Anticipating the future: A pedagogical policy-making process guided by AI.

Special Session: S69 - Embedding Eco-Social Justice in Europe's Twin Transition: Multi-Method Approaches for Policy Innovation (RP)

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Abstract.

The European policy discourse increasingly recognises the need to embed eco-social justice within the governance of sustainability transitions. However, translating justice principles into operational policy reasoning remains difficult. Policymakers must assess multi-dimensional impacts across economic, social, environmental, and fundamental rights domains, while navigating uncertainty, institutional constraints, and competing interests. This paper presents a pedagogical framework from the FITTER-EU project that harnesses conversational probing—an interactive process where a large language model (LLM) iteratively questions and refines a policymaker's reasoning about specific policies. Applied to Energy, Transport, and Housing sector across six European countries (Ireland, Spain, Portugal, Germany, Italy, Hungary), the framework is enabled by an AI / LLM powered FITTER Digital Platform for structured impact evaluation and mitigation co-development. Early implementation shows that conversational probing enhances systemic awareness, surfaces intersectional blind spots, and fosters more nuanced, equity-sensitive policy reasoning.

Keywords: Large Language Model (LLM), Conversational Probing, Agentic AI, policy design, Policy Reasoning, Digital Platform, Policy Impact

1. Introduction

Europe's twin transition is generating profound structural change across economic systems, labour markets, governance arrangements, and regional development. While central to climate neutrality and technological competitiveness, these transformations risk deepening existing inequalities and creating new socio-economic divides. A significant gap remains in intersectional equality impact assessments, which are essential for identifying, preventing, and mitigating inequalities that transitions may exacerbate or generate. These uneven effects highlight the need for policy approaches that are anticipatory, inclusive, and attentive to eco-social justice.

Traditional policymaking often operates in silos rather than interconnected systems. This fragmentation obscures cascading effects—for example, how electric vehicle subsidies may strain public transport budgets or how housing insulation mandates

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could widen energy poverty gaps. Linear planning also overlooks long-term feedbacks, power imbalances, and non-linear dynamics that amplify vulnerabilities. There is therefore a pressing need for pedagogical interventions that equip policymakers to interrogate these complexities—not through prescriptive tools, but through structured experiences that cultivate critical reflection, systems awareness, and eco-social justice evaluation skills.

AI-driven conversational probing responds to this need by engaging policymakers in targeted dialogue. Instead of delivering static scores or classifications, an intelligent system challenges implicit assumptions, clarifies ambiguities, broadens stakeholder consideration, and surfaces cross-domain effects. Conversational probing unfolds iteratively, producing progressively refined reasoning rather than prescriptive outputs, making normative choices and cognitive gaps explicit.

Large language models (LLMs), when fine-tuned with domain-specific and normative constraints, provide a powerful medium for operationalising this approach. An LLM can analyse a policymaker's qualitative assessment of an electric vehicle subsidy across economic, social, environmental, and rights dimensions, then probe with questions such as which groups may be excluded or what assumptions underlie a given impact score. This scaffolding strengthens systems thinking without dictating conclusions, fostering reflexive capacities essential for anticipatory governance under uncertainty.

The FITTER digital platform applies LLM-driven conversational probing as a pedagogical device, offering structured learning experiences in which policymakers and stakeholders explore systemic dynamics, surface mental models, and examine how twin-transition policies may reinforce or reduce inequalities. AI-enabled interactive methods create reflective spaces for experimenting with alternative narratives and futures without steering users toward predefined solutions. The framework combines systems inquiry and systems thinking through dialogue complemented by visual outputs that enhance comprehension. Users engage in AI-mediated conversations simulating decision contexts, enabling "what if" experimentation in safe environments. This pedagogical emphasis distinguishes FITTER-EU by building reflexive capacities for ongoing policy assessment and guiding users toward eco-social justice framing rather than ready-made solutions.

By foregrounding learning, self-reflection, and critical engagement, the framework strengthens the capacity to design, assess, and revise policies in recognition of systemic interdependencies and the lived realities of vulnerable groups. The core contribution of this paper is conceptual and methodological: it advances AI-driven conversational probing as a reflexive systems-thinking pedagogy for twin-transition policymaking in Europe. Throughout this text, AI and LLM are used interchangeably to reflect contemporary usage in the modern AI era.

2. Methodology

At its core, policymaking is a cognitive and interpretive activity. Decisions emerge not only from data but from how actors frame problems, evaluate impacts, and imagine futures. In complex transition contexts, many distributive effects remain hidden within institutional mental models. Eco-social justice cannot be embedded in policy unless policymakers are prompted to critically examine these models.

Conversational probing refers to a structured dialogic process in which an intelligent system does not merely provide answers but actively questions the user's reasoning. Rather than generating prescriptive solutions, it facilitates reflection through iterative inquiry. Conceptually, conversational probing draws on traditions of dialogical pedagogy and systems thinking, where learning emerges through questioning assumptions, identifying feedback loops, and reframing problems. In the context of Europe's twin transition, conversational probing serves three interconnected functions:

1. **Cognitive externalisation** — making policymakers articulate implicit assumptions underlying policy evaluations.
2. **Systemic interrogation** — exposing cross-sector interdependencies and long-term distributive effects.
3. **Justice-oriented reframing** — embedding eco-social justice considerations upstream in policy reasoning.

Conversational AI enables dynamic interaction. The system adapts its questioning based on user responses, thereby tailoring the pedagogical process to individual reasoning pathways. This interactivity is particularly significant in transition governance, where no two policy contexts are identical.

The FITTER-EU AI-enabled pedagogical methodology is designed as a reflexive, dialogue-based environment supporting policymakers engaged in energy, transport, and housing policies within the European twin transition framework. The FITTER Digital Platform supporting the methodology does not simulate abstract global scenarios; rather, it supports contextualised reflection on European governance realities.

2.1 AI-driven Platform Architecture: Fine-Tuned LLM and OpenAI Integration

The system architecture combines a fine-tuned large language model with OpenAI API-based inference capabilities. At its foundation lies an OpenAI base model, accessed through secure API calls. On top of this base model sits a specifically instruct-trained and fine-tuned LLM trained on curated FITTER-EU knowledge assets. These include:

- Research findings on twin-transition inequalities.

- Sectoral analyses in energy, mobility, and housing
- Policy briefs and project deliverables
- Case-based evidence on distributive impacts
- Structured eco-social justice criteria

Fine-tuning ensures that the model's reasoning is aligned with the conceptual framework of embedding eco-social justice in policy design. Rather than generating generic sustainability advice, the system produces contextually grounded inferences consistent with FITTER-EU outcomes.

When users interact with the platform, their inputs are processed through a layered pipeline. First, the OpenAI API retrieves and structures relevant contextual information. Second, the fine-tuned LLM filters and refines outputs according to project-specific interpretive constraints. The final inference is then returned to the user in dialogic form.

This hybrid architecture ensures both breadth (via general language capabilities) and depth (via domain-specific fine-tuning) as is shown in Figure 1.

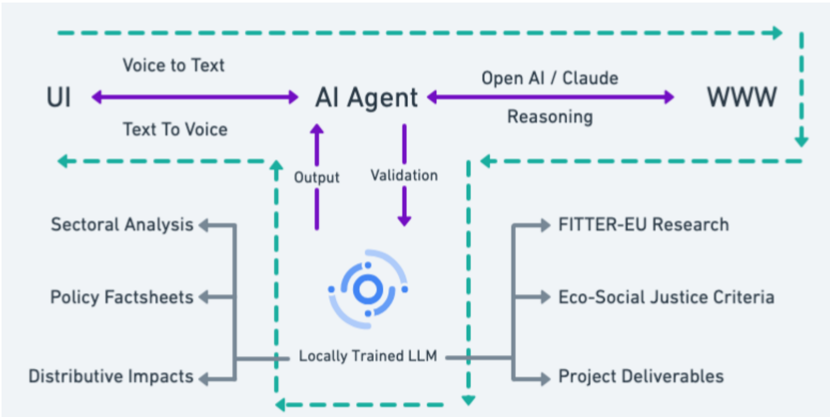

Figure 1: Architecture of the conversational probing system enabled by AI

2.2 Conversational Probing Workflow

The user journey comprises five reasoning based dialogic stages, blending input prompts, LLM probing, and visual feedback:

a. **Policy selection & Insights:** Users choose a twin-transition policy within the scope of FITTER-EU research, contextualised to their local area via country-sector filters. This generates important data points for the user as captured in the research phase of the project, including - potentially disadvantaged demographic groups, and their perceived hazards and negative impact of the policy in question. While the policies and the potential hazards come from the desk research conducted under FITTER-EU, the quantitative insights come from the perception-based survey launched across the six case study countries among different socio-demographic / socio-economic groups to understand the factors that influence the perception more than the others. The platform uses a sequence of statistical methods to derive robust conclusions through quantitative methods. This sets the ground for the dialog with the end-user preparing them to start a critical analysis for the local areas based on the available research data.

b. **Impact Evaluation:** Users score impacts on four dimensions—economic (e.g., job shifts), social (e.g., accessibility), environmental (e.g., emissions), fundamental rights (e.g., mobility equity)—on a 1–10 scale. At this stage, conversational probing begins. The AI does not simply record responses; it interrogates them. For example, if a user assigns a high economic score, the system may ask: "Which socio-economic groups benefit most from this policy, and are there groups excluded from these benefits?" Such probing encourages distributional specificity. The system may cross-question reasoning, identify inconsistencies, or request clarification. This iterative dialogue transforms impact assessment into a reflexive learning process leading to refined outcomes that align with the FITTER-EU rationale. Such probing encourages distributional specificity.

c. **Mitigation Measure Co-Development:** Based on the negative or uneven impacts identified, the platform invites the user to propose mitigation measures. Again, conversational probing operates as the pedagogical engine. The AI examines feasibility, equity implications, and systemic alignment. It may ask whether the proposed measure addresses root causes or merely symptoms, thereby invoking systems-thinking logic.

d. **Visual Comparison and simulations:** Mitigation pathways are visualised through comparative graphs and performance indicators across the four justice dimensions. Visual feedback enhances comprehension of trade-offs and synergies. It supports the deeper dialogic process. The platform illustrates the effects of the mitigation policies on the disadvantaged groups and the respective hazards identified previously in "**a) policy insights**". This enables the users to select the mitigation measures optimally.

e. **Report Generation:** The interaction culminates in the generation of an evaluation report synthesising policy impacts and mitigation reasoning. Anonymised conversation data are stored to enrich the knowledge base, enabling cumulative refinement of the model's probing capacity.

The above structured multi-stage dialogue enables The FITTER platform to offer a modular, scalable, and transparent digital environment for policy appraisal. It integrates predictive modelling, risk assessment, systems thinking, and stakeholder engagement, helping users visualise hazards, identify disadvantaged groups, and plan mitigation strategies.

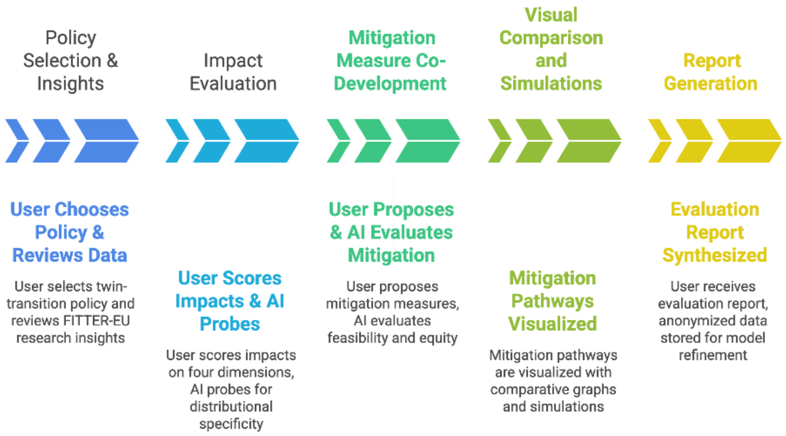

Figure 2: Conversational probing journey on the FITTER digital platform

3. Results

Preliminary implementation demonstrates that AI-driven conversational probing enhances policymakers' critical engagement with twin-transition policies. Users report increased awareness of distributive trade-offs, cross-sector interdependencies, particularly regarding affordability barriers in renewable energy deployment and access inequalities in electric mobility infrastructure. The dialogic format encourages deeper reasoning compared to static impact-assessment templates. Policymakers are prompted to articulate why a policy scores positively or negatively, leading to greater transparency in decision-making logic.

The cumulative data architecture also enables collective learning. As more policymakers engage with the system, the knowledge base expands, allowing refined questioning patterns and increasingly nuanced eco-social justice framing.

In FITTER-EU, the methodology powers Dr. Transition - An AI agent on the FITTER Digital Platform, which guides the platform user through the journey of self-reflection and eco-social justice embedded deeper reasoning for policy-making.

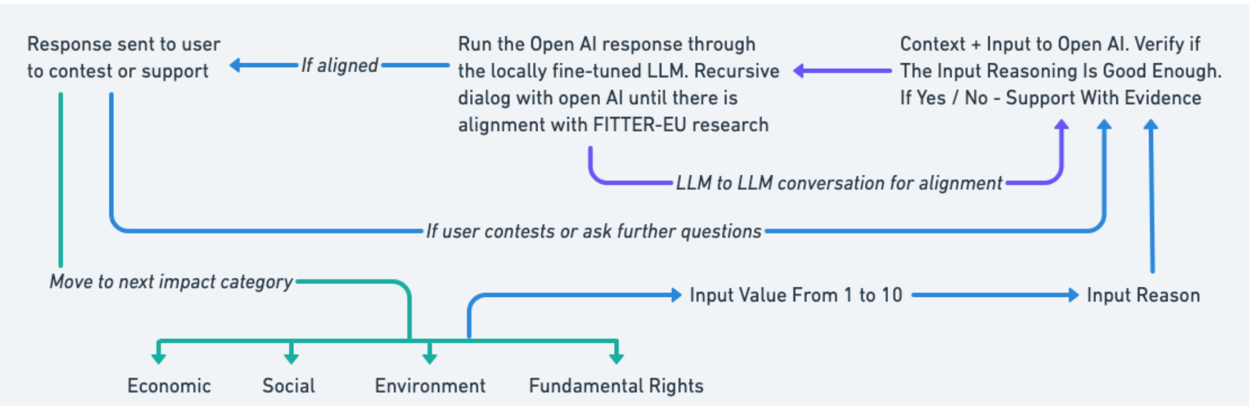

Fig 3 - Final Impact category dialog flow between the user and Dr. Transition

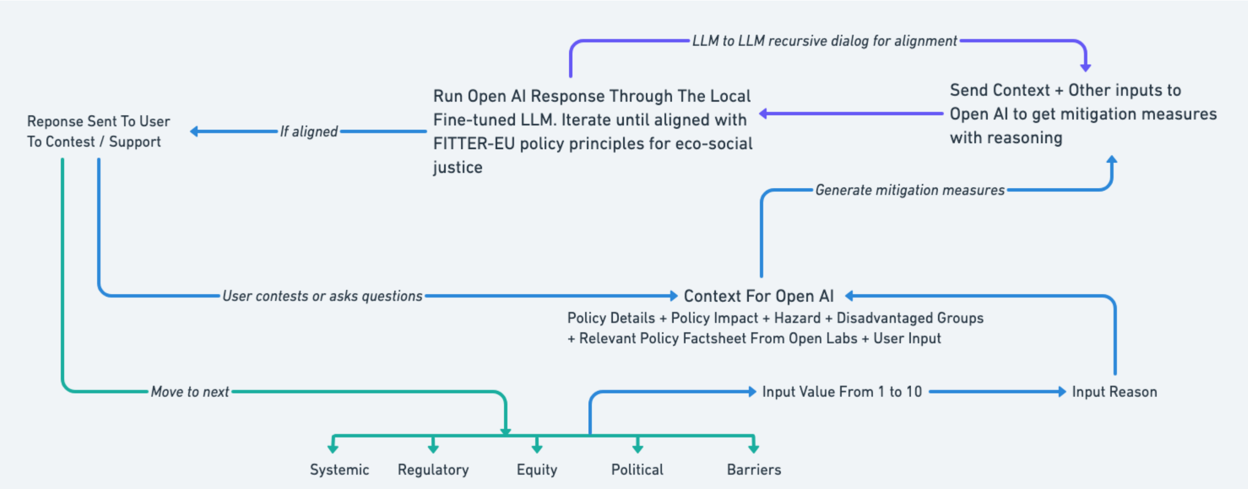

Fig 4 - Mitigation measure assessment dialog cycle per hazard

4. Discussion

The conceptual significance of AI-driven conversational probing lies in repositioning artificial intelligence within policymaking. Rather than automating decisions or prescribing optimal solutions, AI serves as a dialogic facilitator of reflexivity. This approach addresses a core limitation of conventional policy tools, which cannot dynamically challenge user assumptions. Conversational AI, by contrast, adapts in real time, tailoring questions to individual reasoning patterns. Such adaptability is especially valuable in the European twin transition context, where institutional diversity and policy heterogeneity demand flexible analytical engagement.

The fine-tuned LLM architecture ensures alignment with eco-social justice principles. By embedding project-specific knowledge, the platform foregrounds distributive fairness and fundamental rights.

Ethical and governance considerations remain central. Transparency in model training, clarity about AI assistance, and safeguards against over-reliance are essential to preserve human agency. The platform recognises its limitations, including data quality and predictive uncertainty, and emphasises the importance of qualitative dialogic insights alongside quantitative analysis derived from perception survey data collected during the research phase.

5. Conclusion

This paper advances AI-driven conversational probing as a pedagogical instrument for embedding eco-social justice within Europe's twin-transition policymaking. By integrating a fine-tuned LLM with OpenAI APIs, the FITTER Digital Platform creates a structured dialogue environment that stimulates critical reflection rather than automates policy design.

Through iterative questioning, multi-dimensional justice evaluation, mitigation co-development, and cumulative learning, the platform transforms AI from a predictive tool into a reflexive governance facilitator. As Europe navigates complex sustainability transformations, such dialogic AI systems may play a crucial role in supporting more inclusive, anticipatory, and equitable policy reasoning.

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