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## Exploring the Potential of Artificial Intelligence in System Mapping

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Rapid population growth, inequalities, and technological disruption create interconnected societal challenges driven by dynamic interactions among social, technological, and environmental factors. System mapping, while vital for understanding these complexities, is resource intensive. Generative AI (GenAI) can potentially accelerate the study of such issues, though its practical application remains underexplored. This research employs a mixed-methods approach to examine GenAI's role in system mapping, identifying three dimensions: the potentials of GenAI in system mapping, its challenges and limitations, and the benefits of managing complexity through Human-AI Collaboration. These findings provide a foundation for further exploration and practical applications in addressing complex problems.

Keywords: Generative AI, System Mapping, Systems Thinking, Participatory Modelling

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## **Introduction**

In a world full of growing disparities, misalignments and ongoing challenges, such as climate change, poverty, and educational inequalities (WEF 2024), there is a need to understand the root causes of such problems to solve them sustainably and holistically (Meadows 2009). For this reason, researchers in social science and engineering disciplines have worked with systems thinking since the emergence of this discipline in the last century (Forrester JW 1961). With the emergence of Generative AI, the fast adoption rates of user-based tools like Chat GPT, Google Gemini, and other technologies have become more accessible than ever before.

While literature covers systems thinking, system mapping, and GenAI applications in modelling, a significant gap exists at their intersections. Research has explored system mapping for understanding complex interdependencies and GenAI's capabilities in automation and data-driven insights. However, little attention has been given to how GenAI can enhance system mapping to improve efficiency, accessibility, and decision-making for addressing systemic challenges (Shrestha et al. 2022; Giabbanelli and MacEwan 2024). This gap was further reinforced in a preliminary study conducted inside Nova SBE's Scaling Systems Initiative, which revealed the time-consuming process of assessing system complexity. This thesis investigates the potential of GenAI tools to enhance system mapping, enabling actionable strategies for changemakers and establishing a basis for further study.

To close this gap, the following research question is going to be investigated:

**"What is the potential of generative AI to enhance system mapping processes and outcomes?"**

The research question was chosen openly due to the exploratory nature of this research. System mapping is considered causal mapping.

Here, there is no clear focus on a system mapping methodology as system mapping as a discipline entails multiple mapping approaches, ranging from simple iceberg models to causal loop diagrams or fuzzy cognitive maps (Barbrook-Johnson and Penn 2022). With Gen AI in this research question, the focus is on Generative AI (GenAI), the most proliferating technology (McKinsey 2024). Furthermore, the aim is not only to deliver focused results on system mapping but also to show more possibilities surfacing in the realm of this study. As system mapping is a means to an end, according to practitioners, it is essential to understand the practical implications.

This thesis is structured into six sections. The **Introduction** provides context. The **Literature Review** examines foundational theories and identifies gaps in existing research. The Methodology outlines the mixed methods approach according to the phases with details regarding the data collection and analysis. The **Findings and Analysis** section presents key insights into GenAI's role in system mapping, followed by a **Discussion** that evaluates these findings in relation to theory and practice. The **Conclusion** draws the outcome.

## 1. Literature Review

### *What is Complexity?*

System mapping, as part of systems thinking, helps us understand and navigate the interconnectedness of complex problems (Barbrook-Johnson and Penn 2022). When engaging in this, a common understanding of complexity is needed. Horst Rittel and Melvin Webber coined the term "Wicked Problems" to describe social policy issues like poverty alleviation, urban planning, and traffic congestion, which are difficult to solve using scientific methods due to their interconnectedness, dynamics, and boundaries. Rittel and Webber say wicked problems are

complex to understand since reducing them to a hypothesis only tackles half of the problem. Due to their interdependence, it is impossible to perceive a definitive solution endpoint, which keeps the problem reoccurring. Solution evaluation is subjective and generally depends on stakeholders' views; hence, solutions cannot be incorrect or correct but just good or terrible. Solutions have profound and often permanent effects that take months to show. Wicked problems are typically indicators of other issues and might be viewed differently. As the last trait of wicked problems, "No Right to Be Wrong", warns that mistakes might have dire repercussions that need cautious judgment (Rittel and Webber 1973). Due to their interconnection and multidimensionality, wicked problems exhibit several systems-thinking traits (Meadows 2009).

x synergistic analytic skills used to improve the capability of identifying and understanding systems, predicting their behaviours, and devising modifications to them to produce desired effects. These skills work together as a system” (Arnold and Wade 2015, 675).

### *Foundational Elements of Systems Thinking*

Systems thinking as a discipline also has its foundational concepts and terminology. This section aims to give a concise overview of selected foundational elements incorporating stocks and flows, feedback loops, leverage points, nonlinearity and emergence. Please find this tabular overview:

**Table 1 – Fundamental Elements of Systems Thinking**

| <i>Element</i>           | <i>Description</i>  | <i>Source</i>                |
|--------------------------|---|------------------------------|
| Stocks                   | Accumulations or resources within a system, e.g. water reservoirs or fish populations,  | (Meadows 1999)               |
| Flows                    | Flows are the rates of change, like rainfall or fish reproduction   | (Meadows 1999)               |
| Feedback Loops           | Cyclical cause-and-effect relationships that shape system behavior  | (Meadows 1999)               |
| Nonlinearity & Emergence | Minor inputs can lead to disproportionate outcomes, emphasizing the unpredictable nature of complex systems                     | (Meadows 1999)               |
| Dynamic Thinking         | Identification of patterns over time to understand feedback loops   | (Richmond 1993; Arnold 2017) |
| Structural Thinking      | Organization of system elements   | (Arnold 2017)                |
| Perspective Taking       | Incorporation of diverse viewpoints and mental modelling simplifies complex systems to test assumptions and predict behaviours. | (Arnold 2017)                |
| Managing Uncertainty     | Iterative decision-making, even with incomplete information   | (Arnold 2017)                |

### *System Mapping*

A fundamental tool for comprehending and evaluating intricate systems is system mapping. Two techniques provide a complementary means of visualizing and investigating system dynamics: Fuzzy cognitive mapping (FCM) and causal loop diagramming (CLD). Causal loop diagrams distinguish between reinforcing and balancing dynamics to expose leverage points and systematic behaviour (Meadows 2009). In qualitative research especially, they help to deepen knowledge of system structures and their interactions.

In contrast, FCMs integrate stakeholder knowledge and represent systems as directed weighted graphs, where relationships between variables are defined using fuzzy logic (Barbrook-Johnson and Penn 2022). This method makes semi-quantitative modelling possible, so enabling quantified scenario testing and uncertainty exploration. Suitable for complex systems, FCMs are flexible and capture quantitative approximations and qualitative insights. Participatory modelling in group settings enhances both methods by involving stakeholders in the group model-building exercises within causal loop diagrams (CLDs) to facilitate the identification of variables, the definition of feedback loops, and the establishment of system boundaries, ensuring that maps reflect diverse perspectives in a collaborative environment (Barbrook-Johnson and Penn 2022). FCMs utilize participatory approaches, allowing stakeholders to collaboratively establish the strength and direction of relationships, thereby ensuring that models accurately represent collective knowledge and priorities. Participatory techniques encourage stakeholder commitment and participation while enhancing the quality and usefulness of system maps. (Barbrook-Johnson and Penn 2022)

The effectiveness of established system mapping methods is evident; however, as discovered from initial studies and practical application uncovered that system mapping is resource-intensive and time-consuming. This highlights the necessity to investigate the potential of emerging tools like GenAI to improve these processes. This research, being exploratory, does not concentrate on a

particular mapping method. It examines the wider potential of GenAI in facilitating diverse system mapping methodologies.

### *Artificial Intelligence*

GenAI signifies a notable progression in the field of artificial intelligence. GenAI concentrates on pattern recognition within datasets to generate original content, such as text, images, and audio. In contrast to conventional AI models, GenAI demonstrates superior capability in producing outputs that closely mimic real-world structures through the utilization of unlabelled data (Michaelis et al. 2024). Innovations such as the Transformer architecture (Vaswani et al. 2017), which supports tools like GPT-4 and ChatGPT, have transformed tasks, including text summarization, conversational AI, and question-answering. Techniques such as Generative Adversarial Networks (GANs) (Goodfellow et al. 2014), Diffusion Models (Sohl-Dickstein et al. 2015), and Variational Autoencoders (VAEs) (Kingma and Welling 2013) improve their capabilities, enabling applications in image synthesis, voice generation, and content customization.

The interaction between humans and AI is referred to as Human-AI collaboration. A framework for Human-AI collaboration has been established to improve decision-making processes and enhance efficiency. Human-AI collaboration comprises four key components: tasks, goals, interaction, and task allocation (Fragiadakis et al. 2024). The notion of organizational intelligence has evolved from an exclusive emphasis on human capital to an integration of both human and AI capabilities (Kolbjørnsrud 2024).

Using AI within Human-AI collaboration responsibly entails leveraging a framework for its ethical use. For this, the concept of responsible AI emphasizes explainability, fairness, robustness, transparency, and privacy, ensuring that the models used are ethical and possible to interpret in real-world applications. IBM's Pillars of Trust approach defines fundamental ideas for producing responsible artificial intelligence. It emphasizes explainability by accurate forecasts, traceability,

and decision-oriented understanding. Fairness using diverse data, bias-aware algorithms, mitigating strategies, and heterogeneous teams supervised by ethical review boards. Robustness is meant to handle exceptional events. Transparency is stressed in the framework to increase user knowledge of GenAI capabilities and limitations as well as privacy to safeguard personal data and guarantee adherence to regulations such as the General Data Protection Regulation (GDPR). These concepts enable artificial intelligence's moral and consistent development (IBM 2024).

In the context of systems thinking, GenAI is increasingly recognized as a valuable tool for system mapping, particularly with methods like causal loop diagrams (CLDs) and fuzzy cognitive maps (FCMs). These techniques facilitate the visualization of feedback loops, examination of interdependencies, and testing of scenarios to identify leverage points within complex systems. Recent studies demonstrate that GPT-based systems can automate the creation of causal maps from text-based datasets, thereby decreasing the time needed to identify variables and relationships and enhancing the accuracy of systemic analyses (Newberry and Carhart 2024). GenAI has demonstrated efficacy in participatory modelling by integrating stakeholder inputs into coherent causal maps, uniting qualitative and quantitative insights, and enhancing access to these tools (Giabbanelli and MacEwan 2024).

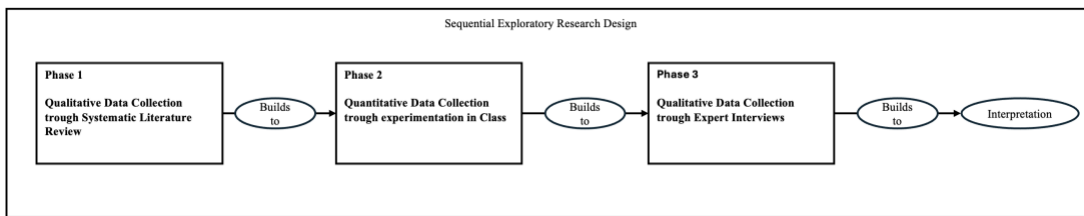
Looking at advanced use cases for GenAI-supported system mapping, Hosseinichimeh developed a system dynamics bot that helps to automate causal loop diagramming with an accuracy of 59% in identifying causal relationships and 66% in feedback loops. Although the evaluation is not very accurate, it still contributes to a faster mapping process (Hosseinichimeh et al. 2024).

The dynamic agent-based simulation developed by Ghaffarzadegan is another example of a use case that uses large language models to mimic human decision-making and emergent behaviours, offering insights into dynamics (Ghaffarzadegan et al. 2024).

Approaches such as system dynamics and agent-based modelling, along with static causal analysis in causal loop diagrams, can be integrated with dynamic simulations to enhance understanding of a system. In both cases, the researchers stress the importance of human oversight when working with those tools.

## 2. Methodology

Exploring the possible uses of GenAI in system mapping to tackle complex societal issues requires an extensive and multifaceted research methodology.



**Figure 1 – Sequential mixed method approach**

The recent development of GenAI highlights a significant research gap at the intersection of AI and system mapping, necessitating a methodology that integrates both theoretical advancements and real-world applications. A sequential exploratory mixed-methods approach (Creswell and Creswell 2018) was utilized and adapted to the specific research context.

This tailored method begins with a systematic literature review to provide a robust theoretical foundation, advances to an experimental phase for practical application assessment, and concludes with expert interviews to validate findings and integrate real-world insights.

By expanding the traditional two-phase design, this methodology accommodates the novel and exploratory nature of the research, ensuring a comprehensive and multi-dimensional understanding of GenAI's role in system mapping. Each phase builds upon the previous one, synthesizing

academic literature, practitioner perspectives, and experimental results to provide actionable insights into the potential applications of GenAI in addressing complex systemic challenges.

### *Stage 1: Systematic Literature Review*

Before recognising potentials, a researcher must understand the existing level of GenAI for system mapping. Systematic literature reviews help establish a study's theoretical foundation. Wolfswinkel's (2013) systematic literature review procedure combines grounded theory and an organized method of locating and identifying literature.

Therefore, researchers can provide the groundwork for exploratory inquiry. The Literature review aims to identify initial dimensions to inform the latter investigation of stages. **Data Collection:**

The methodology comprises five steps (define, search, analyze, and present), beginning with defining the search strategy. First, inclusion and exclusion criteria were set. When Scopus and Ebsco failed to identify sufficient information, Google Scholar became the main database. A broad sample was achieved by excluding inclusion or exclusion criteria. The search string was defined next and can be found in Appendix I. In the next phase of the systematic literature review, the research string was applied to Google Scholar and yielded n=600. The Google Scholar literature base is frequently updated. Therefore, search results may fluctuate over time. The following process selects and narrows the literature for assessment. The process followed a four-step approach, which can be found in Appendix I. After the selection stage, 20 papers remained.

Gioia is a recognized qualitative method for producing new concepts from qualitative data (Gioia, Corley, and Hamilton 2013). **Data Analysis:** Firstly, open code snippets related to one study question dimension were tagged. First-order concepts were connected to second-order themes, and the theoretical framework was built in the second step. The core categories, or aggregated dimensions, were determined in the last stage of selective coding. Max QDA was used to facilitate

the coding process. Chat GPT was utilized to challenge the data structure. The output of this stage were the aggregated dimensions: Technological and Human Foundations, Challenges and Risks, Knowledge Transformation and Communication and Strategic and Ethical AI Deployment which can be found in Appendix I.

### *Stage 2: Experimentation*

The experimentation phase was designed to test the identified knowledge transformation dimension, previously identified through Phase 1. The experiment was conducted in the context of the „Systems Thinking" class of Professor Milton Sousa, which is a class that conveys the basic concepts of system thinking to students.

**Data Collection:** The Fish banks simulation (MIT 2024), a known exercise in systems thinking education emphasizing resource management dynamics, was employed in this class. A custom GPT tool was created by reverse engineering academic papers, leading to a question-answering system that employs a step-by-step methodology to derive causality from data (Giabbanelli and Witkowicz 2023) and utilizes Anish Shrestha’s research for relationship identification (Shrestha et al. 2022). With this, a custom GPT was created that guides users through system mapping by sequentially asking the questions. After an introduction by the Professor and an introduction by the researcher of the tool, 38 Students in nine groups modelled the fish banks example.

A guide was supplied to the students, which can be found in Appendix II. They identified causal relationships, generated system maps, and explored leverage points. Students collaborated in groups to employ the GPT assistant for the analysis of system components, the construction of visualizations, and the understanding of feedback loops.

A survey was conducted post-experiment to record the participants' experiences. The survey incorporated themes derived from the literature review and featured both quantitative and qualitative questions. The survey assessed participants' familiarity with system mapping and generative AI tools, the ease and helpfulness of the Custom GPT's guidance, its clarity in concept explanation, and its effectiveness in identifying system components.

**Data Analysis:** The data obtained through Microsoft Forms was quantified by assigning numerical values to the response options. The final outputs of the survey were employed to strengthen the key aspects of phase three, the interview phase. The Outputs of the Data Analysis can be found in Appendix II.

### *Stage 3: Interviews*

After the experimentation stage, interviews were used as an additional phase to inform the outcome.

The decision was made to introduce a more robust practitioner perspective to the research design.

**Data Collection:** For this, an initial interview guide was prepared to gain insights concerning the dimensions of the initial systematic literature review, which were Knowledge transformation and communication, Challenges and risks, and Strategic AI deployment. The interview did not consider technological and human foundations, as its main aim was to evaluate the applicability of AI in system mapping. The experiment highlighted a significant emphasis on knowledge transformation, communication, and capability building. The selected interviews included well known key practitioners promoting systems change. Nine interview partners were engaged, providing a range of expertise in system mapping, participatory modelling, and AI tools. In total, nine interview partners were interviewed, ensuring diverse expertise in system mapping, participatory modelling,

and AI tools. These practitioners were chosen based on their hands-on experience with system mapping, focusing on their practical knowledge of the challenges and opportunities in applying AI tools in real-world contexts.

The interviews yielded valuable insights regarding GenAI's capacity to facilitate stakeholder alignment, streamline mapping processes, and visualize system dynamics, while also addressing ethical issues such as biases.

Besides biases trust in AI-generated outputs, and transparency in collaborative environments were identified. The nine interview guides were conducted in an agile manner, reflecting the focus of the interviewee and the exploratory nature of the research. **Data Analysis:** Data from the interviews were analyzed using the Gioia methodology, with findings synthesized into higher-order themes that complemented and refined the initial framework. Max QDA was used to facilitate the coding. The use of GenAI tool was conducted to challenge the coding categories. The Data structure can be found in Appendix I.

#### *Stage 4: Synthesis*

The final synthesis of findings from the systematic literature review, experiment, and interviews resulted in the three unified dimensions for understanding the potential of generative AI in system mapping. The themes were categorized into three aggregated dimensions: the **potential of AI in system mapping, challenges and limitations of AI and managing complexity through Human-AI collaboration**. The coding process in grounded theory is an iterative and highly subjective process, which may lead to other outcomes when conducted by other researchers. ChatGPT was used to challenge the coding structure. The presentation of these findings will follow in the Findings and Analysis Section.

#### *Limitations*

This study used a sequential mixed method approach with an additional qualitative phase based on the researcher’s decision to extend the data collection to be able to gain a practitioner’s perspective. The utilized methods are limited by the scope of this thesis, resulting in a low sample size for the experiment. Utilizing GenAI as a challenge to the coding structure could lead to biases, although the researcher's biases must be considered, too.

#### 4. Findings and Analysis

During the study, a sequential mixed method methodology was used to uncover the Potential of GenAI in system mapping. From the analysis of the interviews grounded in the literature and

informed by experimentation, three aggregated dimensions emerged. The first dimension, **Opportunities for Generative AI in System Mapping**, describes emerging use cases and application methods of Huma-AI augmentation to how AI influences the building of better models. The **Challenges**

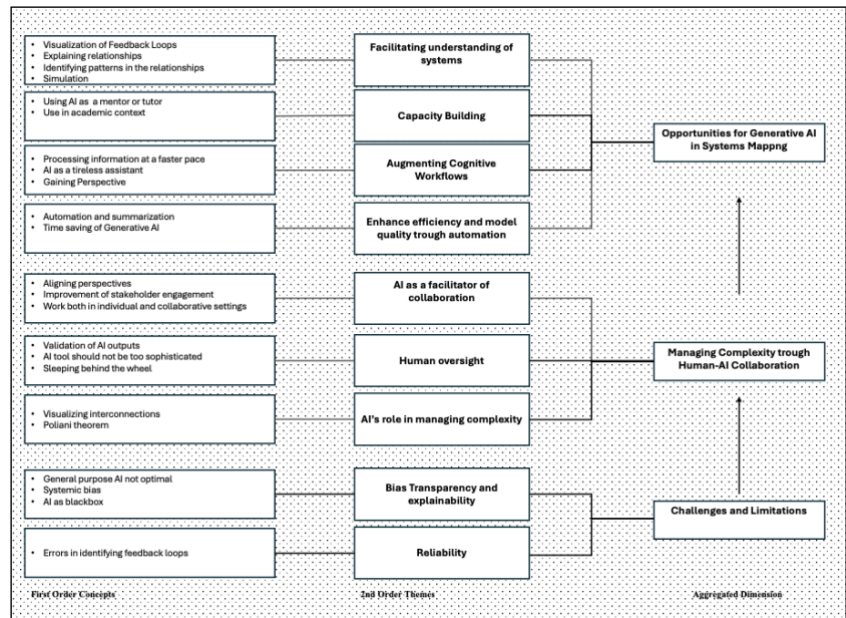


Figure 2 – Datastructure

and **Limitations of Generative AI** uncover related issues. The final dimension, **Managing Complexity Through Human-AI Collaboration**, links the opportunities and challenges faced by users, specifically humans, to the necessary interactions between AI and humans. The analysis enhances understanding by connecting participant insights to existing literature, illustrating how

GenAI's potential, limitations, and collaborative implications match with or contrast with previous research. For the detailed Gioia Table, please refer to the Appendix I.

### **Opportunities for Generative AI in System mapping**

Based on the research conducted, practitioners see opportunities to enhance causal mapping in systems thinking by improving understanding, augmenting cognitive workflows, automating repetitive tasks, and improving the overall quality of models.

#### *Facilitating understanding of systems*

GenAI plays a crucial role in simplifying relationships, visualizing feedback loops, and clarifying interconnections, which enhances the understanding of systems. Participants highlighted the significance of GenAI in explaining different aspects of the system and uncovering the relationships among actors or components. This is consistent with Shrestha's discussion of how GenAI tools might help people understand system dynamics by turning complex causal maps into narratives (Shrestha 2024). Additionally, the WEF report highlights that GenAI enables users to identify patterns and relationships in complex data systems, a critical function for enhancing systemic understanding (WEF 2024).

The quantitative results from the experiment indicate that 92% of participants reported that the Custom GPT facilitated the identification of system components. This dimension draws upon the "Enhancing Stakeholder Collaboration and System Understanding" dimension identified in the prior Systematic Literature Review.

In alignment with the findings of Ghaffarzadegan et al., practitioners observed the potential advantages of simulating mapping outcomes to enhance system comprehension (Interview 9 2024). This method is relevant for both mapping exercises and training sessions, as simulations can improve participants' sense of connection. The simulation aspect was anticipated within an academic framework, applicable to various stakeholder contexts (Interview 6 2024).

With GenAI helping to facilitate understanding of systems a reoccurring challenge of the accessibility barrier of systems thinking due to the complex terminology is addressed.

By simplifying relationships, GenAI offers the opportunity to reduce the cognitive strain of participants when organizing relationships. This reduction is crucial for helping engage individuals in system mapping exercises therefore acting as an accelerator and facilitator for building capacities in the system mapping domain and creating more system thinkers.

### *Capacity building*

The data gathered supported the application for capacity building in relation to system understanding. An interviewee with over 40 years of experience characterizes systems thinking as a proprietary language that frequently hinders participant engagement with the methodology (Interview 2 2024). Several interviewees recognized accessibility as a barrier to engaging novices in systems thinking and mapping (Interview 2 2024; Interview 3 2024). Researchers are developing intricate terminology, and GenAI can function as a co-moderator or co-facilitator to improve engagement with the methodology (Interview 6 2024; Interview 8 2024).

This is especially interesting in an academic context where capability building is a strong focus. Moreover, supporting internal stakeholders inside international agencies is extremely important and can help make system thinking more approachable when addressing language barriers (Interview 9 2024). In the experiment, 84% of participants reported that the custom GPT improved their understanding of system mapping concepts. The newly identified dimension was influenced by the AI-driven transformation of knowledge and communication resulting from the structured literature review. Utilizing GenAI for this purpose can address a challenge identified by practitioners.

Most of the population thinks in linear ways as the complexity & terminology of systems creates a large accessibility barrier and mental hurdle. By making system mapping and systems thinking

more accessible to the vast majority, pluralism could be fostered in organizations. By lowering the accessibility barrier and building capabilities faster, participants can engage in higher-order thinking tasks supported by GenAI to augment cognitive workflows.

### *Augmenting cognitive workflows*

Beyond improving comprehension and building capacities, GenAI supports human cognitive capacity by processing large datasets, identifying patterns, and accelerating workflows. Participants noted that GenAI acted as a “tireless assistant” during the exploration phase, “processing information at a faster pace” (Interview 1 2024) and enabling quicker sense-making. These insights align with Giabanelli et al., who highlight the importance of tools that assist in identifying leverage points and feedback loops in complex systems (Giabbanelli and MacEwan 2024). Additionally, it was often mentioned that one of the main advantages of GenAI was its ability to manage enormous volumes of data, especially in terms of streamlining the exploration process by making it simpler to identify patterns and linkages (Interview 2 2024). Through this, GenAI can enhance stakeholder involvement by streamlining processes and visualizing relationships, thereby facilitating cooperation during the system mapping process. These capabilities align with findings by Giabbanelli and Shrestha (2023), who link GenAI tools with identifying causal links through answering systems, and Newberry and Carhart (2024), who emphasize GenAI’s role in data analysis. The experiment results also reinforce these observations, with 79% of participants highlighting GenAI’s usefulness in understanding complex topics. This theme was informed by the “AI strengths in Decision Making and Automation” dimension from the systematic literature review.

In addition to facilitating complex analytical tasks, GenAI's ability to automate data processes, including data organization and transcription, enables practitioners to concentrate on strategic decision-making. The interaction between augmentation and automation establishes a workflow

that enhances systemic insights. GenAI's capacity to enhance cognitive workflows empowers practitioners to navigate complexity and make informed decisions; however, its role extends further to encompass automation.

Automating repetitive tasks, such as automated map creation with Kumu (Interview 2 2024), enhances workflow efficiency for practitioners and has the potential to produce higher-quality models.

### *Enhance efficiency and model quality through automation*

Participants indicated the potential for automating repetitive tasks that currently form their workflows. Participants indicated that AI tools could automate tasks such as transferring text into Kumu or summarizing conversations for mapping processes. Academic research supports the assertion that GenAI enhances causal loop diagramming processes through the automation of data transformations from extensive interview datasets (Newberry and Carhart 2024).

Similarly, it highlights the importance of automation in freeing up human resources for more strategic tasks, allowing users to focus on analysis and decision-making. Those tasks occur in the domain of structuring of the maps. Also, in the participatory setting a freeing up of resources can lead to a productivity shift for practitioners to focus on higher order tasks like stakeholder alignment. This theme was informed by the "AI strengths in Decision Making and Automation" dimension from the systematic literature review.

GenAI's ability to improve the overall quality of models was mentioned. GenAI could support the creation of more accurate and robust models by, e.g. modelling a systemic problem according to different system archetypes (Interview 2 2024). Participants noted that GenAI improves model construction and improves documentation, thereby facilitating usability and communication. The literature indicates that GenAI's processing capabilities can be employed to understand large-scale systemic challenges, offering new opportunities for addressing complex societal issues (WEF

2024). This dimension originated exclusively from the interviews, but it can be associated with the current literature. The dimensions illustrate the interconnected opportunities of GenAI in system mapping.

GenAI allows practitioners to manage complexity more efficiently by facilitating understanding, building capacity, enhancing cognitive workflows, and automating repetitive tasks. This accelerates workflows, leading to higher-quality models and ultimately driving more impactful interventions in complex systems.

### **Managing Complexity Through Human-AI Collaboration**

Now, after looking at the opportunities and challenges of GenAI in system mapping, the importance of collaboration between humans and AI needs to be highlighted. Human oversight and contextual knowledge are essential to making sense of GenAI outputs and ensuring their ethical use. All corresponding themes were informed by human-centered applications of GenAI themes from the systematic literature review.

#### *GenAI as a facilitator of Collaboration*

GenAI's role was often described as a potential facilitator of collaboration, enabling stakeholders to align perspectives and engage in discussions about system dynamics (Interview 5 2024; Interview 4 2024). AI enhances collaboration and stakeholder engagement through the organization of information and the provision of shared visualizations (Interview 6 2024).

The conversational nature facilitates collaborative mapping by system mappers, even in solitary contexts (Interview 2, 2024). The World Economic Forum emphasizes the importance of uniting cross-sector stakeholders to foster more inclusive and effective systemic solutions (WEF 2024). 84% of participants deemed custom GPT effective for comprehending basic concepts. This finding, along with the professor's observations, contributed to the formation of this category.

#### *Human oversight*

Participants emphasized that GenAI can't substitute for human judgement. Human oversight is essential for the validation of AI outputs and their refinement for contexts (Interview 2 2024).

Participants emphasized the necessity of keeping the human in the loop to evaluate outcomes and guarantee the ethical application of AI-generated insights (Interview 6 2024; Interview 7 2024).

This can also be triangulated with GenAI, leading to errors or incorrect results (Shrestha 2024).

Also, 95% of the experiment participants would recommend the custom GPT to peers, would not—95% of the participants needed to adjust the prompts.

### *GenAI's role in managing complexity*

Participants acknowledged the role of GenAI in managing complexity. GenAI facilitates users' navigation of the complexities inherent in systems thinking by visualizing interconnections and adjusting various levels of granularity (Interview 1 2024; Interview 3 2024). This is also connected to the theme identified in the "Augmenting human cognition" section. Participants emphasized the necessity of human expertise to refine outputs and ensure their applicability in real-world contexts (Interview 2 2024). Meadows reinforces this observation, highlighting that systems thinking necessitates tools for comprehension while depending on human insight for result interpretation (Meadows 2009). The WEF report (WEF 2024) indicates that effectively addressing complexity requires the integration of human contextual understanding and ethical oversight. This aligns with the Polyani theorem, which posits that humans frequently possess knowledge through intuition, a capacity that GenAI cannot replicate (Interview 6 2024). 98% of experiment participants identified the custom GPT as effective for recognizing interconnections, thereby facilitating complexity management.

### **Challenges and Limitations**

While potentials are always promising, and GenAI is showing potential in diverse stages along the mapping process, challenges and limitations must always be considered. Due to the immense social

nature of the domain of system mapping, participants highlighted several challenges that limit its practical application in causal mapping.

Furthermore, the literature shows initial research challenges. These include bias in the model itself, transparency issues, reliability concerns, and methodological misalignment.

### *Bias, transparency and explainability*

Bias was a recurring topic throughout the Interviews. Bias is a tendency to believe that some people, ideas, etc., are better than others, which usually results in mistreating some people. Participants worried that GenAI tools, reliant on training data based on the past, could embed systemic biases into their outputs (Interview 4 2024; WEF 2024). This aligns with the findings of Newberry and Carhart (2024), who warn that AI-generated causal maps might unintentionally mirror biases present in the input data, resulting in distorted or insufficient insights. Ghaffarzadegan (2024) underscores the necessity of addressing data biases to guarantee that AI-generated insights are fair and equitable. The experiment indicates that 95% of participants required adjustments to questions or prompts. This dimension was informed by the systematic literature review focusing on the theme of challenges and limitations in AI implementation.

Transparency and explainability were also recurring challenges. Participants characterized GenAI as a "black box," which complicates the trust and validation of its outputs (Interview 6 2024). AI-generated system maps frequently exhibited a lack of clarity, characterized by inadequate diagramming capabilities that impeded their effectiveness in participatory contexts (Interview 6 2024; Interview 3 2024).

According to Ribeiro, Singh, and Guestrin, explainable GenAI tools are crucial for building trust and facilitating group decision-making (Ribeiro, Singh, and Guestrin 2016). These issues align with their results. The World Economic Forum highlights the necessity of explainability for non-

expert stakeholders to effectively interpret and utilize AI-generated outputs (World Economic Forum, 2024).

Although 87% of respondents reported that the custom GPT was user-friendly, 13% expressed neutrality or provided fewer responses, indicating concerns about transparency, particularly in relation to inadequate diagramming. This theme originated exclusively from the interviews.

### *Reliability*

Reliability constituted a notable concern. Participants observed that GenAI occasionally simplifies relationships or misidentifies interconnections (Interview 2 2024). Effective training and validation mechanisms are necessary to resolve these issues (Interview 6 2024). Shrestha recognized the problem of oversimplification (Shrestha et al. 2022). The World Economic Forum highlights the importance of rigorous testing and validation protocols to improve the reliability of GenAI systems in dynamic contexts (World Economic Forum 2024). Furthermore, practitioners mentioned general concern about the effectiveness of “Layering AI” onto a poor process (Interview 7 2024), affecting the reliability of those tools. 29% of the experiment participants rated the custom GPT as average or below, indicating potential concerns about its reliability.

### *Synthesis*

The findings reveal that GenAI holds significant potential for enhancing causal mapping in systems thinking, augmenting cognitive workflows, enhancing model quality and capacity building. Those individual potentials help practitioners with the creation of higher quality models in shorter time. Furthermore, the capacity building part adds value by making system thinking more accessible to a broader audience. Humans need to still have the oversight over system maps to be able to counter biases within the data to leverage the true potentials of those opportunities. Just through a conscious application of GenAI within system mapping the true opportunities can be leveraged.

## 5. Discussion

To answer the question of "What is the potential of generative AI to enhance system mapping processes and outcomes?" a sequential mixed method approach was conducted. This yielded three main dimensions from literature and qualitative interviews partially triangulated with experimental data. The three dimensions, Opportunities of Generative AI in System Mapping, Challenges and Limitations of Generative AI and Managing Complexity through Human-AI collaboration, provide a multiperspective view of the potential of GenAI in system mapping. Through the exploratory nature of this study in a new field, the results should be seen as possibilities rather than fully realized applications. Within this discussion section, the findings will be situated within systems thinking and GenAI research, and the implications for theory and practice, limitations, and future research directions will be addressed.

### *Theoretical implications*

To discuss the previous results from the finding and analysis section an evaluation is going to be conducted whether the results extend, enforce or contradict existing theories.

Starting off with the facilitation of system understanding and enforcement of theory can be seen in support of the works of (Shrestha et al. 2022), in which he utilized GenAI for the explanation of causal maps. The validation from practitioners to see a practical application within this field enforces his work. The opportunity of capacity building, even though new to the systems thinking domain, is an addition to theory. The field of capacity building emerged solely from the interviews and is not situated in the current literature set. This can as a starting point for further investigation and research. Looking at the next finding, the augmentation of cognitive workflows enforces existing theories as researchers already investigated the applicability of artificial intelligence for analyzing large amounts of interview data (Newberry and Carhart 2024).

Within this finding the addition to theory can be regarded as the concrete application to the exploratory phase. Newberry and Carhat used GenAI for a preliminary map creation where the practitioners pointed out an application within the participatory process. The recognition of patterns and relationships can be situated as an enforcement of theory, as Giabanelli and Shreshta already developed a question-answering system for causal map creation (Giabbanelli and Witkowicz, 2023).

Furthermore, the automation of different processes can be seen as an extension of theory as the automation capabilities have not been found within the literature however it could also be regarded as an enforcement of the works of Giabanelli and MacEwan. The improvement of the overall quality of models is an insight that extends theory, as it has not been mentioned.

Looking at the second dimension, Managing complexity through Human AI collaboration, the emergence of GenAI as a facilitator of collaboration emerged from the data and can be categorized as an addition to theory. The category of the importance of human oversight is enforcement of theory, especially in regard to responsible AI and Human-AI collaboration (Fragiadakis et al. 2024). GenAI's role in managing complexity extends the theory of Meadows, who says that system thinking needs aids while relying on humans to understand the results (Meadows 2009).

The challenges and limitations of GenAI align majorly with the works (Newberry and Carhart 2024; Ghaffarzadegan et al. 2024). Concerning the transparency and explainability and need for the importance the results enforce the theory of (Ribeiro, Singh, and Guestrin 2016).

### *Practical Implications*

Concerning practical application, GenAI could streamline time-consuming workflows like data analysis and give system thinkers opportunities for more meaningful tasks.

Furthermore, quickly generating visualizations and aligning different perspectives could add a meaningful dimension to participatory sessions by clarifying cognitive complexity. Although those applications seem promising, they remain speculative and must be explored further.

Another layer for practitioners is capacity building within organizations and academic institutions, where GenAI could help reduce the barriers of entry to successful systems thinking methodology training. Also, GenAI can support cross-sector collaboration by summarising discussions and visualizing system dynamics. As a last point, organizations must address challenges like user resistance, training needs, and workflow integration. When GenAI is applied to complex systems, transparency and explainability are critical to fostering trust in GenAI tools. Mitigating bias in GenAI outputs is essential to ensuring equitable and inclusive systemic interventions. Organizations must implement safeguards to address ethical concerns.

### *Limitations*

Concerning the limitations, several factors need to be considered when looking at the exploratory nature of this study; first, the literature selection, which depended on Google Scholar and potentially excluded relevant findings from other databases. In a follow-up study, this could be encountered by integrating more databases like Web of Science, EBSCO host or Scopus to drive the rigidity of this research further. Broad inclusion criteria ensured a comprehensive review but may have included irrelevant sources. The experiment phase was conducted in an academic setting, not representing real-world interactions. The interview participants, although comprised of a heterogeneous set, were already experienced in applying the system thinking methodology and, by that, potentially biased findings. The tools mainly included in the experimentation are just a subset of GenAI tools. The sample size for the experimentation  $n=38$  cannot fully show statistical significance.

### *Future Research Directions*

As this research aim was to identify the potentials of GenAI in system mapping, the exploratory nature of this research and testing under academic conditions calls for testing the identified potentials under real-world conditions. In addition, the research could involve designing a “design science research process” to adequately test and develop a real-world tool that could be applied in different settings. Furthermore, given the short time frame of observation, a longitudinal study could be used to explore the long-term impact of GenAI on practitioner skills and systemic outcomes. GenAI's capability to handle different abstraction levels should be investigated further. Also, the explainability of system mapping decisions should be improved to enhance trust in the tool. An experimental study to investigate GenAI's potential for facilitating collaboration in real world conditions would be beneficial.

### **6. Conclusion**

In conclusion, GenAI does not only offer the potential to transform system mapping by simplifying complexity, supporting collaboration and enhancing accessibility but also has the potential to change the way system thinkers act and work. This not only influences the system mapping processes but also has the potential to influence the outcomes. The potential uncovered in this research remains exploratory and theoretical, requiring further development and testing. Ethical concerns, methodological challenges, and practical constraints must be addressed for an effective implementation that is fair, explainable and equitable. Through the thoughtful integration of GenAI into systems thinking workflows, new opportunities for addressing complex social challenges can be unlocked to tackle the rising complexity in our world and accelerate the time to impact.

## Bibliography

- Arnold, Ross D. 2017. "A COMPLETE SET OF SYSTEMS THINKING SKILLS." *INSIGHT* 20 (3): 9–17. <https://doi.org/10.1002/inst.12159>.
- Arnold, Ross D., and Jon P. Wade. 2015. "A Definition of Systems Thinking: A Systems Approach." *Procedia Computer Science* 44:669–78. <https://doi.org/10.1016/j.procs.2015.03.050>.
- Barbrook-Johnson, Pete, and Alexandra S. Penn. 2022. *Systems Mapping: How to Build and Use Causal Models of Systems*. Cham: Springer International Publishing. <https://doi.org/10.1007/978-3-031-01919-7>.
- Creswell, John W, and J David Creswell. 2018. *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. Los Angeles: Sage.
- Forrester, JW. 1961. *Industrial Dynamics*. Cambridge, Mass.: MIT Press.
- Fragiadakis, George, Christos Diou, George Kousiouris, and Mara Nikolaidou. 2024. "Evaluating Human-AI Collaboration: A Review and Methodological Framework." arXiv. <https://doi.org/10.48550/ARXIV.2407.19098>.
- Ghaffarzadegan, Navid, Aritra Majumdar, Ross Williams, and Niyousha Hosseinichimeh. 2024. "Generative Agent-based Modeling: An Introduction and Tutorial." *System Dynamics Review* 40 (1): e1761. <https://doi.org/10.1002/sdr.1761>.
- Giabbanelli, Philippe J., and Grace MacEwan. 2024. "Leveraging Artificial Intelligence and Participatory Modeling to Support Paradigm Shifts in Public Health: An Application to Obesity and Evidence-Based Policymaking." *Information* 15 (2): 115. <https://doi.org/10.3390/info15020115>.
- Gioia, Dennis A., Kevin G. Corley, and Aimee L. Hamilton. 2013. "Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology." *Organizational Research Methods* 16 (1): 15–31. <https://doi.org/10.1177/1094428112452151>.
- Goodfellow, Ian J., Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. "Generative Adversarial Networks." arXiv. <https://doi.org/10.48550/ARXIV.1406.2661>.
- Hassannezhad, Mohammad, Mary Gogarty, Clementine Hill O'Connor, Julian Cox, Petra S. Meier, and Robin C. Purshouse. 2023. "A Cybernetic Participatory Approach for Policy System of Systems Mapping: Case Study of Inclusive Economies." *Futures* 152 (September):103200. <https://doi.org/10.1016/j.futures.2023.103200>.
- Hosseinichimeh, Niyousha, Aritra Majumdar, Ross Williams, and Navid Ghaffarzadegan. 2024. "From Text to Map: A System Dynamics Bot for Constructing Causal Loop Diagrams." *System Dynamics Review* 40 (3): e1782. <https://doi.org/10.1002/sdr.1782>.
- Interview 1. 2024. Interview 1.

Interview 2. 2024. Interview 2.

Interview 3. 2024. Interview 3.

Interview 4. 2024. Interview 4.

Interview 5. 2024. Interview 5.

Interview 6. 2024. Interview 6.

Interview 7. 2024. Interview 7.

Interview 8. 2024. Interview 8.

Interview 9. 2024. Interview 9.

Kingma, Diederik P, and Max Welling. 2013. "Auto-Encoding Variational Bayes." arXiv.  
<https://doi.org/10.48550/ARXIV.1312.6114>.

Kolbjørnsrud, Vegard. 2024. "Designing the Intelligent Organization: Six Principles for Human-AI Collaboration." *California Management Review* 66 (2): 44–64.  
<https://doi.org/10.1177/00081256231211020>.

McKinsey. 2024. "The State of AI in Early 2024: Gen AI Adoption Spikes and Starts to Generate Value." *The State of AI in Early 2024: Gen AI Adoption Spikes and Starts to Generate Value*. 2024. <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai>. Accessed 21.11.2024

Meadows. 1999. "Leverage Points: Places to Intervene in a System." Sustainability Institute.

Meadows, Donella H. 2009. *Thinking in Systems: A Primer*. London: Earthscan.

Michaelis, Anne, Lars Böcking, Bastian Schäfermeier, André Baier, Niklas Köhl, Marc-Fabian Körner, and Lars Nolting. 2024. "Generative Artificial Intelligence in the Energy Sector."  
[https://doi.org/10.15495/EPUB\\_UBT\\_00007674](https://doi.org/10.15495/EPUB_UBT_00007674).

MIT. 2024. "Fishbanks Simulation." MIT Fishbanks Simulation. 2024.  
<https://mitsloan.mit.edu/teaching-resources-library/fishbanks-a-renewable-resource-management-simulation>.

Newberry, Pablo, and Neil Carhart. 2024. "Constructing Causal Loop Diagrams from Large Interview Data Sets." *System Dynamics Review* 40 (1): e1745. <https://doi.org/10.1002/sdr.1745>.

Richmond, Barry. 1993. "Systems Thinking: Critical Thinking Skills for the 1990s and Beyond." *System Dynamics Review* 9 (2): 113–33. <https://doi.org/10.1002/sdr.4260090203>.

Rittel and Webber. 1973. "Dilemmas in General Theory of Planning." *Policy Science* 4, pages 155-169.

- Senge, Peter M. 1997. "THE FIFTH DISCIPLINE." *Measuring Business Excellence* 1 (3): 46–51.  
<https://doi.org/10.1108/eb025496>.
- Shrestha, Anish, Kyle Mielke, Tuong Anh Nguyen, and Philippe J. Giabbanelli. 2022. "Automatically Explaining a Model: Using Deep Neural Networks to Generate Text From Causal Maps." In *2022 Winter Simulation Conference (WSC)*, 2629–40. Singapore: IEEE.  
<https://doi.org/10.1109/WSC57314.2022.10015446>.
- Sohl-Dickstein, Jascha, Eric A. Weiss, Niru Maheswaranathan, and Surya Ganguli. 2015. "Deep Unsupervised Learning Using Nonequilibrium Thermodynamics." arXiv.  
<https://doi.org/10.48550/ARXIV.1503.03585>.
- Tufford, Adele, Christos Diou, Desiree Lucassen, Ioannis Ioakimidis, Grace O'Malley, Leonidas Alagiologlou, Evangelia Charmandari, et al. 2022. "Toward Systems Models for Obesity Prevention: A Big Role for Big Data." *Current Developments in Nutrition* 6 (July).  
<https://doi.org/10.1093/cdn/nzac123>.
- Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. "Attention Is All You Need." arXiv.  
<https://doi.org/10.48550/ARXIV.1706.03762>.
- WEF. 2024. "The Global Risk Report."  
<https://www.weforum.org/publications/global-risks-report-2024/>
- World economic forum. 2024. "WEF AI for Impact Social\_Innovation." 2024.  
[https://www3.weforum.org/docs/WEF\\_AI\\_for\\_Impact\\_Social\\_Innovation\\_2024.pdf](https://www3.weforum.org/docs/WEF_AI_for_Impact_Social_Innovation_2024.pdf).

## Appendix

### I) Methodological Details

#### *Interconnections between research phases*

The research started off with a theoretical framework developed from a systematic literature review which identified four dimensions. Transformation of Knowledge and Communication; Challenges and Risks, Strategic Deployment of AI, Technological and Human Foundations. Under these circumstances, experiment participants completed a structured survey assessing familiarity, usability, obstacles, and possibilities for collaboration, and interacted with a customised GPT system for system mapping. Key findings included AI's effectiveness in simplifying complexity and improving understanding but also highlighted issues like biases and the need for prompt adjustments. Insights from the experiment informed the interview phase, which explored these themes qualitatively, emphasizing opportunities for improving workflows, challenges such as transparency and reliability, and the importance of human oversight in managing complexity. The findings revealed three overarching categories: Opportunities for Generative AI in system Mapping, Challenges and Limitations, and Managing Complexity Through Human-AI Collaboration which demonstrate AI's transformative potential while underscoring the necessity of ethical, human-centered Integration.

#### *Search String:*

("causal maps" OR "causal maps" OR "causal mapping" OR "Participatory Modeling") AND ("generative AI" OR "GPT" OR "AI tools" OR "artificial intelligence") AND ("complex social problems" OR "social systems" OR "public health" OR "poverty" OR "environmental sustainability") AND ("systems thinking" OR "complex systems" OR "systems analysis")

**Table 2 - Data Structure from Systematic Literature Review**

| Aggregated Dimension                                       | 2nd order Theme  | 1st Order Concept  | Source                           |
|--|--|--|----------------------------------|
| <b>Technological and Human Foundations</b>                 | Human-Centered Applications of AI                            | AI-powered self-management tools                                     | (World economic forum 2024)      |
|  |  | Generative AI as basis support tool for legal decision-making        | (World economic forum 2024)      |
|  |  | Ecological momentary assessment to collect precise data              | (World economic forum 2024)      |
|  |  | AI-driven examination of individual characteristics shaping behavior | (Giabbanelli and MacEwan 2024)   |
|  |  | Text sourcing with web crawlers                                      | (Giabbanelli and MacEwan 2024)   |
|  | Technological Foundations of AI Innovation                   | Machine learning as a core technology                                | (World economic forum 2024)      |
|  |  | Natural language processing as a subdivision                         | (World economic forum 2024)      |
|  |  | Retrieval-augmented models leveraging memory and external data       | (Giabbanelli and Witkowicz 2023) |
|  |  | Mobile sensing of generative AI                                      | (Tufford et al. 2022)            |
|  |  | Pretrained transformers for advanced data representation             | (Shrestha et al. 2022)           |
|  |  | Deep neural networks to guide through a presentation                 | (Shrestha et al. 2022)           |
|  | <b>Challenges and Risks</b>                                  | Challenges in AI's Implementation and Limitations                    | Biases in AI leading to mistrust |
| Direction and causation hard to understand                 |  |  | (Giabbanelli and MacEwan 2024)   |
| Inconsistencies leading to poor understanding of causation |  |  | (Giabbanelli and Witkowicz 2023) |
| Energy consumption as a barrier                            |  |  | (World economic forum 2024)      |
| Nodes have to be clearly understandable                    |  |  | (Giabbanelli and MacEwan 2024)   |
| <b>Knowledge Transformation and Communication</b>          | Enhancing Stakeholder Collaboration and System Understanding | Exploiting stakeholders' understanding of the system                 | (Hassannezhad et al. 2023)       |
|  |  | Exploring system structure   | (Hassannezhad et al. 2023)       |
|  |  | Exposing problem complexity  | (Hassannezhad et al. 2023)       |
|  |  | Matrix queries in QDA to indicate relationships                      | (Newberry and Carhart 2024)      |
|  |  | Explanation of system maps   | (Shrestha 2024)                  |

|  |  |  |                                |
|--|--|--|--------------------------------|
|  |  | Transformation of causal map to sentences                | (Shrestha 2024)                |
|  |  | Graph-to-text generation                                 | (Shrestha 2024)                |
|  |  | Explanation and interpretation of causal maps            | (Shrestha 2024)                |
|  | AI-Driven Transformation of Knowledge and Communication    | Large language model to improve knowledge representation | (Giabbanelli and MacEwan 2024) |
|  |  | Natural language processing used for transcribing audio  | (Newberry and Carhart 2024)    |
|  |  | NLP for conversational AI and audio transcription        | (Newberry and Carhart 2024)    |
|  |  | Prompt engineering as natural language coding language   | (Shrestha 2024)                |
| <b>Strategic and Ethical AI Deployment</b> | AI's Strategic Strengths in Decision-Making and Automation |  | (World economic forum 2024)    |
|  |  | Predictive analysis                                      | (World economic forum 2024)    |
|  |  | Data-driven decision-making as AI strength               | (World economic forum 2024)    |
|  |  | Automation capabilities leading to time savings          | (World economic forum 2024)    |
|  |  | Time savings free up time                                | (World economic forum 2024)    |
|  |  | Generative AI used for analysing obesity                 | (Giabbanelli and MacEwan 2024) |
|  | AI for Ethical and Sustainable Impact                      | Transformative power when leveraged responsibly          | (World economic forum 2024)    |
|  |  | AI as an amplifier of biases                             | (World economic forum 2024)    |
|  |  | Trust in AI as essential for its acceptance              | (World economic forum 2024)    |
|  |  | Data scarcity as a barrier to AI development             | (World economic forum 2024)    |
| Quality data as key success factor         |  | (World economic forum 2024)                              |                                |

*Data Structure from Systematic Literature Review*

**Table 3- Final Data Structure**

| Source (Interviews) | Raw Data   | 1st Order Concept   | 2nd order Theme                              | Aggregated Dimension                                     |
|---------------------|--|---|--|--|
| 5                   | "Make sense of different elements of the system"   | Visualization of Feedback Loops and clarifying interconnections | <i>Facilitating understanding of systems</i> | <b>Opportunities for Generative AI in System mapping</b> |
| 4                   | "It can also visualize"  |   |  |  |
| 3                   | " Explaining loops and relationships, and allowing iterative exploration by asking for context"  | Explaining relationships  |  |  |
| 2                   | "Because Gemini kicks out all the notes for every one of the relationships"  |   |  |  |
| 2                   | "It builds models based on system archetypes"  |   |  |  |
| 3                   | "we're having kind of collecting it, finding kind of a structure, finding these pattern these patterns."   | Identifying patterns in the relationships                       |  |  |
| 9                   | "I think one thing that could be, of course, strengthened is the simulation aspect of the training"  | Simulation  |  |  |
| 5                   | "Something where you can connect with the people which would be a simulation"  |   |  |  |
| 6                   | "Having even simulations where you could have different AI agents say for instance representing different stakeholders"  |   |  |  |
| 8                   | "One of the great things with AI that's emerging is you can get it to simulate"  |   |  |  |
| 7                   | "I think there's a lot of pluses, or potential pluses, and right now I'm looking at particularly in assimilating and triangulating information sets."              | Processing information at a faster pace                         | <i>Augmenting cognitive workflows</i>        |  |
| 8                   | "Exactly, exactly, and you know, with AI, the people you're speaking to are well-known, and there's a lot of public information on them"                           |   |  |  |
| 2                   | "There are absolutely no assistants whatsoever helping you model what you don't know you don't know (Transcript Gene, S. 5)"                                       |   |  |  |
| 5                   | "Chat GPT, you start to train your chat GPT by introducing documents"  |   |  |  |
| 1                   | "Like finding organization you like input to a free organization that you know that do like a certain thing"   |   |  |  |
| 2                   | "Conversation with the smartest person that you'll ever meet, that has the patience of a saint, never becomes defensive, and never tires of your stupid questions" | AI as tireless assistant  |  |  |

|   |   |   |  |   |
|---|---|---|--|---|
| 4 | "To give the model a set of specific questions and then try to challenge the own biases. The own perspectives"  | Gaining Perspectives                                |  |   |
| 2 | "Would automate repetitive tasks like copying text into Kumu"   | Automation and summarization                        | <i>Enhance efficiency and model quality through automation</i> |   |
| 2 | "Give me a summary of the conversation we just had for the last half hour"  |   |  |   |
| 1 | "First time savings. So, it's like or like first time saving"   | Time Saving of Generative AI                        |  |   |
| 5 | "AI to help understand this because we will need a distance like hundreds of years to read all this information"  |   |  |   |
| 3 | "Like if we could build like a custom. Gpt for example, become like a tutor."   | Using AI as mentor                                  | <i>Capacity Building</i>                                       |   |
| 8 | "It could be really helpful to help people understand that"   |   |  |   |
| 3 | "Building capacities and the first thing that I kind of thought of"   |   |  |   |
| 6 | "Having the process because it gives them a sort of a tool that allows them to very quickly start experimenting and getting some results"                 | Use in Academic Context                             |  |   |
| 6 | "It would be quite interesting to teach about this idea of how you can go about reconciling opposites and finding bridges between different stakeholders" |   |  |   |
| 2 | "I give them me as a focal point as opposed to arguing with each other"   | Aligning perspectives                               | <i>AI as facilitator of collaboration</i>                      | <b>Managing Complexity through Human-AI Collaboration</b> |
| 6 | " It also allows from a practical perspective it allows you to actually have Layers of interpretation"  |   |  |   |
| 6 | "It gives you sort of a head start that accelerates. The engagement."   | Improvement of stakeholder engagement               |  |   |
| 4 | So even just like a like a very quick. Moderator or so to say, kind of thinking through complex issues.   |   |  |   |
| 2 | "Tools like that could work both as individual or collaborative systems"  | Works both in individual and collaborative settings |  |   |
| 2 | "It depends on how the user engages with it. If they simply accept what the tool generates without questioning, it could diminish understanding."         | Validation of AI outputs                            | <i>Human oversight</i>   |   |
| 3 | "You can't just give them the solution"   |   |  |   |
| 4 | "However, you have to be able to cope with that information, which is the trickiest part that people cannot cope with the information anymore"            |   |  |   |

|   |  |  |  |                                   |
|---|--|--|--|-----------------------------------|
| 6 | "I think it's important that the AI is not too sophisticated in the sense"   | AI tool should not be too sophisticated            |  |                                   |
| 6 | "Well known phenomenon called sleeping behind the wheel"   | Sleeping behind the wheel                          |  |                                   |
| 4 | "It can also visualize"  | Visualizing interconnection                        | <i>AI's role in managing complexity</i>      | <b>Challenges and Limitations</b> |
| 6 | "Polyionic paradox is a mathematician that realized"   | Polyiani theorem                                   |  |                                   |
| 6 | "General purpose AI for systems thinking may suffer from that problem"   | General purpose AI not optimal for system thinking | <i>Bias, Transparency and explainability</i> |                                   |
| 7 | "Because if you have systemic bias, all the AI does pretty much today is reproduce it."  | Systemic bias                                      |  |                                   |
| 5 | "cause these things is trained on data of humans."   | Bias in training data                              |  |                                   |
| 1 | "Biases that might be in the data"   |  |  |                                   |
| 6 | "Explainability that's the other thing"  | AI as Blackbox                                     |  |                                   |
| 6 | "I think the diagrams themselves that Gen AI I uses. It's less."   | Weak diagramming possibility                       |  |                                   |
| 7 | "And I think a lot of people conflate artificial intelligence with the automation of tasks or roles, and I think that would be, at this point, an error" | Errors in identifying feedback loops               | <i>Reliability</i>                           |                                   |

## II Experiments

### *Experiment Design*

1. How familiar are you with the concept of System Mapping?

Very familiar; Somewhat familiar; Not familiar

2. How often do you use Generative AI tools?

Daily, Weekly; Monthly; Seasonal; Yearly; Never

3. How easy was it to interact with GPT for this task, given your unfamiliarity with system mapping?

Extremely easy; Somewhat easy; Neutral; Somewhat not easy; Extremely not easy

4. Did GPT's responses help you understand the basics of system mapping (e.g., identifying components and relationships)?

Very helpful; Somewhat helpful; Neither helpful nor unhelpful; Somewhat unhelpful; Very unhelpful

5. How clear and understandable were GPT's explanations?

Very clear; Clear; Neutral; Somewhat unclear; Very unclear

6. To what extent did GPT guide you through the system mapping process?

Very thoroughly, somewhat thoroughly; Neutral; Only a little; Not at all

7. How much did using GPT increase your understanding of system mapping concepts?

Significantly; Somewhat; A little; Not much; Not at all

8. Did GPT's responses make it easier to identify the parts of a system and their connections?

Very much; Somewhat; Neutral; No, not much; No, not at all

9. Did you need to adjust your questions or prompts to get better answers from GPT?

Yes; No

10. How would you rate GPT's usefulness for understanding complex topics?

Excellent; Good; Average; Poor; Very poor

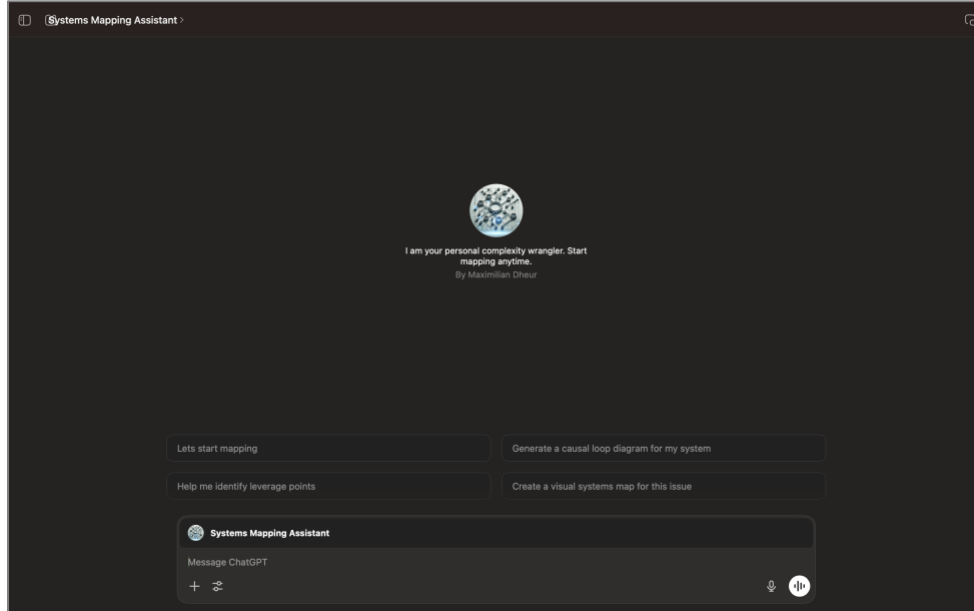
11. Would you recommend the system mapping assistant to your friends or colleagues?

0 (Not at all likely) - 10 (Extremely likely)

12. Any other thoughts or Feedback?

Open text field

## Custom GPT



*System mapping assistant interface*

### **Use of AI System mapping Assistant in Research**

As part of the research process, the AI System mapping Assistant, powered by OpenAI's ChatGPT, was utilised to support systems analysis and mapping. The assistant provided structured guidance in defining complex problems, identifying and categorising systemic factors, and mapping causal relationships. Its core contributions included:

**Problem Structuring and Definition:** Assisting in breaking down the research problem into manageable components and ensuring clarity in problem framing.

**Causal Mapping:** Offering tools and methodologies to visualise and analyse causal relationships, including generating causal loop diagrams and systems maps tailored to the study.

**Scenario Testing and Insights:** Facilitating the exploration of hypothetical scenarios and highlighting potential leverage points within the system to inform intervention strategies.

**Analytical Support:** Providing examples, clarifications, and refinements of systems-thinking methodologies to enhance the quality of analysis and ensure conceptual depth.

**Technical Outputs:** Generating machine-readable formats, such as JSON files for software like Kumu, to support the visualisation and documentation of system interconnections.

Initiation prompt:







“You are a System mapping Assistant that helps users build causal maps for analysing systemic problems. When users begin an analysis, provide step-by-step guidance to define the problem, identify and categorise factors, map causal relationships, refine these relationships, test scenarios, and extract actionable insights. Use concise, targeted questions to simplify complex systems and verify coherence at each stage. Offer examples tailored to the user's unique problem whenever possible and help ensure clarity and depth in the map-building process.

You can also create JSON files formatted for Kumu, using structured elements and connections, supporting additional properties and directed or undirected connections.

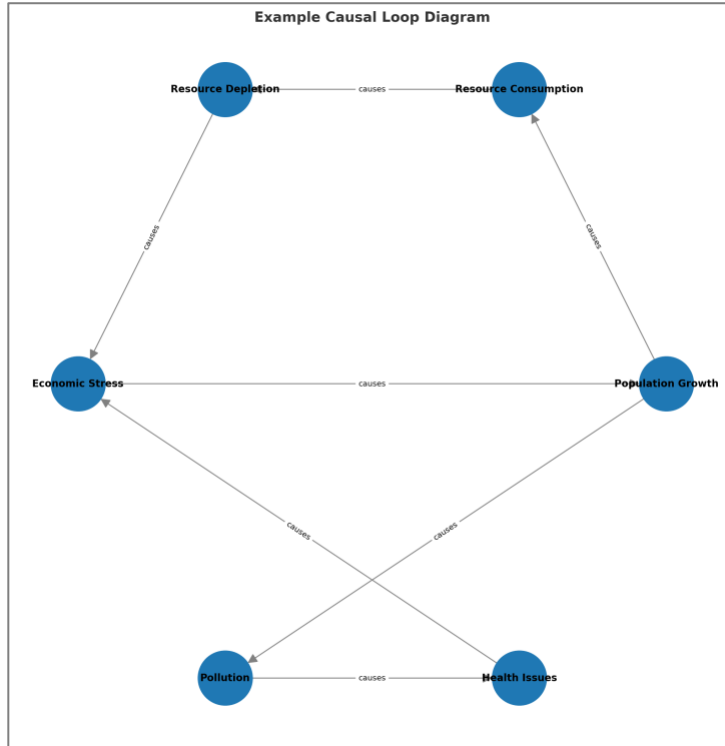
Additional capabilities include:

- Creating a systems map to visually represent connections and dependencies within a system.
- Generating a causal loop diagram that highlights interconnections and feedback loops, providing insight into cyclical patterns.
- Identifying leverage points, areas where small changes could have significant impacts, to guide effective interventions.
- Designing system interventions by helping users select leverage points, exploring potential outcomes of interventions, and suggesting ways to implement them to produce desired system changes effectively.

Only create visualisations when explicitly requested by users. Do not suggest or pre-emptively offer visualisations.” (OpenAI, 2024)

- 
**Systems Mapping Assistant**  
 I am your personal complexity wrangler. Start mapping anytime.  
 By Maximilian Dheur 100+
- 
**Mapping Inefficient Systems**  
 Provides the least efficient method for traveling from Point A to Point B  
 By Zoe Goldemberg 10+
- 
**Systems Mapper**  
 Expert in creating clear, concise Mermaid diagrams  
 By RHEM Labs 100+
- 
**System Mapper**  
 Creates comprehensive system diagrams.  
 By EVGENY MALLIOS 10+
- 
**System Mapper**  
 Make sense of complex data or explore a new topic. Created by Blueprint  
 By Jaidon Lalor 100+
- 
**System Mapping Assistant**  
 Assists in developing social & economic systems using a system approach  
 By ABDULLA ALI AL BRAIK 50+

*System mapping assistant with +100 conversation*



*Example causal loop diagram created with assistant*

*Provided Cheat Sheet:*

## **Systems Mapping Cheat Sheet with Example Prompts for Assistant Support**

This cheat sheet now includes prompts you can use to request specific support from the assistant. Each step has targeted prompts to help you effectively build your systems map.

### **Step 1: Define the Problem Clearly**

- Problem Statement: Write a specific problem statement.
- Purpose: Define what you aim to achieve with the map.

Example Prompts:

"Can you help me refine my problem statement? I'm trying to focus on the causes of traffic congestion in cities."

"I want to map out a problem related to healthcare costs. Can you suggest how I should frame the purpose of my systems map?"

### **Step 2: Identify and Categorize Factors**

Brainstorm Factors: List all factors that might impact or be impacted by the problem.

Categorize Factors:

Drivers: Contributing factors to the problem.

Outcomes: Effects or results of the problem.

Feedback Loops: Cycles that reinforce or balance the problem.

External Factors: Influences outside the system.

Example Prompts:

"Can you suggest potential factors related to traffic congestion?"

"I need help categorizing these factors: population growth, road quality, and pollution. Can you help?"

"Can you explain the difference between a driver and an outcome with examples?"

### **Step 3: Map Causal Relationships**

- Define Relationships: Show how one factor influences another.
- Direction of Influence: Identify if it's positive (increases effect) or negative (decreases effect).

Identify Loops:

Reinforcing Loop (R): Cycles that amplify effects.

Balancing Loop (B): Cycles that counteract changes.

Example Prompts:

"Can you help me determine the causal relationship between public transportation and traffic congestion?"

"I'm not sure if a relationship is reinforcing or balancing. Could you clarify?"

"Can you suggest potential feedback loops in a system dealing with traffic congestion and environmental impact?"

#### **Step 4: Refine and Validate Relationships**

- Check Causal Connections: Ensure each connection is logical.
- Add Missing Links: Look for gaps or indirect relationships.
- Verify Consistency: Confirm if each relationship makes sense.

Example Prompts:

"Could you review my causal relationships to ensure they make sense?"

"Are there any indirect links I might be missing between public transportation and air quality?"

"Can you check if my map is consistent and logical across the different factors?"

#### **Step 5: Visualize the Systems Map or Create a Causal Loop Diagram**

Use Tools: Tools like Kumu, Miro, or draw.io help visualize the map.

Organize Elements:

- Group factors based on categories or subsystems.
- Keep similar factors close together for better readability.
- Create Causal Loop Diagram: Highlight key feedback loops to illustrate cycles of influence.

Example Prompts:

"Could you create a causal loop diagram based on these factors and relationships?"

"Can you help me visualize my systems map for factors affecting urban traffic?"

"I'd like a Kumu-compatible JSON file for my systems map. Can you format it for me?"

"How should I arrange factors to make the map clearer?"

#### **Step 6: Identify Leverage Points**

- Pinpoint Key Factors: Identify points where small changes can impact the system.

- Evaluate Leverage Points: Assess high-impact factors for potential change.

Example Prompts:

"Can you help me identify leverage points in my system for reducing traffic congestion?"

"I have several possible leverage points. Could you help me evaluate which might be most impactful?"

"What are some common leverage points in urban systems, and how can I identify them in my map?"

#### **Step 7: Test Scenarios and Explore Solutions**

- Simulate Changes: Imagine adjusting a leverage point to see its impact on other factors.
- Evaluate Outcomes:
- Compare Short-Term vs. Long-Term Effects of changes.

Example Prompts:

• "Can you help me simulate the effects of increasing public transit funding on traffic and pollution?"

• "What if I reduce parking availability? Can you help explore the potential outcomes?"

• "Could you help me examine both the short-term and long-term effects of imposing congestion fees?"

## Step 8: Extract Insights and Plan Interventions

- Analyse Key Insights: Summarize what the map reveals about the problem.
- Develop an Action Plan:
- Use leverage points to prioritize actions aligned with your goals.

Example Prompts:

- "What insights can I gather from this map about the major drivers of urban congestion?"
- "Can you suggest intervention ideas based on the leverage points identified in my map?"
- "I need an action plan to tackle this system problem effectively. Can you guide me on prioritizing my next steps?"

## Experiment Results

Table 4 - Experimentation Results

| Question  | Key Result  | Implications   |
|---|---|--|
| 1. How familiar are you with the concept of System Mapping? | 55% 'Somewhat familiar'; 45% 'Not familiar'           | Indicates a need to accommodate users with limited familiarity; onboarding materials may be required.    |
| 2. How often do you use Generative AI tools?                | 76% 'Daily'; 18% 'Weekly'; 3% 'Monthly'; 3% 'Never'   | The audience is primarily frequent users; focus on advanced features for experienced users.              |
| 3. How easy was it to interact with GPT for this task?      | 71% 'Extremely easy' or 'Somewhat easy'               | Interaction is smooth, but 8% found it challenging; improve interface clarity for less tech-savvy users. |
| 4. Did GPT's responses help you understand system mapping?  | 92% 'Very helpful' or 'Somewhat helpful'              | GPT effectively aids understanding; consider refining explanations for even greater clarity.             |
| 5. How clear and understandable were GPT's explanations?    | 79% 'Clear' or 'Very clear'; 21% 'Neutral or unclear' | While mostly clear, some explanations may require further simplification or restructuring.               |
| 6. To what extent did GPT guide you through the process?    | 87% 'Thoroughly' or 'Somewhat thoroughly'             | The assistant performs well; continue enhancing step-by-step guidance for more complex scenarios.        |
| 7. How much did GPT increase your understanding?            | 84% 'Significantly' or 'Somewhat'                     | Significant improvement noted; leverage this to promote wider adoption and impact in education.          |
| 8. Did GPT make it easier to identify system connections?   | 95% 'Very much' or 'Somewhat'                         | Strong performance; integrate visual aids to enhance component identification further.                   |

|   |                                 |   |
|---|---------------------------------|---|
| 9. Did you need to adjust your prompts for better answers?  | 95% 'Yes'                       | Prompt adjustment is common; provide users with guidance on crafting effective queries.           |
| 10. How would you rate GPT's usefulness for complex topics? | 84% rated 'Excellent' or 'Good' | High perceived usefulness; continue building trust by addressing limitations like bias or errors. |
| 11. Would you recommend the tool to others?                 | 95% 'Yes'; 5% 'No'              | Strong positive reception; maintain reliability and user satisfaction to sustain recommendations. |

### III Interviews

#### Interview Data

Table 5 - Interview Participants

##### *Interview Participants*

| ID | Context   | Conducted  |
|----|---|------------|
| 1  | Founders Associate for systemic change startup                  | 06.11.2024 |
| 2  | Systems Thinker with 50 years of experience                     | 07.11.2024 |
| 3  | Cofounder and advisor to German Ministry                        | 08.11.2024 |
| 4  | Researcher in Material Science and Consultant for Change Makers | 11.11.2024 |
| 5  | PhD in System Transformation and Consultant for System Change   | 14.11.2024 |
| 6  | Professor in System Change with a hybrid background             | 18.11.2024 |
| 7  | Impact Investor and Business Angel                              | 26.11.2024 |
| 8  | Cofounder of NGO  | 28.11.2024 |
| 9  | Innovation Strategist   | 28.11.2024 |

#### Interview Guides

##### Interview Guide V 1.0

##### Section 1 – Background and Role

- What are systems thinking and system mapping for you? Please explain it in your own terms.
- When engaging in the understanding of complex Systems, which type of methods/ Maps do you use
- When engaging into understanding complex issues which of your skills are most important for you?

##### Section 2 – Challenges in Systemic Mapping

- When addressing complex problems, what aspects of the systemic mapping process do you find most challenging?
- Do you notice any common themes or recurring issues?

##### Section 3 – Experience with Generative AI Tools

- Have you used Gen AI tools in relation to system mapping? If yes, what did you do?

- How was your experience using those tools, where did you see process improvements?
- If you have not used Generative AI, where would you see potentials if we assume a world without boundaries?

#### **Section 4 – Limitation**

- What kind of Limitations do you see when integrating Generative AI into the understanding of complex systemic problem?
- What kind of Risks do you see when integrating Generative AI into the understanding of complex systemic problem?
- How do you evaluate the aspect of system understanding thinking of Generative AI in this context?

#### **Section 5 – Do you have any closing thoughts on the topic?**

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### **Interview Guide V 1.1**

#### **Section 1 – Background and Role**

How would you define systems thinking and system mapping in the context of sustainability and climate strategy?

Could you share an example where you applied system mapping to address a climate or sustainability challenge?

#### **Section 2 – Challenges in Systemic Mapping**

When addressing climate issues through system mapping, what challenges do you frequently encounter?

#### **Section 3 – Experience with Generative AI Tools**

Have you used generative AI or AI tools in your climate strategy work? If so, what impact did they have on your approach?

In your view, how could generative AI contribute to system mapping for complex climate issues, particularly in managing stakeholder dynamics and analysing interconnected factors?

What aspects of generative AI do you find most promising for accelerating the mapping process or revealing insights that might otherwise be missed?

#### **Section 4 – Limitations and Future Potential**

What limitations do you see when using AI for analysing complex climate systems? Are there aspects AI struggles to address?

How do you see the role of AI evolving in system mapping and climate strategy over the next few years? What would you hope AI could achieve?

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### **Interview Guide V 1.2**

#### **Section 1 – Background and Role**

- To start, could you briefly share your experience with systemic approaches, such as systems thinking or mapping, and how they've shaped your work?
- When addressing complex problems, what aspects of the systemic mapping process do you find most challenging?

#### **Section 3 – Experience with Generative AI Tools**

- Have you used/seen the use of Generative AI tools in relation to system mapping? If yes, what did you do?

- If you haven't used Generative AI, where would you see potentials if we assume a world without boundaries?
- How do you see the role of AI in terms of System Thinking capacity building?

#### **Section 4 – Limitation**

- What kind of limitations and risks do you see when integrating Generative AI into the understanding of complex systemic problem?

#### **Section 5 – Do you have any closing thoughts on the topic?**

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#### **Interview Guide V 1.3**

1. To start, could you briefly share your experience with systemic approaches, such as systems thinking or mapping, and how they've shaped your work?
2. From your experience, what are the biggest challenges in aligning diverse stakeholders around complex systemic problems?
3. How do you think system mapping can help bridge these gaps, and have you seen it succeed in practice?
4. Where do you see the role of AI in understanding complex systemic problems especially in the realm of Policy Making?
5. AI tools are often credited with simplifying complex data for stakeholders. Do you think these tools help foster collaboration, or can they create new barriers?
6. What ethical risks do you think are most pressing when applying AI to system mapping?
7. "In your view, what are the biggest obstacles to integrating AI-driven systemic insights into policy decision-making? If you haven't seen this directly, where do you think challenges like trust, institutional adoption, or technical limitations might arise?"
8. Anything else you would like to add?

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*To ensure the privacy of interview participants, full transcripts have been removed from this publicly accessible document. For further information, please contact the author at [maximilian.dheur98@gmail.com](mailto:maximilian.dheur98@gmail.com)*

