

AI-driven Strategic Intelligence for Policy- and Decision-making

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Abstract

Technology foresight is often constrained by reliance on publications and patents, limiting early detection of emerging science, technology and innovation (STI) trends. We demonstrate a hybrid AI-expert approach that combines the breadth and speed of Large Language Models (LLMs) with expert validation and contextualization. The framework is applied to three policy challenges: (i) analyzing structured policy documents, (ii) nowcasting STI indicators from proxy data, and (iii) transforming unstructured web content into structured datasets. Case studies in Dutch innovation policy, offshore wind, growth markets, R&D nowcasting, and critical raw material supply risks show that the approach delivers in hours what previously took weeks, and incorporates previously inaccessible data sources. The resulting workflow, consisting of collection, normalization, AI transformation, expert gating and audit trails, was reviewable by design. It limited model hallucinations and expert tunnel vision, while allowing low cost updates as new data or sources emerged.

Keywords: technology foresight; strategic intelligence; large language models; nowcasting; unstructured web data; policy analysis

1 Scientific motivation

Identifying developments in innovation is complex because of the variety in the forms in which it exists (knowledge publications, patents, descriptions, R&D, etc.). Technology foresight therefore aims to support policy and decision-making by examining longer-term future developments and conducting trend analysis (Da Costa et al. [1]). Although the data-driven side of the foresight discipline constantly aims to improve such analyses by utilizing new or additional data sources, and proposing innovative methods and approaches for better trend insights (Mühlroth and Grottke [3]), scientific publications and patent data remain the most established data sources used in such foresight studies (see e.g. Block et al. [5]; Han et al. [6]; Wustmans et al. [4]).

Artificial intelligence offers unique opportunities to enrich understanding of complex, fast-evolving STI developments through continuous input of big data and new AI-driven methods, making foresight more embedded, responsive, and real-time (Geurts et al. [2]). While previous research by Geurts et al. [2] demonstrated the potential of hybrid AI-expert approaches for strategic STI-intelligence, practical implementation across the foresight process to address

policy challenges remains an open question. How can organizations leverage the potential of a hybrid AI–expert foresight approach to improve strategic intelligence on STI?

This paper showcases our exploration of the application of a hybrid AI–expert based approach in technology foresight within three distinct policy challenges: analyzing structured policy documents, estimating real-time indicators for STI from proxy data, and converting unstructured web content into structured datasets. Through various case studies spanning innovation policy and supply chain risk assessment, we demonstrate the value of the hybrid AI–expert foresight approach. Our implementations reveal that the framework amplifies rather than replaces expert capabilities. Each application requires distinct expert knowledge: validation and contextualization of AI-generated insights, domain-specific indicator selection for estimation models, and expert guidance for interpreting unstructured data sources. These methodologies address common policy research challenges while providing insights up to 12 months earlier than traditional approaches and enabling systematic incorporation of previously inaccessible data sources.

2 AI approach

We explore AI applications across three policy challenges: structured document analysis, AI-based nowcasting, and unstructured web data processing.

2.1 AI-driven Structured Document Analysis

Challenge: Policy researchers and analysts face document processing challenges that exceed manual capabilities due to increasing volume, complexity, and interlinkage of information. Comprehensive analysis across large sets of policies, regulations, or technical reports is increasingly difficult using purely manual methods.

AI Component: Large language models (LLMs) extract themes, map concept relationships, and synthesize cross-document patterns, generating structured output such as technology-policy overviews and summaries.

Expert Component: Experts validate AI-generated insights through structured review sessions. Rather than building analyses from scratch, they review, correct, and expand the AI outputs. This speeds up the analytical process, improves the focus of expert time, and enhances the quality of final results by combining broad AI coverage with deep expert judgment.

Case studies: Three separate projects for the Dutch Ministry of Economic Affairs and the Dutch Enterprise Organization applied the method: (i) innovation policy, extracting five priority challenges and twelve emerging technologies; (ii) offshore wind, mapping ten key enabling technologies to different stages in the value chain; and (iii) growth markets, identifying promising technology–market intersections.

2.2 AI-based Nowcasting

Challenge: Many key policy and economic indicators are published with significant delays, limiting timely response and strategic policy- and decision-making. For example, R&D expenditure data is published with 12+ month delays, limiting timely policy insights.

AI Component: Machine learning models process high-frequency proxy data to produce early estimates of current indicator values. The approach can integrate search activity, transaction data, or other timely signals alongside historical series to model real-time trends and provide early signals to support technology foresight.

Expert Component: Expert knowledge ensures that the selected proxy variables genuinely reflect the underlying phenomenon, filtering out noise from unrelated trends.

Case study: We developed nowcasting models using Google Trends and macroeconomic indicators, testing neural networks, random forests, and econometric approaches. Expert input selected relevant search terms, to capture activity of all relevant parties in the innovation ecosystem. The approach delivered reliable estimates a year ahead of official figures and can be adapted to other innovation-related indicators.

2.3 Unstructured Web Data Processing

Challenge: Valuable research and market intelligence often reside in unstructured web content, making it difficult to extract and organize systematically.

AI Component: Automated crawlers and parsing routines collect and clean large volumes of online text. LLMs then apply targeted analytical frameworks to transform this content into structured datasets, such as mapping organizations to specific activities, technologies, or dependencies.

Expert Component: Experts guide the definition of relevant criteria, target sources, and interpretation rules. This ensures the AI focuses on meaningful distinctions rather than superficial matches.

Case study: To assess Japanese industry's dependence on Rare Earth Elements (REEs), large-scale website content was converted into structured company profiles. Experts set precise criteria to distinguish genuine REE import dependencies from use cases later in the value chain, avoiding false positives. The result was a graded (1–5) dependency index across five thousand companies, providing a foundation for assessing vulnerabilities and contextualizing events such as the 2010 Chinese export restrictions.

Technical implementation All AI-assisted analyses were conducted using ChatGPT 4.1 (and its predecessor GPT-4o) through the Microsoft Azure OpenAI Service. Within this setup, data are processed inside TNO's secure Azure environment, ensuring full EU data residency and compliance. The same framework could, in principle, also be applied to sensitive datasets by encrypting data and processing it on locally run GPUs using open-source models.

3 Results & Potential for Impact

Based on these case studies, we find that the use of AI provides promising new avenues to further develop the hybrid AI–expert based approach introduced by Geurts et al. [2] to support future-oriented collective intelligence to anticipate and navigate evolving trends and developments in STI. Across the case studies, a consistent pattern emerged: LLMs create breadth and speed; experts add precision, relevance, and accountability. In document analysis, LLMs produced cross-policy maps and candidate linkages in hours rather than weeks, allowing experts to concentrate on adjudicating what matters. In nowcasting, machine-learning models delivered credible signals up to 12 months before official releases. In web data processing, automated collection plus LLM structuring turned unstructured online text into decision-ready datasets (e.g., firm-level REE dependency scores), something infeasible by manual monitoring alone.

The quality gains came from how the human and machine steps were coupled. AI outputs were treated as traceable artefacts, so experts could verify, correct, and extend them. This “reviewable by design” workflow reduced the typical failure modes of both sides: model hallucinations and expert tunnel vision. It also made updates cheap: new documents, sources, or proxies could be reprocessed without rebuilding the pipeline. This emerging practice can make collective intelligence more effective.

An additional strength is the very low expert learning curve. Experts do not need to operate AI models directly; they only review and refine outputs, enabling fast and lightweight participation. This allows more experts from diverse domains to contribute in less time, resulting in analyses that integrate a broader range of expertise.

The contribution is also operational: the framework scales because it is modular. Each pattern uses repeatable components (collection, normalization, AI transformation, expert gating, audit trail). That makes it portable across policy domains.

4 Discussion

The hybrid AI–expert based approach for technology foresight provides a practical answer to the core question of systematic application across heterogeneous information problems to characterize STI-policymaking. The key takeaway is to adopt AI to detect a small set of reusable patterns and to next embed expert judgment. Doing so delivers broader coverage (continuous monitoring of sources previously out of reach), and higher decisional quality (expert-validated and traceable outputs) without sacrificing rigor. As such, the application of hybrid AI–expert based approaches can make strategic intelligence more effective, decreasing efforts needed to identify potential future policy-driven technological developments in a given context, while increasing the quality of the input delivered by experts. In addition, such approaches can make intelligence more timely as it offers real-time assessments that enhance longer-term future explorations.

Hence, the hybrid AI-expert driven approach can make policy and decision-making also more adaptive to changes that might otherwise take a longer time to materialize or be signaled. As AI evolves further, the opportunity is not to replace strategic intelligence expertise but to refactor it to move expert time from search and first-pass synthesis to calibration, judgment, enrichment, and governance.

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