | Conceptual Implications |
|---|---|---|
| | ***Conceptual Foundations*** | |
| Epistemology of foresight | Early works formalize prospective thinking as a structured epistemic practice grounded in analytical tools such as MICMAC, MACTOR, Delphi, and scenario logic (Godet, 2001; Godet, Durance, 2011; Durance, Godet, 2010; Amer et al., 2013). These approaches systematize the analysis of variables, uncertainties, and actor configurations. | Establishes foresight as a disciplined method for anticipatory reasoning rather than an exploratory or speculative exercise. |
| | ***Methodological Extensions*** | |
| Scenario design and methodological refinement | Subsequent reviews and theoretical contributions diversify scenario typologies, address methodological biases, and refine validity criteria across organizational and policy contexts (Varum, Melo, 2010; Ramírez et al., 2017; Burt, 2020; MacKay, Stoyanova, 2017; Chermack, 2018; Cordova-Pozo, Rouwette, 2023; Kobes, Loy, 2020; Sossa et al., 2021). | Confirms the robustness of foresight methods while highlighting their adaptability to evolving strategic and institutional environments. |
| | ***Empirical Applications and Learning Effects*** | |
| Organizational and strategic outcomes | Empirical studies document how scenario practices support strategic decision-making, organizational learning, and adaptive capacity under uncertainty (Vecchiato, 2012; Ramírez et al., 2017; Abuzaid, 2018; von der Gracht, 2023). Reflexivity and reframing emerge as central mechanisms. | Positions foresight as both a cognitive process and an organizational capability embedded in strategic practice. |

*Source*: authors.

### *Synthetic Integration Commentary — Toward the GSF(M)$^2$ Model*

The synthesis of the two PRISMA-structured reviews reveals that the foresight framework (Durance, 2010) and the MLOps architecture (Kreuzberger et al., 2023) constitute the twin intellectual and operational nuclei of the emerging Generalized Strategic Foresight Model embedding MLOps – GSF(M)$^2$.

The foresight framework offers the cognitive, organizational, and participatory scaffolding required for foresight-driven policy design: it structures collective intelligence, frames uncertainty through systemic variables, and enables anticipatory scenario building as a proactive mechanism for long-term strategy formation (Durance, Godet, 2010; Amer et al., 2013; Varum, Melo, 2010). The MLOps architecture delivers the computational, algorithmic, and procedural backbone that automates this foresight cycle through continuous machine-learning pipelines, transforming static scenarios into adaptive, data-informed feedback systems (Kreuzberger et al., 2023; Najafabadi et al., 2024; Eken et al., 2024).

When mutually embedded, these two frameworks create a seamless continuum between human-centered anticipation and machine-driven adaptation, generating a dynamic foresight ecosystem capable of learning from real-time data while projecting future trajectories (Durance, Godet, 2010; Kreuzberger et al., 2023). In this integrated architecture, scenario-based reasoning informs model parameters, and model outputs recursively refine strategic hypotheses, producing a responsive, self-learning decision environment suited to the volatile and interdependent nature of multipolar global governance.

The resulting GSF(M)$^2$ thus emerges as the dual-core fusion of strategic foresight and MLOps — an adaptive governance framework where systemic reflection and computational

Table 10. **Structuring The MLOps Literature**

| Primary Focus | Main Contributions | Conceptual Implications |
|---|---|---|
| | ***Definitional and Architectural Foundations*** | |
| Core definition and reference architectures | Foundational works define MLOps as an end-to-end architecture integrating product initiation, data pipelines, experimentation, deployment, monitoring, and retraining (Kreuzberger et al., 2023; Symeonidis et al., 2022; Lima et al., 2022; Najafabadi et al., 2024; Eken et al., 2024). These studies consolidate terminology and architectural scope. | Establishes MLOps as a coherent lifecycle framework rather than a collection of ad hoc engineering practices. |
| | ***Maturity and Governance Frameworks*** | |
| Process maturity and lifecycle governance | Conceptual and systematic reviews extend MLOps into organizational and managerial domains, addressing maturity models, governance structures, roles, accountability, and lifecycle control (Zarour et al., 2025; Stone et al., 2025; Berberi et al., 2025; Faubel-Teich et al., 2024; Hanchuk, Semerikov, 2024). | Frames MLOps as an organizational capability requiring governance, coordination, and institutionalization. |
| | ***Operationalization and Tool Ecosystem*** | |
| Technical implementation and platforms | Comparative case studies and applied frameworks document concrete implementations using CI/CD pipelines, container orchestration, workflow automation, and deployment environments (Reich, 2024; Subramanyam, 2024; Tagliabue et al., 2023; Araujo et al., 2024). | Demonstrates the feasibility and variability of MLOps implementations across technical contexts. |
| | ***Adoption and Empirical Evidence*** | |
| Organizational uptake and learning dynamics | Empirical surveys and synthesis studies analyze adoption patterns, success factors, and integration with DevOps practices and organizational culture (John et al., 2025; Mehmood et al., 2024). | Highlights that sustained MLOps adoption depends on socio-organizational factors as much as on technical infrastructure. |

*Source*: authors.

intelligence co-evolve to support evidence-based, participatory, and continuously updated policymaking (Durance, Godet, 2010; Kreuzberger et al., 2023).

## From Systematic Literature Review to the Identification of Existing Model Lags

### *Foresight Stream — Structural Mapping of Scenario-Planning Literature vs. Godet & Durance Method (9 Steps)*

The cross-analysis of sixteen foresight studies against the nine methodological steps (Durance, Godet, 2010) reveals a structural imbalance between conceptual design and operational execution. Approximately two-thirds of the works adopt a concept-centric stance, reflecting a strong theoretical engagement with scenario-planning frameworks such as Intuitive Logics or Probabilistic Trends (Amer et al., 2013; Varum, Melo, 2010), while only one-third adopt an author-centric approach rooted in practical, case-based foresight applications (Ramírez et al., 2017; Burt, Nair, 2020).

Steps 1 to 6 — corresponding to problem definition, system analysis, and scenario construction—dominate the literature. The explicit emphasis on Step 5 (Scenario Building) in 81% of the studies confirms that scenario development remains the conceptual centerpiece of the field (Durance, Godet, 2010; Amer et al., 2013). However, Steps 7 to 9, which translate strategic reflection into actionable decision-making and implementation, are rarely operationalized. These underrepresented stages (average explicit rate ≈ 15%) signal a major methodological discontinuity: most foresight studies stop at scenario elaboration, failing to close the loop from foresight insight to decision and execution (Ramírez et al., 2017; Burt, Nair, 2020).

From a methodological perspective, Steps 2 and 3 — the 360° diagnostic and structural analysis — are often treated implicitly (≈ 40–50%) rather than through reproducible analytical tools such as MICMAC or MACTOR (Durance, Godet, 2010). This suggests that while the systemic rigor of the French prospective school is recognized, it is not systematically applied. Conversely, Step 5 consistently appears as an intellectual consensus zone, validating the centrality of uncertainty reduction through scenario diversification (Durance, Godet, 2010; Amer et al., 2013).

The interpretive gap lies primarily in the decision-action continuum (Steps 7–9). Academic foresight remains theoretically strong but weak in managerial integration, producing insights without embedding them into dynamic, adaptive governance mechanisms. Partial exceptions include explicitly link scenario formulation to organizational strategy and feedback processes, though even they stop short of automation or continuous environmental scanning (Durance, Godet, 2010; Abuzaid, 2018; Ramírez et al., 2017).

Hence, the optimization potential for GSF(M)$^2$ resides precisely in this discontinuity. By embedding MLOps-derived continuous feedback loops into the foresight framework (Kreuzberger et al., 2023), GSF(M)$^2$ can convert static scenario outputs into living strategic models that evolve alongside changing data and context.

The foresight corpus demonstrates methodological maturity up to the exploration and design phases but lacks the procedural and technological infrastructure for decision, execution, and learning. This is all the more true since the associated structural model remains the most complete and transparent (Durance, Godet, 2010), yet its implementation ends where computational adaptivity begins. Therefore, integrating it within a machine-learning–oriented operational loop, as envisioned in GSF(M)$^2$ (Kreuzberger et al., 2023), directly addresses the core deficiency of the field: the absence of a self-updating, data-responsive foresight mechanism.

### *MLOps Stream — Structural Mapping of Machine-Learning Lifecycle Studies vs. Kreuzberger et al. (2023)*

The comparative analysis of sixteen MLOps studies against the considered $A_1$–$D_2$ architecture spanning business problem formulation to continuous training (Kreuzberger et al., 2023), reveals an imbalance almost inverted relative to the foresight literature. The technically oriented phases — architecture design ($A_2$), model experimentation ($C_1$), and automated pipeline orchestration ($C_2$) — are overwhelmingly documented, while strategic framing, socio- organizational alignment, and long-term governance remain comparatively weak (Najafabadi et al., 2024; Eken et al., 2024).

The field retains a concept-centric majority (≈ 60 %) with a strong engineering orientation. Steps $A_2$ and $C_1$ emerge as the unambiguous methodological anchors: both are explicitly addressed in 100 % of reviewed studies, confirming a consensus around designing robust ML architectures and optimizing training–validation workflows. By contrast, $D_1$ and $D_2$ — covering deployment, monitoring, and continuous retraining — are only 44 % and 25 % explicit respectively, exposing persistent gaps in lifecycle governance and adaptive maintenance (Kreuzberger et al., 2023; Symeonidis et al., 2022). These deficiencies underscore that while MLOps excels in building efficient pipelines, it still lacks the mechanisms required to preserve model relevance under shifting conditions.

Upstream stages — $A_1$, $B_1$, and $B_2$ — are also uneven. Strategic problem formulation ($A_1$) is explicit in only 31% of studies, with 50 % addressing it only partially. Data acquisition and labeling ($B_1$) show higher maturity (69% explicit), whereas feature engineering ($B_2$) remains split between explicit (50%) and partial (38%) coverage. Few studies articulate how ML objectives derive from organizational strategy or sociotechnical context, revealing a strategic abstraction gap that mirrors the foresight field's operational discontinuity (Kreuzberger et al., 2023; Najafabadi et al., 2024).

The interpretive pattern is therefore clear:

- Foresight research is strategically rich but operationally incomplete (Durance, Godet, 2010; Ramírez et al., 2017).
- MLOps research is operationally robust but strategically blind (Kreuzberger et al., 2023; Najafabadi et al., 2024).

This complementarity reinforces the rationale for an integrated model.

The considered MLOps architecture detailing the complete $A_1$–$D_2$ sequence (Kreuzberger et al., 2023) offering the procedural backbone necessary for automation, while lacking the strategic reflexivity characteristic of foresight.

Integrating Godet's foresight logic into Kreuzberger's adaptive architecture enables GSF(M)$^2$ to address two symmetrical gaps: (1) connecting foresight to real-time, data-driven evolution, and (2) embedding strategic and participatory intelligence within automated ML workflows. This integration transforms linear processes into a closed-loop system linking problem identification, scenario construction, algorithmic prediction, and policy action.

Although the MLOps literature exhibits strong technological maturity in experimentation, architecture design, and workflow automation, its weakest dimension — $D_2$ continuous monitoring and retraining — exposes the field's Achilles heel: insufficient capacity for self-correction and adaptation.

Through MLOps–foresight embedding, GSF(M)$^2$ directly replaces this missing feedback function, ensuring that algorithmic outputs not only support decisions but continually inform strategic reframing. The resulting hybrid architecture couples foresight's interpretive depth with MLOps' adaptive precision, producing an anticipatory governance model in which strategic reasoning and technical execution co-evolve dynamically (Durance, Godet, 2010; Kreuzberger et al., 2023).

### *Synthetic Insight: From Parallel Gaps to a Unified Model*

When both research domains are examined through the lens of PRISMA-informed structural mapping (Durance, Godet, 2010; Kreuzberger et al., 2023), a striking symmetry emerges between their respective limitations and potentials. The scenario-planning field rooted in systemic foresight demonstrates exceptional conceptual maturity, it excels in understanding complexity, engaging collective intelligence, and constructing structured narratives to anticipate long- term uncertainty (Godet, Durance, 2011). However, it exhibits a critical executional discontinuity: foresight insights often stop at the scenario-building phase, lacking mechanisms for real-time data assimilation, automated feedback, and continuous operational validation (Ramírez et al., 2017; Abuzaid, 2018). Strategic foresight remains largely dependent on human deliberation cycles, which, although cognitively rich, are inherently static and slow to respond to evolving conditions.

In contrast, the MLOps field achieves high procedural completeness and automation efficiency (Kreuzberger et al., 2023; Najafabadi et al., 2024; Eken et al., 2024). It offers robust architectures for data acquisition, feature engineering, experimentation, model deployment, and continuous training. Yet its strength in technical precision coincides with a notable deficiency in contextual and strategic orientation. MLOps systems frequently lack frameworks for interpreting results within socio-organizational contexts, ethical frameworks, or long-term strategic objectives. Consequently, these models risk operating as closed technical systems — optimized for efficiency but detached from broader human, institutional, or geopolitical considerations (Kreuzberger et al., 2023; Symeonidis et al., 2022).

The proposed Generalized Strategic Foresight Model embedding MLOps (GSF(M)$^2$) emerges precisely at this intersection of cognitive foresight and computational intelligence, offering a synthesis that compensates for the shortcomings of each. By embedding machine learning operations within a strategic foresight scaffolding, GSF(M)$^2$ transforms traditional scenario planning into a living, self-updating ecosystem. The model's feedback loops — borrowed from MLOps — enable foresight scenarios to be continuously refined based on real-world data flows, emerging trends, and contextual shifts. Conversely, foresight principles introduce interpretive, participatory, and normative dimensions into the MLOps workflow, ensuring that algorithmic adaptations remain aligned with evolving strategic visions and societal goals (Godet, Durance, 2011; Kreuzberger et al., 2023).

This fusion produces a closed-loop, reflexive decision architecture in which data, foresight, and action coexist dynamically. Machine learning pipelines no longer function as isolated prediction engines but as anticipatory agents within a broader foresight cycle, informing and being informed by human judgment and collective sense-making. Decision-makers can thus operate within a continuously learning governance framework — capable of detecting early signals of systemic change, simulating alternative futures, and automatically recalibrating strategic priorities as conditions evolve (Durance, Godet, 2010; Kreuzberger et al., 2023; Symeonidis et al., 2022).

In practice, GSF(M)$^2$ redefines policymaking from a linear, episodic endeavor into a perpetual learning system. Strategic planning becomes iterative, data-driven, and contextually adaptive, blending quantitative analytics with qualitative foresight. Governance institutions can integrate diverse information sources — economic, social, environmental, and geopolitical — into a coherent, continuously updated decision model. This enhances resilience through adaptive feedback, responsiveness through real-time insight generation, and legitimacy through transparent, evidence-based adaptation (Godet, Durance, 2011; Kreuzberger et al., 2023).

Ultimately, GSF(M)$^2$ embodies a new epistemology of governance—one that reconciles human strategic intuition with the precision and scalability of machine learning. It bridges the gap between foresight's interpretive depth and MLOps' operational immediacy, enabling global actors to navigate complexity through a framework that is simultaneously anticipatory, adaptive, and accountable. In doing so, it establishes the foundation for a next- generation decision ecosystem where scenario-based anticipation and data-based automation co-evolve to sustain informed, participatory, and ethically grounded governance in a rapidly transforming, multipolar world (Godet, Durance, 2011; Kreuzberger et al., 2023; Symeonidis et al., 2022).

## Structural Modeling of GSF(M)$^2$

The structural modeling of the Generalized Strategic Foresight Model embedding MLOps (GSF(M)$^2$) constitutes the formal articulation of the dual- core framework emerging from the systematic literature review. This section details the conceptual and operational components of the model, organized through a stepwise architecture that integrates foresight methodologies with machine-learning operations. The resulting structure synchronizes the proactive logic of strategic foresight, rooted in systemic inquiry and scenario construction, with the pre-active logic of MLOps, grounded in automation, lifecycle governance, and continuous learning. Each step below constitutes a theoretical building block of the GSF(M)$^2$ architecture and anticipates its technical instantiation in the implementation pipeline.

### *GSF(M)$^2$ Core Architecture — Step-by-Step Theoretical Description*

*Step 1 — Problem Formulation and Data Sourcing.* The first stage of the GSF(M)$^2$ model initiates a collective clarification of the strategic problem. In the foresight tradition, this phase structures a shared understanding of the challenge through participatory workshops mobilizing multidisciplinary expertise. Approaches such as PESTEL[1], SWOT, HUMINT, and structured debate allow participants to formulate the problem by identifying constraints, systemic tensions, and emerging uncertainties. This human-centered diagnostic ensures that the model's subsequent phases remain anchored in the lived realities, strategic intentions, and interpretive frameworks of stakeholders. Complementing this qualitative grounding, the model incorporates a systematic process of data sourcing that assembles the contextual signals required for analytical depth. Drawing on methods such as OSINT, expert-in-the-loop knowledge extraction, and augmented retrieval techniques, this step consolidates the raw indicators that document the state and evolution of the system under study. In contrast with traditional foresight approaches, GSF(M)$^2$ recognizes that data sourcing may precede or inspire the problem-formulation phase, as early data exploration often reveals implicit tensions or emerging themes that reframe the initial inquiry.

*Step 2 — Phenomenon Study, General Environment, and Data Labeling.* This step deepens the inquiry by systematically characterizing the phenomena and environments shaping the issue. The phenomenon study targets the internal dynamics of the system through pattern recognition, opinion surveys, and the formalization of internal variables. It relies on structured matrices of risks, control factors, and performance indicators to reveal recurrent mechanisms, systemic weaknesses, and organizational rigidities. In parallel, the general-environment analysis explores the system's external conditions. It scans signals of change — weak signals, early warnings, discontinuities, and emergent trends — using mapping techniques grounded in pattern recognition. This outward-looking approach identifies drivers, constraints, and disruptions that frame the range of plausible futures. These analytical layers are supported by a comprehensive data-labeling process. Contextual indicators are systematically indexed and categorized using contemporary uncertainty frameworks such as VUCA[2] and BANI[3]. By encoding attributes of volatility, fragility, non-linearity, and incomprehensibility, the model aligns the narrative complexity of foresight with the structured rigor required for computational modeling.

*Step 3 — Structural Analysis (MICMAC), System Outline, and Variable Classification.* The structural analysis phase translates raw indicators into a coherent systemic representation through the MICMAC[4] method. This involves constructing an influence/dependence matrix that surfaces the variables exerting the strongest causal leverage on the system. The matrix enables practitioners to identify key variables — both influential (drivers) and dependent (outcomes) — and illuminates the architecture of interdependencies shaping the evolution of the issue. Once the structural matrix is established, the system is outlined as a dynamic conceptual model. Variables are refined and updated iteratively, integrating stakeholder feedback to ensure that the system's boundaries and causal pathways reflect both analytical rigor and experiential insight. This reflexive refinement minimizes blind spots and strengthens the robustness of the model. The classification of influential and dependent variables marks the completion of this step. It provides the foundation for scenario design, as the future trajectories of these variables determine the range of plausible and desirable futures that can be constructed.

*Step 4 — Data Versioning, Retrospective Analysis, Trends, Drivers, and Seeds of Change.* This step introduces a temporal dimension to the modeling process by integrating retrospective analysis and version-controlled data interpretation. Data versioning ensures that the evolution of datasets, indicators, and interpretive decisions is traceable over time, facilitating dialogue among stakeholders and supporting transparent, iterative refinement. Retrospective analysis focuses on the historical mechanisms that have shaped past controversies and strategic decisions. By mapping these mechanisms and identifying the drivers that influenced past trajectories, the model builds an understanding of recurrent causal patterns and structural inertias. Simultaneously, the model evaluates the current state of the system by identifying seeds of change — weak signals embedded in stakeholder behaviors, institutional initiatives, technological disruption, or contextual shifts. These seeds of change highlight potential bifurcations in system evolution and foreshadow future scenarios. Tools such as the Cynefin framework[5] and Wardley mapping[6] enrich this analysis by accounting for systemic complexity, evolving value chains, and strategic positions within contested environments.

*Step 5 — Actor Roles Analysis, MACTOR Method, and Actor Strategies.* The fifth step systematically analyzes the role, influence, and strategies of actors within the system. Actor analysis integrates insights from retrospective drivers and contemporary seeds of change to build a multi-level assess-

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[1] Complex analysis of Political, Economic, Social, Technological. Environmental/Ecological. and Legal factors.

[2] Volatile-Uncertain-Complex-Ambiguous.

[3] Brittle-Anxious-Nonlinear-Incomprehensible.

[4] Cross-Impact Matrix Multiplication Applied to Classification.

[5] https://www.complexsystemsframeworks.ca/framework/cynefin/, accessed 07.02.2026.

[6] https://blog.gardeviance.org/2015/02/an-introduction-to-wardley-value-chain.html, accessed 07.02.2026.

ment of actor power, interests, and influence at international, national, public, and local levels. This multi-scalar analysis recognizes that strategic foresight operates across nested layers of governance and social interaction. The MACTOR[7] method operationalizes this step by mapping convergences, divergences, alliances, and conflicts among stakeholders. Through structured matrices of objectives and power relations, MACTOR clarifies how actors shape both present dynamics and future trajectories. The resulting analysis provides a detailed representation of strategic tensions and cooperation opportunities. In parallel, the model identifies actor strategies through an economic-intelligence lens. Offensive strategies (e.g., monitoring, influence) and defensive strategies (e.g., data protection, asset security) are mapped to reveal how actors seek to shape the informational and strategic environment. This dual role of influence and protection enhances the foresight model's capacity to account for power asymmetries and knowledge control within the system.

*Step 6 — Expert Inquiries (SMIC-Prob-Expert), Model Architecture, and Futures Assumptions.* This step focuses on reducing uncertainty through structured expert elicitation and computational support. The SMIC-Prob-Expert[8] method estimates subjective probabilities of key events and their possible recombinations, clarifying the space of plausible futures. By explicitly confronting expert judgments with formal probability structures, the method mitigates cognitive biases and improves the credibility of scenario-building assumptions. Simultaneously, the model begins to formalize its computational architecture. Automated processes generate, test, and reclassify hypotheses derived from the structural matrix. Models are trained and evaluated to simulate variable recombinations, estimate probabilistic outcomes, and identify emergent patterns that inform scenario development. The outcome of this step is a consolidated set of future assumptions—partial scenarios anchored in the evolution of key variables. These assumptions serve as the building blocks for later scenario construction and morphological exploration.

*Step 7 — Model Versioning, Morphological Analysis, and Scenario Construction.* The seventh step systematically constructs the model's exploratory capacity. Model versioning captures and archives each iteration of computational simulations, ensuring that model evolution remains transparent, auditable, and reproducible. Morphological analysis decomposes the system into its fundamental dimensions and explores the full combinatorial space of futures. This technique identifies plausible reconfigurations of system parameters, allowing scenarios to emerge from structured recombination rather than conjectural extrapolation. The step concludes with the formulation of scenarios, roadmaps, images of the future, and foresight narratives. These outputs synthesize analytical rigor with narrative clarity, enabling decision-makers to visualize and compare alternative futures grounded in the structural dynamics of the system.

*Step 8 — Model Deployment, MULTIPOL Assessment, and Strategic Options.* Once scenarios are constructed, the model transitions to strategic evaluation and deployment. Deployment operationalizes the computational model by transferring it from a staging environment to a production environment where it can support ongoing decision-making. The MULTIPOL[9] method then evaluates strategies and alternatives across multiple criteria, policies, and risk dimensions. By comparing action profiles and ranking options through multi-criteria analysis, MULTIPOL clarifies how each scenario shapes strategic choices and trade-offs. This step concludes with the articulation of strategic options — structured bundles of actions and orientations that express the negotiated stance of decision-makers across short-, medium-, and long-term horizons. It formalizes how organizations may navigate uncertainties while aligning actions with desired futures.

*Step 9 — Prediction Monitoring and Action Plan.* The final step establishes the feedback mechanisms that allow GSF(M)² to function as a living, adaptive model. Prediction monitoring evaluates the accuracy and reliability of forecasts in real time, identifying thresholds beyond which prediction accuracy declines and triggering feedback loops that prompt model retraining or structural reassessment. The Action Plan translates the insights from scenarios, strategic options, and predictive monitoring into a coherent program of intervention. It structures the operationalization of desirable futures by guiding the allocation of resources, the sequencing of initiatives, and the continual adaptation of strategies through iterative replanning. Through this combination of monitoring and action design, the GSF(M)² model becomes an engine for anticipatory, adaptive, and reflexive governance.

### *GSF(M)² Model Implementation — Step-by-Step Technical Pipeline*

The GSF(M)² implementation pipeline translates the theoretical foresight architecture into a fully operational, computationally supported system capable of continuous learning, automated scenario generation, and adaptive strategic guidance. This section provides a detailed technical account of how the model is executed through a hybrid pipeline combining data engineering, machine learning lifecycle governance, and foresight-driven analytical workflows. The resulting implementation enables the system to dynamically incorporate new information, maintain traceability, and refine strategic insights in real time (Figure 4). Each step below mirrors its theoretical counterpart but expresses its logic through the instrumentation of MLOps tools, automation mechanisms, and computational processes that allow the model to operate at scale and with reproducible rigor.

*Step 1 — Data Sourcing and Problem Formulation.* The implementation process begins by operationalizing data sourcing through automated ingestion pipelines capable of consolidating heterogeneous information streams. Web scrapers, API-

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[7] Matrix of Alliances and Conflicts: Tactics, Objectives and Recommendations.

[8] SMIC abbreviation refers to a French acronym for Cross Impact Systems and Matrices.

[9] MULTIPOL refers to "MULTI-criteria" and "POLicy" with an integrated participatory approach to policy-making.

Figure 4. **GSF(M)² Model Implementation — Step-by-Step Technical Pipeline**

| | |
|---|---|
| Data Sourcing | **Agility, scalability, and ethical sourcing:** Dynamic Web Scraping, Data Parcing Algorithms, NLP, and AI-driven sentiment analysis |
| Problem formulation (Prospective workshop) | **AI bots:** Roam of research articles, news pieces and social media, NLP to analyze constraints, ML for context 5 «W» aware questions, human feedback, human-in-the-loop |
| Data Labeling | **Agility, scalability, and ethical sourcing:** Dynamic Web Scraping, Data Parsing Algorithms, NLP, and AI-driven sentiment analysis. |
| Phenomenon study (internal variables) | **AI for in-depth phenomenon studies:** Conduct sentiment analysis, internal variables from Pattern recognition, human feedback, human-in-the-loop. |
| General environment (external variables) | **AI for in-depth environment studies:** Signals of change scan, external variables from Pattern recognition, human feedback, human-in-the loop. |
| Structural analysis, MICMAC METHOD | **Agility, scalability, and ethical sourcing:** Dynamic Web Scraping, Data Parsing Algorithms, NLP, and AI-driven sentiment analysis. |
| System outline and search for key variables | **AI for system outlining and updates:** textmining integrating with ML for updating and refining key variable. |
| Influent variables Dependent variables | **AI for variables classification:** Ranking algorithms for accurate classification, human feedback, human-in-the-loop. |
| Data Versioning | **Agility, scalability, and ethical sourcing:** Dynamic Web Scraping, Data Parcing Algorithms, NLP, and AI-driven sentiment analysis |
| Actors roles analysis, Constraints Argumentation Methods | **Human-AI collaboration to analyze actors' roles:** NLP for sentiment analysis, and pattern on conflict recognition and clusters. |
| Retrospective, Mechanisms, Trends, Driver actors | **AI for retrospective analysis:** ML to identify key drivers, trends, and actors. Dynamic updating mechanisms for CI/CD. |
| Current state, seeds of change, Actors projects | **AI to capture potential catalysts for change, and actors' initiatives:** NLP for entity recognition, and semantic understanding. |
| MACTOR Method | **AI for creativity boost:** data-driven insights, NLP for sentiment analysis, human feedback, human-in-the-loop. |
| Model architecture, training and evaluation | **Modular and adaptable model architectures:** Deep learning frameworks, online learning techniques, real-time evaluation metrics. |
| Actors' strategies | **AI-enabled horizon scanning:** NLP to interpret vast datasets, to address the 'blackbox' challenge and to enhance the strategic acumen for actors. |
| Experts inquiries SMIC-PRO-Experts Method | **AI for variables combination:** Process large volumes of data, trend and customer data analysis, robust framework for identifying outliers, weak signals, and wild cards. |
| Assumptions about the futures using keys variables | **Select final hypothesis as partial scenario yield by key variables:** Storytelling formulation based on key variables to refine hypothesis design. |
| Model Versioning | **Systematic model versioning:** Version control systems, containerization, CI/CD pipelines, human-in-the-loop validations. |
| Possible futures Analysis Morphol Method | **AI to generate scenarios:** AI-based horizon scanning, and generative AI to systematically explore and anticipate change. |
| Scenarios, Road, Images, Forecast | **Scenarios, Road, Images, Forecast:** Storytelling formulation of scenarios. |
| Model deployment | **Prioritize seamless, scalable deployment with versioned models:** orchestration tools, continuous monitoring, interpretability in the dynamic context. |
| Strategies and alternatives assessment, Multipol Method. | **AI-assisted multi-criteria decision analysis:** Deep learning for preference learning, sentiment analysis and sustainability performance evaluation. |
| Strategies Options | **Select valuable features and scenarios:** Least squares support vector machine (LS-SVM) feature elimination. |
| Prediction Monitoring | **AI to enhance the predictive and prescriptive capabilities:** DL for predictive analytics, RL for prescriptive recommendations. |
| Actions plan | **Human-machine for storytelling:** Identify nascent trends, uncover potential disruptions, and make informed decisions based on data-driven storytelling. |

*Source*: authors

based connectors, document parsers, and real-time data feeds collect both structured and unstructured data relevant to the problem domain. These pipelines integrate metadata capture and data-provenance logging, ensuring each piece of information is traceable to its origin. In parallel, the model incorporates the problem formulation derived from stakeholder workshops by encoding qualitative insights into machine-readable structures. Summaries, constraints, domain ontologies, and strategic goals are transformed through natural language processing into a semantic layer that informs subsequent computational modeling. This step effectively bridges human contextual knowledge and machine-executable representations, enabling the system to reason within the boundaries defined during the foresight inquiry.

*Step 2 — Data Labeling, Phenomenon Study, and Environmental Characterization.* At this stage, data is processed, cleaned, and labeled with domain-specific tags aligned with the uncertainty frameworks employed in the theoretical analysis. Automated techniques — such as entity recognition, pattern matching, topic modeling, and sentiment analysis — accelerate the labeling process, while human-in-the-loop corrections ensure semantic accuracy. The phenomenon study and environmental analysis are implemented through analytical modules that detect internal and external patterns across the dataset. Internal dynamics are extracted via clustering, correlation detection, and temporal decomposition, while environmental signals are identified through trend-mining algorithms, weak-signal detection modules, and event-sequence extraction. The computational outputs from this stage form a structured representation of the evolving ecosystem that the foresight model must interpret.

*Step 3 — Structural Analysis Automation and System Modeling.* This step operationalizes the structural analysis by encoding the MICMAC method into a computational workflow. Influence and dependence scores are calculated using cross-impact matrices enriched with machine-learning techniques such as conditional probability modeling and mutual- information estimation. Ranking algorithms help identify the variables most likely to shape systemic evolution. The system outline is generated automatically through graph-modeling techniques. Variables are represented as nodes, and their interactions as weighted edges, producing a dynamic systems map that updates automatically as new data enters the pipeline. This iterative update mechanism ensures that the computational model remains aligned with real-time knowledge and stakeholder insights.

*Step 4 — Versioning, Retrospective Computation, and Detection of Drivers and Seeds of Change.* The fourth step introduces temporal governance and model memory into the pipeline. Data versioning is implemented using distributed version-control systems and model registries that capture snapshots of datasets, metadata, and analytical decisions at each iteration. This framework provides transparency, reproducibility, and accountability. Retrospective analysis modules examine historical data to detect structural mechanisms and recurrent causal patterns. Time-series analysis, causal- inference algorithms, and change-point detection models reconstruct the drivers that historically shaped the system. Simultaneously, anomaly detection, pattern divergence metrics, and vector-based semantic drift analysis are used to identify "seeds of change," signaling emergent transformations within the system.

*Step 5 — Actor Roles Modeling, MACTOR Automation, and Strategy Extraction.* Actor analysis is operationalized by embedding graph-based social network analysis and NLP-driven role-detection into the pipeline. These tools identify actor groups, extract their stated objectives from textual corpora, and classify their behaviors across scales (international, national, public, local). The MACTOR method is encoded through automated construction of actor–objective matrices, influence matrices, and convergence–divergence maps. Machine-learning augmentation further enhances MACTOR by estimating latent alliances, conflict probabilities, and influence propagation. The system also infers actor strategies using behavioral modeling, clustering, and risk-profile estimation to differentiate offensive (proactive influence- seeking) from defensive (asset-protection) behaviors.

*Step 6 — Expert Inquiry Engine (SMIC Automation), Model Training, and Hypothesis Evaluation.* Expert elicitation is operationalized through a hybrid SMIC-Prob-Expert computation engine that collects structured expert input, validates consistency, and automatically calculates probabilities of event combinations. Bayesian updating and Monte Carlo simulation expand the classical SMIC method by quantifying uncertainty ranges and identifying high-impact event pairs. Simultaneously, the core model architecture is instantiated through modular machine-learning components. Models are trained, validated, and evaluated using distributed computing environments, enabling the system to simulate futures, predict variable trajectories, and test hypotheses. Automated evaluation pipelines continuously benchmark model performance and detect when retraining is necessary. The outcome is a set of machine-generated future assumptions — computationally refined proto-scenarios ready to undergo morphological and scenario-building processes.

*Step 7 — Model Versioning, Morphological Computation, and Scenario Generation.* Model versioning governs the lifecycle of computational artifacts by storing model weights, hyperparameters, training logs, and evaluation metrics. Each version is linked to its originating dataset and context, creating a complete lineage that supports auditability. Morphological analysis is executed using combinatorial generation engines that iterate through all structurally coherent future configurations. Constraints derived from MICMAC, MACTOR, and SMIC outputs restrict the combinatorial space to plausible futures, while generative AI models assist in exploring multidimensional configurations and identifying coherent patterns. The scenario engine integrates these morphological outputs into fully formed scenarios, combining quantitative variable evolution with narrative generation modules that translate computational insights into human-interpretable foresight narratives, roadmaps, and images of the future.

*Step 8 — Deployment, MULTIPOL Decision Analysis, and Strategic Pathway Modeling.* Deployment transitions the model into a production environment through containerization, CI/CD pipelines, and orchestration systems. This enables decision-makers to interact with real-time dashboards that integrate scenario outputs, actor dynamics, and predictive indicators. The MULTIPOL method is automated through a decision-analytic engine that evaluates strategies against criteria such as feasibility, desirability, robustness, and risk tolerance. Multi-criteria scoring, adaptive weighting, and scenario-based stress testing together generate a ranked structure of available policy options. Strategic options are then formulated using a synthesis module that combines scenario logic, actor strategies, and decision-analysis outputs to produce context-sensitive strategic pathways for short-term, medium-term, and long-term horizons.

*Step 9 — Monitoring, Drift Detection, and Action-Plan Operationalization.* The final step ensures the system's adaptiveness through continuous monitoring and automated feedback loops. Prediction-monitoring modules track key indicators, model accuracy, data drift, and concept drift, triggering alerts when thresholds are crossed. These alerts initiate retraining cycles, methodological updates, or system recalibration. The Action Plan module translates scenarios and strategic pathways into operational guidelines. It generates timelines, allocates responsibilities, structures execution milestones, and integrates monitoring mechanisms to maintain alignment with evolving conditions. Through this continuous interplay of forecasting, evaluation, and action design, the GSF(M)² implementation pipeline becomes a dynamic strategic intelligence infrastructure capable of supporting anticipatory governance. This further description of the GSF(M)² model demonstrate it synthesizes the complementary strengths of strategic foresight and MLOps into a single, dual-core framework that bridges the conceptual-operational divide in governance and decision-making. By embedding continuous machine-learning feedback loops into scenario-driven foresight, and conversely, introducing strategic, participatory, and ethical reasoning into automated ML pipelines, the model achieves a fully iterative, reflexive, and adaptive decision environment. Each step — from problem formulation to monitoring and action-plan operationalization — demonstrates how cognitive anticipation and computational adaptivity co-evolve, enabling decision-makers to respond dynamically to volatile, uncertain, complex, and ambiguous environments. Having established the architecture and technical implementation of GSF(M)², the subsequent section evaluates its innovative contribution, highlights methodological limitations, and outlines future research perspectives, emphasizing the model's adaptability across diverse geopolitical and governance contexts.

## Discussion and Perspectives

### *GSF(M)² Implementation Deep Description*

By establishing a structural bridge between foresight methodologies and MLOps lifecycle governance, GSF(M)² introduces a continuous, recursive, and fully traceable process that strengthens strategic reasoning as well as technical robustness. This recursive capability emerges from the model's ability to backtrack through every layer of the pipeline — from the latest deployed ML model versions, to the intermediate analytical outputs of morphological combinations, and further back to the prospective scenarios or even the narrative frameworks that articulate them. In practical terms, each of these artefacts becomes a versioned object within the system: updated models, revised scenario assumptions, reinterpreted drivers, and reformulated narratives all possess explicit lineage and traceability.

This architecture enables a systematic re-examination of initial hypotheses whenever contextual shifts, data drifts, or strategic reorientations are detected. Because data versioning is intrinsically linked to the earliest stages of the process—especially during variable selection and initial problem formulation — the model ensures that every adjustment made downstream can be propagated upstream. This creates an integrated logic where the updating of datasets, the refinement of variables, and the reinterpretation of structural and actor-based analyses are all synchronised within a closed learning loop.

Such recursiveness is not merely a technical feature; it constitutes the core epistemic advantage of GSF(M)². It allows the system to combine the dynamics of prospective requestioning — the continuous reframing of uncertainties, hypotheses, and scenario logics — with the operational discipline of data updating — the periodic retraining, recalibration, and redeployment of machine-learning components. As a result, both the anticipatory and computational dimensions co-evolve, ensuring that ML models remain aligned with evolving strategic realities, and that scenario generation remains grounded in the latest empirical evidence and contextual transformations.

Ultimately, this dual-loop mechanism provides organizations with a living strategic intelligence infrastructure capable of reflexively adapting to complexity and volatility. It transforms foresight from a static planning exercise into a dynamic, evidence-driven capability, while simultaneously grounding MLOps operations within a broader interpretive and strategic horizon. This integrative perspective is illustrated in Figure 5 (representation 1.b), which depicts the recursive feedback cycles that underpin the GSF(M)² architecture.

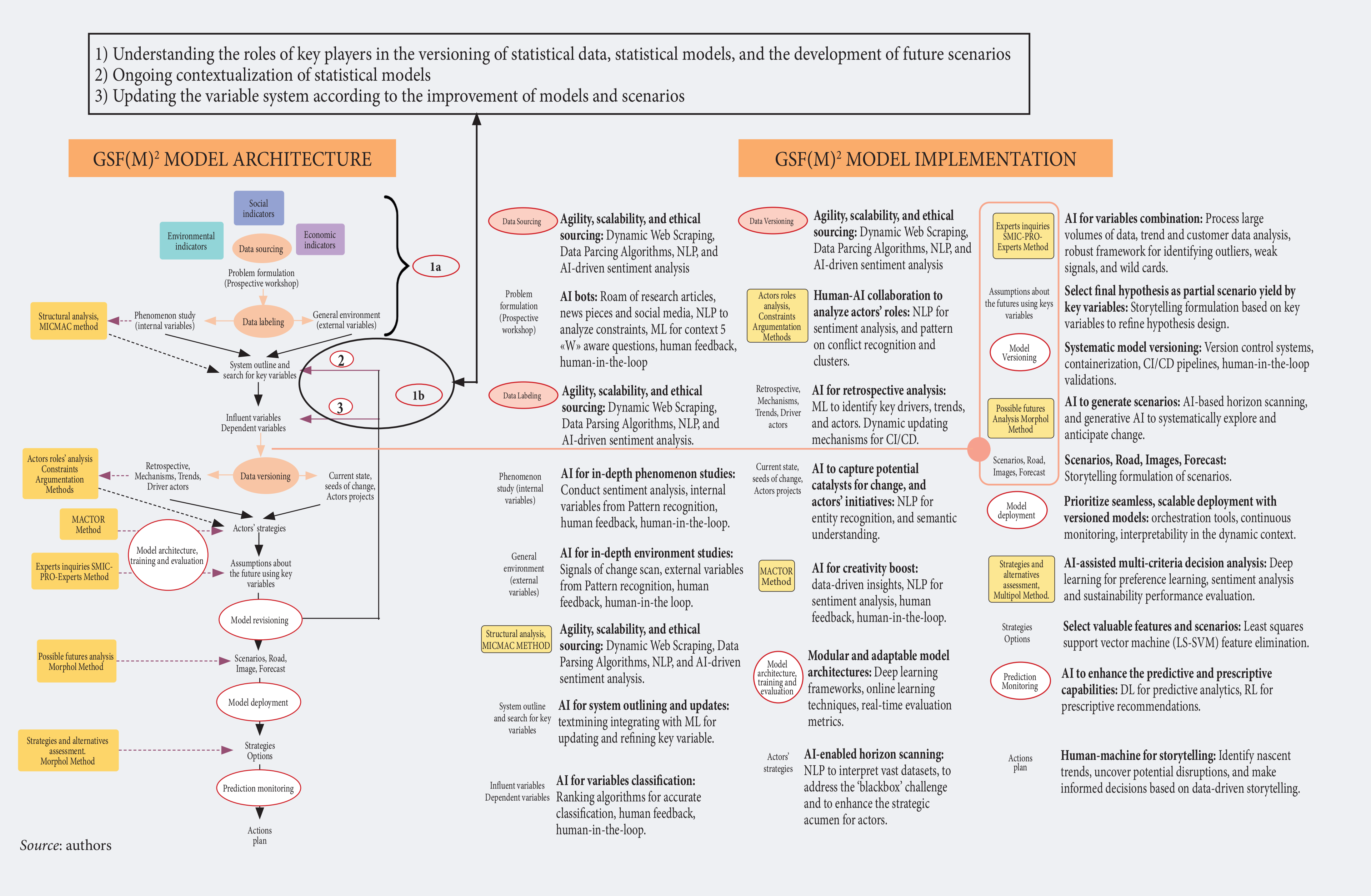
### *Innovation*

GSF(M)² represents the first integrated framework explicitly merging scenario-based strategic foresight with MLOps automation. Its novelty lies in systematically identifying complementary gaps in each field — foresight's operational discontinuities and MLOps' strategic blindness — and designing a hybrid system that mutually compensates for these weaknesses. By doing so, it establishes a continuously learning governance ecosystem capable of combining interpretive depth, anticipatory reasoning, and real-time computational adaptivity. This dual-core architecture transforms static scenario planning into an actionable, data-driven, and reflexive decision model, offering a unique tool for complex policy environments.

### *Limitations*

While GSF(M)² effectively operationalizes foresight within the MLOps lifecycle, the framework is currently constrained to standard ML pipelines. Extending the model toward AIOps — automated IT operations with broader system monitoring, anomaly detection, and predictive mainte-

Figure 5. **GSF(M)² implementation deep description**



1) Understanding the roles of key players in the versioning of statistical data, statistical models, and the development of future scenarios
2) Ongoing contextualization of statistical models
3) Updating the variable system according to the improvement of models and scenarios

**Agility, scalability, and ethical sourcing:** Dynamic Web Scraping, Data Parcing Algorithms, NLP, and AI-driven sentiment analysis

**AI bots:** Roam of research articles, news pieces and social media, NLP to analyze constraints, ML for context 5 «W» aware questions, human feedback, human-in-the-loop

**Agility, scalability, and ethical sourcing:** Dynamic Web Scraping, Data Parsing Algorithms, NLP, and AI-driven sentiment analysis.

**AI for in-depth phenomenon studies:** Conduct sentiment analysis, internal variables from Pattern recognition, human feedback, human-in-the-loop.

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**Agility, scalability, and ethical sourcing:** Dynamic Web Scraping, Data Parsing Algorithms, NLP, and AI-driven sentiment analysis.

**AI for system outlining and updates:** textmining integrating with ML for updating and refining key variable.

**AI for variables classification:** Ranking algorithms for accurate classification, human feedback, human-in-the-loop.

**Agility, scalability, and ethical sourcing:** Dynamic Web Scraping, Data Parcing Algorithms, NLP, and AI-driven sentiment analysis

**Human-AI collaboration to analyze actors' roles:** NLP for sentiment analysis, and pattern on conflict recognition and clusters.

**AI for retrospective analysis:** ML to identify key drivers, trends, and actors. Dynamic updating mechanisms for CI/CD.

**AI to capture potential catalysts for change, and actors' initiatives:** NLP for entity recognition, and semantic understanding.

**AI for creativity boost:** data-driven insights, NLP for sentiment analysis, human feedback, human-in-the-loop.

**Modular and adaptable model architectures:** Deep learning frameworks, online learning techniques, real-time evaluation metrics.

**AI-enabled horizon scanning:** NLP to interpret vast datasets, to address the 'blackbox' challenge and to enhance the strategic acumen for actors.

**AI for variables combination:** Process large volumes of data, trend and customer data analysis, robust framework for identifying outliers, weak signals, and wild cards.

**Select final hypothesis as partial scenario yield by key variables:** Storytelling formulation based on key variables to refine hypothesis design.

**Systematic model versioning:** Version control systems, containerization, CI/CD pipelines, human-in-the-loop validations.

**AI to generate scenarios:** AI-based horizon scanning, and generative AI to systematically explore and anticipate change.

**Scenarios, Road, Images, Forecast:** Storytelling formulation of scenarios.

**Prioritize seamless, scalable deployment with versioned models:** orchestration tools, continuous monitoring, interpretability in the dynamic context.

**AI-assisted multi-criteria decision analysis:** Deep learning for preference learning, sentiment analysis and sustainability performance evaluation.

**Select valuable features and scenarios:** Least squares support vector machine (LS-SVM) feature elimination.

**AI to enhance the predictive and prescriptive capabilities:** DL for predictive analytics, RL for prescriptive recommendations.

**Human-machine for storytelling:** Identify nascent trends, uncover potential disruptions, and make informed decisions based on data-driven storytelling.

*Source*: authors

nance — represents a natural next stage but requires further development in infrastructure integration and operational governance. Additionally, the model's performance in real-world deployments remains to be empirically validated across diverse governance contexts.

***Perspectives***

The model's adaptability opens promising avenues for comparative and context-specific applications. Future studies could explore its implementation in decision-making processes across different governance systems, including:

- Sub-Saharan African policymakers, emphasizing Common Panafrican identity reawakening as the central pillar of geopolitical, political, governance and people dynamics for institution redefinition.
- China and BRICS nations decision-making structures, where open 50 to 50 partenership weighted by techno-strategic coordination are the key.
- Russia and other BRICS nations, considering multipolar world and geopolitical respect and 50 to 50 partnership as the strategic-driver.
- The European Union, characterized by multi-level governance, regulatory harmonization, and territories re-industrialization as keys factors in reviving economic growth.
- The United States and North American contexts, where decentralized structures and market-driven policy mechanisms prevail.

Comparative studies across these systems would test the model's robustness, reveal adaptation strategies, and demonstrate its effectiveness in enhancing anticipatory, adaptive, and participatory governance in heterogeneous political and institutional environments.

## Conclusion

The present study set out to address a critical structural gap in contemporary governance and decision-making systems: the persistent disconnect between long-term anticipatory reasoning and real-time adaptive capability. Through a PRISMA-guided examination of both strategic foresight and MLOps research streams, the analysis demonstrated that each field exhibits methodological maturity precisely where the other reveals systemic limitations. Foresight offers conceptual depth, systemic intelligence, and participatory framing but lacks the procedural and technological infrastructure to sustain continuous decision–action cycles. MLOps, by contrast, provides robust automation, data-driven learning, and lifecycle monitoring, yet remains strategically underdetermined, often detached from interpretive, contextual, and normative considerations.

By synthesizing these complementary strengths, the Generalized Strategic Foresight Model embedding MLOps–GSF(M)$^2$ proposes a unified architecture capable of bridging this long-standing divide. The model integrates the proactive logic of scenario-based foresight with the pre-active computational precision of MLOps pipelines, generating a dual-core governance framework that is at once interpretive, adaptive, and self-updating. Its nine-step foresight structure, coupled with a full MLOps lifecycle implementation, establishes a closed-loop decision environment in which strategic hypotheses, model outputs, and environmental signals co-evolve continuously.

This contribution is significant at both theoretical and operational levels. Theoretically, GSF(M)$^2$ redefines strategic foresight as a living, data- responsive process rather than a periodic exercise, while also grounding MLOps within a coherent anticipatory logic. Operationally, the model offers a scalable blueprint for decision-makers seeking to integrate qualitative insight and quantitative automation into a single governance engine. By operationalizing scenario construction, actor analysis, and uncertainty mapping within automated pipelines, GSF(M)$^2$ transforms foresight into a dynamic intelligence system capable of supporting long-term planning under conditions of structural uncertainty.

Yet this model is not an endpoint. The transition from MLOps to broader AIOps architectures, the contextual adaptation of the model to different governance cultures, and the empirical validation of the pipeline across domains represent crucial next steps. In particular, comparative applications across Sub-Saharan Africa, China and the BRICS region, Russia, the European Union, and North America can illuminate how diverse institutional logics, strategic traditions, and socio-technical infrastructures shape the implementation and performance of GSF(M)$^2$. Such future research will help determine the model's versatility, limitations, and transformative potential across heterogeneous decision ecosystems.

Ultimately, GSF(M)$^2$ charts a pathway toward a new epistemology of governance — one in which anticipatory intelligence and adaptive computation operate in synergy. By coupling human foresight with machine-learning-driven responsiveness, it enables institutions to navigate complexity not as a constraint but as a strategic resource. In doing so, the model contributes to building governance systems capable of learning, evolving, and acting with clarity in an increasingly uncertain and interdependent world.

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