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New perspectives for data-supported foresight: The hybrid AI-expert approach

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Abstract

This paper outlines new perspectives for data-supported foresight by combining participatory expert-based futures dialogues with the power of artificial intelligence (AI) in what we call the hybrid AI-expert-based foresight approach. To this end, we present a framework of five typical steps in a fully fledged foresight process ranging from scoping to strategizing and show how AI can be integrated into each of the steps to enable the hybrid AI-expert foresight approach. Building on this, we present experiences gained from two recent research projects of TNO and Fraunhofer ISI that deal with aspects of the hybrid AI-expert foresight approach and give insights into the opportunities and challenges of the new perspectives for data-supported foresight that this approach enables. Finally, we summarize open questions and challenges for future research.

KEYWORDS

AI, data supported foresight, framework, hybrid AI-expert-based approach, innovation management, strategic decision making, strategic foresight, technology management, trend detection

1 | INTRODUCTION

Science and technology have become increasingly important in research and innovation policy to address societal grand challenges. "[Society] is facing a tremendous challenge to cope with societal challenges such as climate change, security and the aging population. Investing in science, applied research and innovation is essential to come up with solutions for these challenges" (Ministry of Economic Affairs and Climate, 2018). Not only individual nation state but also the European Commission is putting their hopes on technological advances to contribute to addressing these challenges: so-called New and Emerging Science and Technologies (NEST) provide tremendous innovation potential. However, in this time of fast technological change, with high uncertainty, ambiguity, and complexity, how can we trace emerging technologies and novel ideas to promote the most promising innovations to realize societal missions? How can we identify frictions and make decisions regarding the complex puzzles that societal challenges entail? These questions emphasize the continuing need for relevant and timely *intelligence* to support policy and strategy development and decision-making.

Policy makers and strategists can base these types of decisions on foresight studies (see i.e., Coates, 1985; Cuhls, 2020; Da Costa et al., 2008; Miller, 2018; Porter et al., 2004; Salo & Cuhls, 2003). Technology foresight in this sense can be defined as the process of systematically attempting to look into possible longer-time future developments of science, technology, economy, and society to identify emerging technologies likely to yield the greatest economic and societal benefits (Blind et al., 1999; Martin, 1995;

Porter et al., 2004; Rotolo et al., 2015). In these views, technology foresight is closely linked to policy and decision-making processes (Cuhls, 2020). In other words, foresight aims to systematically explore alternative futures. In doing so, it not only produces valuable information for policy makers ("product benefit"/policy informing) but also improves the quality of the reasoning process itself ("process benefit"/policy facilitating) by diversifying mental models and increasing the variety of perspectives considered (Chermack, 2005; Da Costa et al., 2008).

Over time, various qualitative and quantitative foresight research methodologies (see e.g., Bengisu & Nekhili, 2006; Daim & Oliver, 2008; Dalkey & Helmer, 1963; Huang & Zhang, Guo, et al., 2014; Martino, 2003; Porter & Detampel, 1995; Zhu & Porter, 2002) have already been considered to address such foresight questions (for an overview, see Glenn & Gordon, 2009). Although both qualitative and quantitative foresight approaches have their assets and advantages, they also have their challenges. For example, most qualitative methods rely on expert judgments that suffer from expert bias (Schirrmeister et al., 2020). In contrast, most quantitative methods struggle to account for emerging topics (Cozzens et al., 2010) and unknown and "hidden" variables (Goodwin & Wright, 2010). Furthermore, social, psychological, and behavioral dimensions form an integral part of technology foresight as people's relationship to the use and the utilization of technologies is a complex issue (Kaivo-oja, 2017). The integration of quantitative and qualitative data and methods, including participatory processes to enable forward-looking perspectives is, therefore, still a major endeavor in foresight (Cozzens et al., 2010; Kaivo-oja, 2017; Porter et al., 2004; Ranaei et al., 2020; Zhang et al., 2018).

Artificial intelligence (AI) is appearing as an opportunity for foresight studies to explore new horizons, especially when considering emerging topics. AI was established as an academic discipline within computer science in the 1950s. Initially, it was defined as the process of "making a machine behave in ways that would be called intelligent if humans were so behaving" (McCarthy et al., 1955, p. 1). Today, AI can be defined as the scientific discipline and technological practice that encompasses efforts ranging from building a general-purpose machine (broad AI) to AI systems that perform narrow classification, prediction, and optimization tasks (narrow AI) (Boden, 2016; Russell & Norvig, 2009). In this paper, we focus on narrow AI. The current AI hype has been triggered mostly by the introduction of machine learning (ML) algorithms, trained to induce patterns from both labeled or structured data sets and unstructured data sets (LeCun et al., 2015). The field of ML can be divided into different subfields that are characterized by the available data. Within supervised learning (most mature, most frequently used) an ML algorithm is trained on input-output pairs from a real process to produce optimal outputs for unseen inputs. Within unsupervised learning, only input data is given to a model but no output. The machine is then tasked with a learning objective, for example, to find rankings or patterns for this input. Ultimately, ML algorithms can reveal patterns in data without being programmed with an exact set of rules to identify these patterns (Himanen et al., 2019). As a result, emerging topics, trends, or relations between concepts could—possibly—be identified even before they have recognizably been established within a certain domain or been given a name. The continuous input of new data can make this process also more "real-time" than before, identifying shifts and changes in emerging patterns. As such, AI presents the possibility to make predictions or decisions more timely and responsive to changes in context than before.

The increasing availability of data, especially new data sources (e.g., social media data, web data, open data, etc.) on the one hand (Von der Gracht et al., 2015) and of ML algorithms and computing capacity on the other has the potential to change foresight as well. Using big data and AI next to expert knowledge for foresight—which we define as the *hybrid AI-Expert foresight approach*—can enrich understanding of the increasingly complex and fast-evolving science, technology, and innovation developments and support the development of policies and strategies, which are based on a wider range of perspectives, and more timely and responsive to changes in these areas. That is, especially when considering emerging topics and innovations, for which existing information and statistical intelligence is scarce, AI might introduce new opportunities to identify those emerging topics in "real-time" as it is able to reveal patterns in large data sets. While in this paper we focus on technology foresight, the principal approach is not limited to technology; by leveraging the power of AI and big data, a new foundation for data-supported foresight is created that goes beyond current practice. In this paper, we introduce the hybrid AI-expert foresight approach, explore new perspectives the approach offers for data-supported foresight, showcase two case studies in which several steps of the hybrid AI-expert approach were implemented, and discuss some of the remaining possibilities and challenges for future research.

This paper is structured as follows. In Section 2, we discuss the need for integrating new perspectives on data-supported foresight in foresight decision-making processes. We argue that the success of such a new perspective on data-supported foresight depends on delivering results that provide useful, reliable, trustworthy, and transparent information. Section 3 then introduces the hybrid AI-expert foresight approach by discussing a new perspective on data-supported foresight via a framework. This framework shows the different steps of a fully fledged foresight process, and how data retrieval and text mining (i.e., AI methodologies) can go hand-in-hand with expert involvement to identify science, technology, and innovation (STI) trends, assess their potential impact, and design actionable strategies. We further discuss how the foundation of the hybrid AI-expert foresight approach is formed by the knowledge graph—a representation of an ontology that defines the relevant concepts within a given domain and visualizes the strength of the relationships between those concepts. Section 4 presents the experiences gained from two recent research projects that deal with aspects of the AI-expert foresight approach presented in Section 3. These projects give insights into the opportunities and challenges of the approach; (1) TNO's Innovation Outlook project and (2) The

Foresight Fraunhofer project. Finally, Section 5 concludes by summarizing open questions and challenges for future research.

2 | NEW PERSPECTIVES ON DATA-SUPPORTED FORESIGHT—WHY IT IS NEEDED AND WHAT ARE THE CHALLENGES

To optimally benefit from the disruptive potential of emerging technologies to address societal challenges, like quantum technologies, VR/AR, hydrogen technology or solar power, smart and evidence-based decision making is required. This is important for industry and governments to better map, understand, and manage uncertainty and complexity about (disruptive) emerging technologies and innovations and the future goals set by transformative innovation policies. Policy makers and strategists can base these types of decisions on technology foresight studies (see i.e., Coates, 1985; Cuhls, 2020; Da Costa et al., 2008; Miller, 2018; Porter et al., 2004; Salo & Cuhls, 2003).

Technology foresight has always heavily relied on data analyses as important inputs into collective futures dialogues. These data analyses are largely operating on structured data sources, such as patents and publications (see e.g., Abbas et al., 2014; Daim et al., 2006; Glänzel et al., 2004; Huang et al., 2014; Huang & Chang, 2014; Milanez et al., 2014; Small et al., 2017; Zhang et al., 2018). In addition, these data analyses have relied upon the mining of structured, clearly defined databases for environmental scanning, weak signal scanning, or the extrapolation of time-series to forecast technology trajectories (see e.g., Bengisu & Nekhili, 2006; Krigsholm & Riekkinen, 2019; Martino, 2003; Small et al., 2014).

With the rapid advancement of algorithms and computing capacity, these approaches are also now becoming ever more sophisticated (Cozzens et al., 2010; Martino, 2003; Mühlroth & Grottke, 2018; Von der Gracht et al., 2015). Since the beginning of '00's, for instance, researchers have explored and applied new approaches to incorporate additional data sources in foresight processes. Online data sources like social media, research articles, news articles, or project or grant proposals have become much easier to access and offer a variety of new perspectives on innovation and society (i.e., Lee & Park, 2018; Zhang et al., 2018; Zhu & Porter, 2002). This has led to an emerging stream of research in so-called foresight support systems, wherein ICT systems support experts and stakeholders over an entire foresight process to support decision making toward complex futures (Von der Gracht et al., 2015).

By adding the possibility to analyze also unstructured data without a predefined search realm, however, the advancements in big data and AI create unprecedented opportunities to develop data-supported and meaningful insights in future technology and innovation trends and their potential societal impact. That is, due to the rapid development of computing capacity, algorithms to analyze patterns in unstructured data sources—such as natural language processing (NLP), topic-modeling such as latent Dirichlet allocation (LDA), and deep learning methods based on artificial neural networks—are increasingly available (Daas & van der Doef, 2020; LeCun et al., 2015; Mühlroth & Grottke, 2020; Porter, 2019). Recently, a number of proposals have been made on how to mobilize this potential in foresight, especially for identifying early signals of emerging changes (e.g., Krigsholm & Riekkinen, 2019; Lee & Park, 2018; Mühlroth & Grottke, 2018; 2020). Insights from these new data sources can, potentially, show new perspectives on data-supported foresight for experts, policy makers, and strategists and their respective decision-making processes.

We argue, however, that automatized AI-based foresight approaches on their own are not sufficient to support high-quality foresight processes. Rather what is needed are *hybrid* approaches with carefully designed interfaces between human knowledge and AI-supported analyses. There are three core reasons for this argument, which we will discuss next.

First, contrary to other AI approaches that use entity recognition and existing ontologies/knowledge graphs[1], foresight usually deals with novel phenomena; that is, new technologies or concepts, or new fields of application of existing concepts. For AI technologies, such as NLP, this is a specific challenge of doing data-supported foresight as the terminology of some of the trends of interest does not yet exist or the meaning of existing terms in the area of interest changes over time. While AI technologies are already applied in clearly defined areas with well-defined entities, recourse to these concepts in the field of foresight is only of limited help since path dependencies resulting from a lock-in into "past knowledge" must be avoided (Cozzens et al., 2010). Accordingly, most quantitative analyses of emerging technologies are retrospective analyses of pre-determined areas rather than methodological studies designed to identify emerging technologies. As such, the identification of emerging topics remains a challenge to the field of foresight (Braaksma et al., 2020; Cozzens et al., 2010; Goodwin & Wright, 2010; Mühlroth & Grottke, 2020).

Second, as indicated above, foresight also pursues a completely different goal. As the evolution of complex social systems cannot be predicted due to inherent nonlinear feedback loops, foresight focuses on making this "ontological uncertainty" (Debyshire, 2019) manageable. This is done by supporting actors to think through different development paths (i.e., alternative futures) or a wide range of emerging seeds of change hypotheses (Warnke & Schirrmeister, 2016) and consider diverse system views (Floyd, 2008). Through widening and diversifying mental models, reasoning processes become more socially robust and decisions less prone to "folly" (Chermack, 2005). Next to outcomes in the form of possible future pathways or robust strategic options, this "process benefit" in the form of diversified mental models is highly valuable both for individual participants and organizations as it enables them to observe their environment more openly (Schoemaker, 2018). Learning to draw more robust conclusions through the active participation of individual participants and organizations in such processes is therefore an essential contribution of foresight processes.

Finally, current AI-enabled systems produce results that are often hard to understand by users and, as such, hard to assess for their usefulness, reliability, trustworthiness, and transparency (Braaksma et al., 2020). This is further complicated by the high prevalence of bias in the field of AI as AI systems are typically trained on human-selected and human-labeled data (Dignum, 2019). The human design of AI systems and the underlying databases can therefore significantly influence (i.e., supporting or hindering) the insights obtained for decision making (Calvo et al., 2019; Floridi et al., 2018), which is why AI systems should not necessarily be seen as neutral intermediaries (Dignum, 2019; Floridi et al., 2018). This thus warrants a deeper consideration of psychological biases and heuristics in the context of AI and foresight and scenario processes (Schirrmeister et al., 2020; Tversky & Kahneman, 1974).

For these three reasons, we argue that an approach is required that includes both the human (expert) users and AI methodologies when developing a new perspective on data-supported foresight. At present, however, there are no AI approaches that complement the entire foresight process or that provide a basis for the optimal interaction of experts and AI-based methodologies. We fill the gap by introducing the *hybrid data-supported foresight approach* in which AI technologies and domain experts[2] meet.

3 | COMBINING EXPERT-BASED FORESIGHT WITH AI

To combine participatory expert-based foresight with AI, we outline the hybrid AI-expert foresight framework (see Figure 1) that illustrates (1) the steps of a typical fully fledged foresight process and (2) where the integration of both AI and expert-based knowledge can support and add value to the different steps of that process to provide new perspectives for data-supported foresights. We will elaborate on these steps next.

3.1 | The hybrid AI-expert foresight framework: Five steps

To capture indications of possible future pathways for new and emerging science and technologies, we distinguish five steps in the foresight process (see Figure 1). In those steps, expert-based approaches are then combined with state-of-the-art AI methods to provide new data-supported foresight insights. The framework follows the order of scoping and scanning, identification of trends, identification of related impact, and translation of these new insights into a strategy or a strategic perspective. Foresight studies do not necessarily capture the whole framework; they can also focus on one or some parts of the framework.

3.1.1 | Scoping

Scoping is an important first step in the foresight process; it sets the direction for each step afterward. It includes the identification of the research questions, target audience, methodology, and criteria for the selection of data sources (such as news articles, patents, social media, or other), relevant (expert) stakeholders, and the reasoning for their involvement. After the scoping phase, one has defined a clear objective and conceptual model, which defines the search boundaries in the steps thereafter.

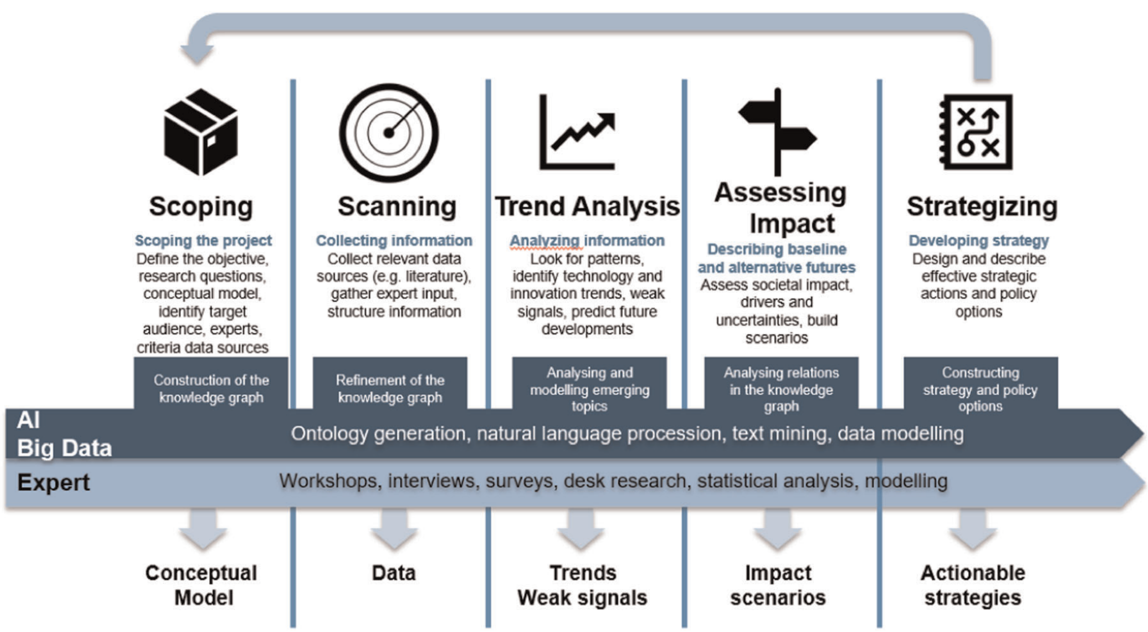

FIGURE 1 Foresight framework and the integration of big data and AI with experts. AI, artificial intelligence

When we combine the scoping step with AI methodologies, the clearly formulated objective, conceptual model, and search boundaries form the input for the construction of a *knowledge graph* (Ehrlinger & Wöß, 2016; Smith, 2003). A knowledge graph can be seen as a representation of the relevant concepts/keywords within one or several domains, which visualizes the strength of the relations between these concepts as a graph. A knowledge graph can be constructed from scratch or can be refined by adding missing (expert) knowledge when relying on a pre-established knowledge graph (Himanen et al., 2019). When aiming to identify new emerging topics and their potential impact in a given domain—which is often a goal in foresight processes—the construction of a new knowledge graph is needed to avoid path dependencies and the reliance on past situations. See Background Section 1 for a more detailed discussion of the knowledge graph.

Background Section 1: The knowledge graph as the backbone of the hybrid AI-expert foresight framework

Throughout the discussion of the hybrid AI-expert foresight framework, the knowledge graph plays a central role—and should thus be introduced further. The knowledge graph was introduced in 2012 as a semantic enhancement of Google's search function (Ehrlinger & Wöß, 2016). A knowledge graph can be seen as a graphical representation that depicts the relevant concepts within one or several domains (such as technologies, innovations, and societal challenges) with a network of keywords and visualizes the strength of the relations between these concepts as a graph (Himanen et al., 2019; Smith, 2003). As a result, the knowledge graph enables the search of text data as the machine has "learned" to "read" text by looking for matches between the text data and the knowledge graph text. As such, the knowledge graph is central to any AI or ML model that is fed with textual data.

Paulheim (2016) makes a distinction between the construction of a knowledge graph and the refinement of a knowledge graph. Construction of a knowledge graph means that a knowledge graph is built from the scratch. Think of it as if an expert is consulted for his/her knowledge, and based on that knowledge a mental model is built that graphically depicts the core concepts and relationships. An ML model is then able to add new data onto the knowledge graph, which might guide the foresight process into new directions. Reversely, in a data-first approach toward the construction of the knowledge graph, (textual) data is collected (e.g., through web scraping or via the collection of data sources, such as patents, scientific publications, social media, etc.), and these text corpora (i.e., the database) are scanned by a machine, which plots document snippets on the knowledge graph. The knowledge graph this plotting delivers can be used to further refine the (constructed) knowledge graph using expert or domain knowledge. Refinement of the knowledge graph means that—based on human-machine interactions—missing (expert) knowledge is added or identified errors are removed from the knowledge graph. Such an approach, whereby the expert knowledge base is combined with the machine's database is an example of a hybrid approach between experts and machines, which can significantly advance the quality of the outcomes of the foresight process.

3.1.2 | Scanning

Scanning focuses on the systematic examination of the gathered data to identify potential threats, opportunities, and developments. Scanning may explore novel and unexpected issues, as well as persistent problems, trends, and weak or future signals (i.e., early signs of an emerging topic) (Amanatidou et al., 2012, Lee & Park, 2018; Van Rij, 2010). Amanatidou et al. (2012) differentiate two different types of scanning: exploratory scanning and issue-centered scanning. The first concentrates on identifying potential emerging issues. The second concentrates on a wide range of existing issues and looks for weak signals or potential emerging topics around that issue. Although these two approaches are based on a different scoping, the outcome in both cases is a long list of (early) signs of emerging topics.

In the hybrid data-supported foresight framework, a wider selection of new, online, and open data sources can be used for the scanning phase—from research articles to Twitter messages. To enable this, AI methodologies can be used to gather data with so-called crawlers and scrapers: tools to obtain data from online sources and for cleaning up that data. By next assigning the collected data to the knowledge graph nodes based on textual similarities, the ontology can be further refined in the scanning phase (Braaksma et al., 2020). An interesting question concerns the relevance of these online data sources for the objective at hand. Twitter might, for example, be an interesting source for an assessment of sentiments toward wind energy, but it might not be the best source for the newest developments regarding hydrogen. An assessment of relevant new, online and open data sources for addressing different types of foresight questions (defined in the scoping phase) could thus be part of this phase.

3.1.3 | Trend analysis

During the *trend analysis* step the long list of issues around a topic is narrowed down to a set of trends and weak signals, which are assessed with regard to their future development as an emerging topic. In classical technology forecasting, this is usually done by assessing certain attributes, such as growth in functional capability, rate of replacement of old technology by a newer one, market penetration, technology diffusion, and the likelihood and timing of technological breakthroughs (see Martino, 2003, Porter et al., 1991). Commonly used foresight approaches to assess the future development of the emerging topics are the Delphi method, roadmapping, and future trend analysis (see i.e., Daim & Oliver, 2008; Dalkey & Helmer, 1963; Glenn & Gordon, 2009; Hussain et al., 2017; Porter & Detampel, 1995).

When combining these approaches with AI methodologies in the hybrid AI-expert foresight framework, the opportunity arises to follow up on new directions—identified in the scanning phase—to create a long list of potential weak signals or trends (i.e., potential fast-growing topics). Such a raw topic list of weak signals generated with a text-clustering algorithm can then be validated using, for example, expert interviews or workshops. It thus still takes an expert to interpret the results and to differentiate the actual trends and their impact from the noise. An additional opportunity of the hybrid AI-expert foresight framework is that when over time more data becomes available, the algorithms behind the knowledge graph "learn" from this data and new knowledge is added to the knowledge graph of the scoping and scanning phase. This new knowledge can guide the scanning into new directions.

3.1.4 | Assessing impact

The previous steps answered the question: what are the emerging trends? Strategy and policy makers like to anticipate opportunities and risks to society, which go beyond science, technology, and innovation trends; what could the effect be of these trends? How could these trends play a role in addressing societal challenges, for example, to assess their potential to contribute to resource efficiency? To help answering these questions the next step in the hybrid AI-expert foresight framework assesses the potential *impact* of the trends identified in the trend analysis step to develop plausible future scenarios. Impact assessments are often associated with social impact or environmental impact assessments, which address factors, such as health (e.g., lifestyle, stress, diet, etc.), social dimensions (e.g., creation or elevation of social divisions, trust in institutions, value, use, and utilization of technology), economic impact (e.g., welfare, employment, workload), and impact on institutions (e.g., regulatory agencies) (Kaivo-oja, 2017; Vanclay, 2002). Typically, impact is therefore the outcome of interactions between trends, events, environmental and social conditions, and the actions of societal actors over time. Different methods are currently employed in foresight processes to study these interactions, for example, system dynamics, scenario planning, and cross-impact analysis (Glenn & Gordon, 2009; Kaivo-oja, 2017; Wright & Cairns, 2011). The outcome of these impact assessments is a deeper understanding of social realities and a set of alternative futures. A complicating factor in such impact assessment is the cognitive bounds of strategists or policy makers. That is, dominant representations, sources of inertia, or the inability to legitimize new strategies could influence strategists' and policy makers' ability to follow up on identified strategic futures (Lehr et al., 2017).

In our hybrid AI-expert foresight framework, the impact assessment within the foresight process can be augmented by looking at the potential future development of the identified trends and weak signals (see trend analysis). That is, a data-supported impact analysis explores the future developments of each topic trend and the development of relationships among topics. This then largely builds upon the ability of knowledge graphs to "learn" from data and add new knowledge (technological, but also social) to the knowledge graph. This new knowledge can not only guide the trend analysis in new directions, as discussed in the previous step. By comparing the knowledge graph over time it also becomes possible to identify fast-growing (hot) or fast-declining (cold) concepts around a topic in real-time (Geurts & Raaijmakers, 2020). The knowledge graph thus helps to improve future scenarios for strategy development (see strategy) as it takes into account not only (potentially new) topics but also (potentially new) relationships between topics that might challenge intuition. We, therefore, expect that when data is projected onto a knowledge graph over time, dynamics will appear that can add unique, different, and perhaps unexpected insights and thereby enrich and extend the information base. This provides opportunities to closely monitor developments and dynamics and make informed decisions that do not necessarily rely on existing strategies, mental models, intuition, and assumptions (cf. Lehr et al., 2017). This remains, however, a research area that needs further exploration (see also Section 5).

3.1.5 | Strategy

The more enriched and nuanced insights of the previous steps finally shift attention toward how policy makers and strategists can make use of these insights for foresight. This process of *strategy* development focuses on the identification of future pathways for change and develops response strategies for those pathways; foresight helps generating strategies for complex futures to advise policy or to prepare decision-making. In this sense, strategy is not a prediction but rather a set of approaches to bring longer-term considerations into decision-making (Cuhls, 2020). Foresight can thus support strategy in, for instance, exploring the effects and range of choices regarding current policies, provide early warnings about potential (unanticipated) difficulties/new opportunities, enable planning, explore possible disruptive developments, or suggest focus/directions (Blind et al., 1999). Typical approaches in this phase are wind tunneling, backcasting, roadmapping, scenario-based strategizing, or more recently the robust portfolio decision analysis (Baker et al., 2020; Lehr et al., 2017; Phaal et al., 2007; Ringland, 1998). Despite the possibilities such approaches provide for strategic decision making for complex futures, cognitive bounds created by existing strategies, mental models, and assumptions tend to limit the strategizing possibilities (Lehr et al., 2017). Furthermore, it remains difficult to draw conclusions based on multiple knowledge sources, even when drawing upon experts; as such approaches are unable to learn or to accumulate knowledge over time similar exercises have to be conducted over time (Mühlroth & Grottke, 2020).

In our hybrid AI-expert foresight framework, the opportunity is introduced to include real-time, dynamic, and emerging information on trends (see trend analysis) and a wider conceptualization of impact (see impact) to formulate actionable strategy “options.” Such options can be more distant, that is, deviate significantly from the status quo (Lehr et al., 2017), to allow the identification of a course of action that creates a competitive advantage. By using a knowledge graph that provides a richer understanding of the concepts and the relationships between those concepts within a system and takes into account real-time dynamics, the hybrid AI-expert foresight approach potentially enables strategists to enrich the formulation of such distant strategy options. For example, in the case of roadmapping, insights on interactions between roadmap layers may be provided as an additional input to the roadmapping dialogue, which might direct the dialogue in more “distant” directions. This is a research area that should be explored in more detail in future research (see also Section 5).

3.2 | The hybrid AI-expert foresight approach: On the interaction between AI and experts

Throughout the discussion of the hybrid AI-expert foresight framework, the notion of a *hybrid* approach has been consistently present. Hybrid in this context means that (participatory) expert-based foresight approaches are combined with a machine-driven foresight approach. In our discussion of the framework in this section, we discuss that this combination has the potential to significantly advance the quality of the outcomes of the foresight process as it can duplicate, extend, or even challenge intuition toward new horizons. In Section 4, we illustrate how this plays out in practice using two use cases.

When considering a hybrid AI-expert-based approach, we focus on the role of experts and the role of machines in the foresight approach. Experts, we argue, rely on their expertise or *knowledge base* to distill a *mental model* of the topic or issue at hand. Machines rely on a *database* to define an *ML model* of the topic or issue at hand. Both the knowledge base/mental model and the database/ML model can, in essence, contribute to the construction and the refinement of the knowledge graph that represents the topic or issue at hand. Figure 2 further depicts this reasoning and provides a graphical illustration of a knowledge graph.

When considering a hybrid-expert-based approach, two basic strategies can be distinguished based on the division of tasks between experts and machine intelligence. On the one hand, experts can go first to predefine concepts and their relationships based on a shared mental model to create a “seed” ontology. With the use of supervised ML methodologies such as text mining this “seed” ontology is then further elaborated on by including new nodes and relations or excluding nodes and relations. On the other, one can also start by scanning documents from a defined area of interest and (automatically, in an unsupervised manner) extract and cluster the topics via the use of unsupervised ML algorithms. Only then these topics are labeled by experts and their relations are elaborated on. The distinction between the two strategies is the sequence of the contribution of experts and AI: the first strategy starts with the expert to direct AI, whereas the second strategy starts with AI to support the expert to create the knowledge graph.

For the hybrid AI-expert approach, (i) setting up a knowledge graph, (ii) using big data and AI to enrich the available and relevant information, and (iii) analyzing how the knowledge graph changes over time, is a process where AI and experts frequently interact. The construction of a knowledge graph in a hybrid approach enables us to avoid path dependencies or over-reliance on intuition or past situations or experiences. Ultimately, the hybrid AI-expert foresight approach can be used to enrich the information base upon which decision makers act and formulate possible future pathways to design actionable strategies or policies. The knowledge graph and its analysis over time thus provide the basis that provides the opportunity to not only identify newly emerging topics and how they evolve, but also to see if the relation between specific technologies, innovations, and impact factors is increasing or decreasing in strength over time. As such, the hybrid AI-expert foresight approach provides new perspectives for data-supported foresight and the integration of qualitative expert and quantitative data knowledge.

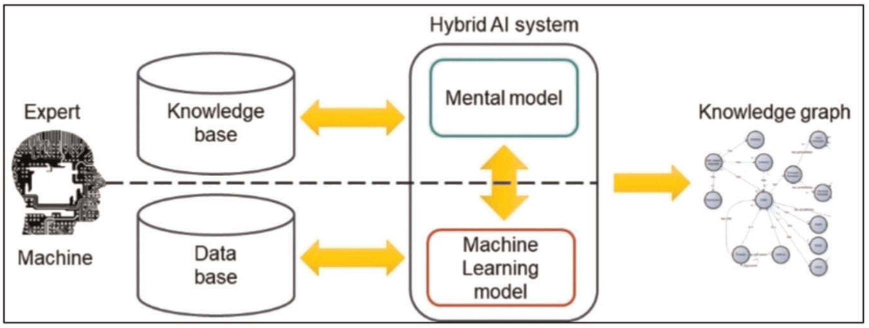

FIGURE 2 Example of an approach to develop and refine a knowledge graph from scratch using (1) expert knowledge base and (2) machine database to define a hybrid knowledge graph (TNO, 2019). AI, artificial intelligence

4 | THE HYBRID AI-EXPERT FORESIGHT APPROACH IN PRACTICE: INSIGHTS FROM TWO RESEARCH PROJECTS

To illustrate the hybrid AI-expert foresight approach in practice, two recent research projects—one by TNO and one by Fraunhofer ISI—have applied and tested the new data-supported approach and gained first-hand practical experience with using Big Data and AI in foresight processes. A brief summary of the two projects is given below.

4.1 | TNO foresight project "Innovation Outlook"

Under TNO's Early Research Program the program "Innovation Outlook" was initiated in 2019 and ran till 2020. The aim of this 1-year multidisciplinary research program was to explore, renew, and test a new hybrid AI-expert foresight approach and framework building upon data-driven tools to identify emerging trends and weak signals in (disruptive) technology and innovation developments, determine their societal impact, and design actionable strategies to form a strategic perspective. The program involved experts from several TNO units with different expertise (foresight experts, experts with in-depth knowledge of system dynamics, experts from data science (specifically NLP), and experts in strategy development). In addition, domain experts (focusing on Mobility-as-a-Service [MaaS]) were involved: to experiment with and test the new framework and methodology a use case has been carried out on MaaS. The aim of the use case was to gain experience with how AI and big data can be embedded in foresight, what is the benefit, and how to organize interaction between experts and AI.

We followed a hybrid AI-expert-based approach from the start. That is, we started by involving experts to develop an ontology for a knowledge graph before using AI methods to project the data onto the ontology and evaluate the topics. That is, we started our project with the scoping phase by formulating specific research questions, and subsequently organizing a workshop with various domain experts (mobility, energy transition, labor) and foresight experts to predefine concepts and their relationships based on a shared mental model to create what we defined as a "seed" ontology (Amanatidou et al., 2012). For the workshop, we made use of the expert-driven Method to Analyse Relations between Variables using Enriched Loops (MARVEL) (Zijderveld, 2007), which helped to structure and map the relevant concepts, (inter)relations, and possible effects to construct the knowledge graph. The experts also provided a primary set of data that was used in the scanning phase to acquire text data from pointers (websites, document repositories, PDF's, etc.). With state-of-the-art AI methodologies, we further text-mined additional data resources (ArXiv, The Guardian, Reuters, and IntelligentTransport) and automatically harvested them using NLP models of knowledge graph data (synonyms and semantic embeddings) and a filter ("only MaaS-relevant documents"). This way, the neural network is trained on a data set to create neural word embeddings and capture neighboring words. It thus enables to search for keywords and add a relation between keywords (see also De Boer & Verhoosel, 2019). During the scanning phase, we followed an iterative process to refine the knowledge graph by labeling the nodes of the ontology with descriptive data and using state-of-the-art AI (i.e., ML) to find topic similarities between ontology nodes and external data and connecting documents (and snippets) to the ontology nodes.

For the next step, trend analysis, an interactive dashboard has been developed (see Figure 3), which presents data and provides insight into the speed of topic growth, amount of growth (density), diversity of growth (new topics), and "word evolution" over time. These insights provide an overview of emerging trends and their development over time, as well as the strength and direction of relations between trends and MaaS concepts. The dashboard also enables users to relabel (conflate, delete, or split) nodes for deeper insights.

The use case provided insight in (i) top emerging trends in MaaS and their development over time, (ii) strength and direction of relations between technological trends, MaaS concepts, and the potential impact of MaaS (i.e., CO_2 emission or jobs), and (iii) visualize the knowledge graph for transparency, accountability, and validation purposes (e.g., capability to edit the associations/terms). The use case further provided valuable insights into the opportunities and boundaries of how AI can be embedded in the hybrid AI-expert foresight approach. The use case revealed the complexity of redesigning, expanding, and eventually refining existing tools with new functionalities, especially when specifically designing for human-machine interaction. The implemented approach yielded new insights into the division of labor between experts, knowledge models (ontologies), and data sources, and how interactions between these can highlight information dynamics over time as well as different types of biases. Finally, the experience from this project highlights the challenge of multidisciplinary collaborations, wherein experts with different backgrounds collaborated. In those instances, we found that the development of a common language and shared understanding are important, as it ensures the continuation of the project. This could be an important issue to take into account for researchers who are planning to embark on the use of comparable methods.

4.2 | Fraunhofer Foresight Project (ISI)

The Fraunhofer Foresight Project was carried out by four Institutes from the Fraunhofer Group for Innovation Research between April 2018 and December 2019 and aimed at identifying emerging topics with potentially high impact for applied research in 2030. The project was divided into two phases: in the first phase, an extensive, multilayered survey across all 72 Fraunhofer Institutes was conducted to condense and assess the 51 most promising so-called "Future-Spotlights" for applied research. In the second phase, it was the aim

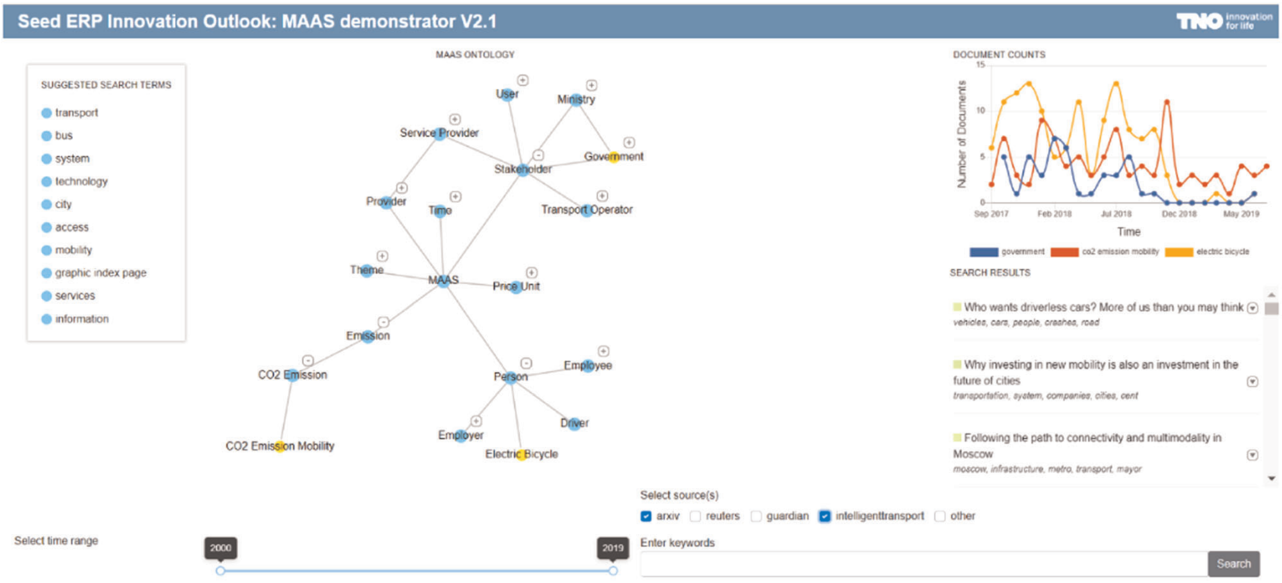

FIGURE 3 Demonstrator of an interactive dashboard for data-supported foresight for Mobility-as-a-Service (TNO, 2019). On the left is a visualization of the knowledge graph upon which the selected data sources (bottom-right) for the years 2000–2019 (bottom-left) are projected. On the right-hand side is a corresponding graph that shows the trend in the selected data for the selected timeframe—focusing on 2017–2019. The topics are the role of the government (blue), CO_2 emission mobility (red), and electric bicycle (orange). Below the graph are the data snippets that can be explored more in depth

to further develop, continue, and standardize the process by integrating AI and Big Data and thereby making use of (partly-) automated processes. The efforts included (i) further optimizing an already well-established tool for scanning structured data from scientific databases, (ii) exploring unstructured data sources to retrieve new Spotlights using News-Sites and Podcasts (Welz et al., 2021), and (iii) identifying market potentials for Spotlights by analyzing corporate press releases via ML algorithms.

At Fraunhofer ISI, we focused on analyzing unstructured data from news sites, that is, identifying emerging topics from relevant web articles by setting up an unsupervised topic model using LDA. LDA is a generative statistical model that uses ML to detect latent topics across text documents via the distribution of words across these documents (Blei et al., 2003). For this procedure, no manual labeling or keyword tagging of the documents that are processed is needed beforehand. This addresses the scoping phase of the hybrid AI-expert foresight framework, as it tested a way to set up an ontology starting with the output of an automated AI model and only then involving experts to evaluate the topics and to find labels and relationships between them.

Before setting up the topic-model, however, the scoping requires identifying suitable sources for the question at hand. For this step, we used expert input in the form of the 51 well-developed Future-Spotlights of the first project phase and their one-page descriptions. By extracting the eight most characteristic keywords from each Spotlight description using Term Frequency—Inverse Document Frequency scores (TF-IDF-scores, see Ramos, 2003) and integrating these keywords in an online search query, we identified potential websites in a widely automated manner, which referred to some but not all of the initial spotlights. After rating the identified websites, the articles of the sites eligible for the task were text-mined for a time span of 6 months and eventually served as input for the LDA topic-model.

Figure 4 shows a two-dimensional projection of a 100-topic solution of the LDA-model using Jensen–Shannon divergence to create a distance matrix on the topic-term distribution and metric multidimensional scaling (mMDS) for dimension reduction. Each circle in the figure represents one topic. Each topic is represented by the most dominant terms within the topic. The example shows the top 25 terms representing "Topic 11." To find appropriate labels for the topics of the model, the meaning has to be derived given the words within the topics and the documents underlying the model (i.e., news articles). In the example, topic 11 was labeled "Cell research in the clinical context."

The project showed that this approach yields meaningful topics for the question at hand. Given the broad focus of the project, which makes it difficult to come up with a shared mental model from scratch, the hybrid AI-expert approach can help as a starting point to reduce complexity for the experts and break up rigid thinking by providing automatically generated topic clusters. This approach can either be used for an exploratory scanning in the sense of Amanatidou et al. (2012) or be further developed into a knowledge graph and thus be one important step within the hybrid AI-expert foresight framework described above (Section 3).

The project results emphasize the vital role that experts have in the interplay with ML concepts, as in-depth knowledge is needed to "make sense" of the discovered patterns. Starting with documents written by experts, followed by semi-automatically selecting eligible

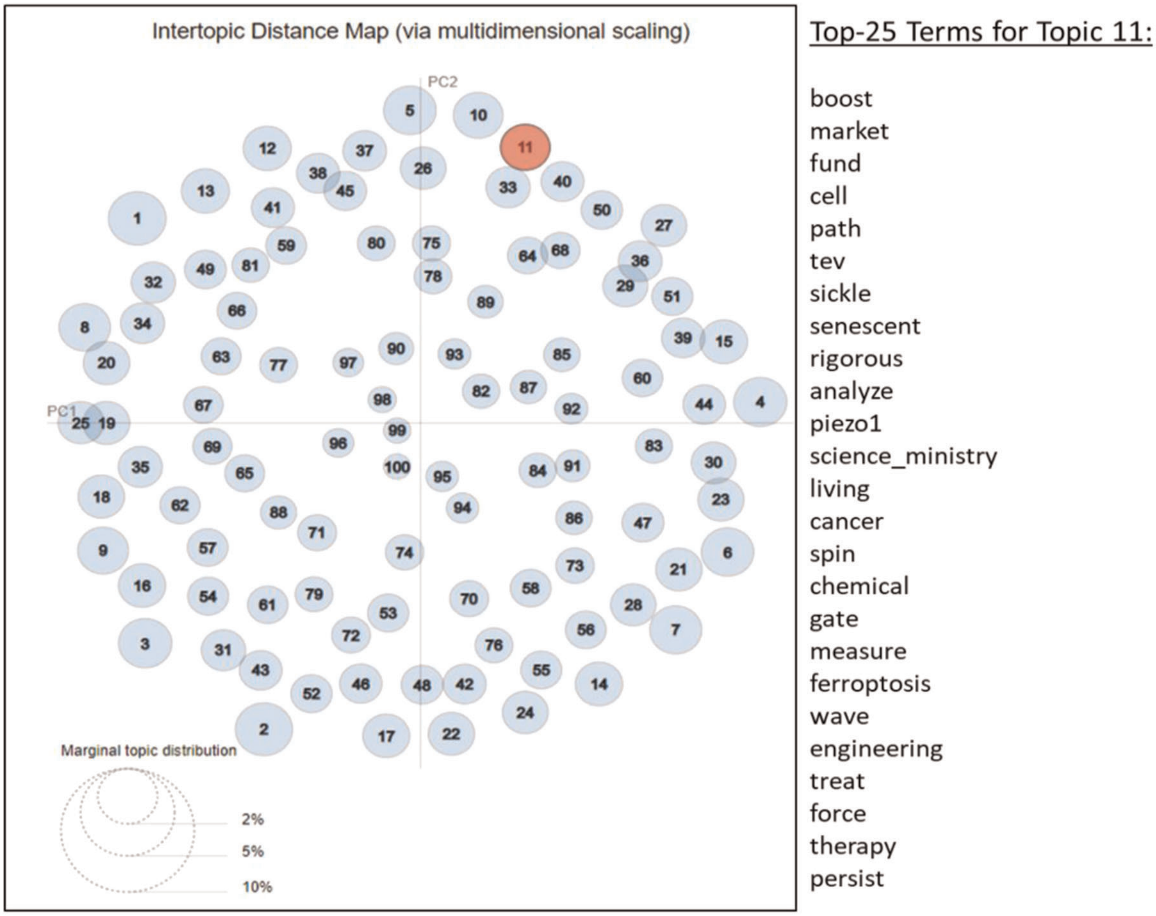

FIGURE 4 visualization of the LDA model with 100 topics and example topic 11, which was labeled "Cell research in the clinical context". LDA, latent Dirichlet allocation

sources, and ending the process with a sense-making process by experts, show that the cooperation of experts and AI is not strictly linear but rather like a loop. To benefit even more from this synergy more experience from use cases and systematic comparison of outcomes is needed to gain insight on how to optimally design this process depending on the aims and scope of the project. To be able to further optimize the topic-model the availability of high-quality text data is fundamental and by incorporating validated ontologies or other external resources (e.g., lexical databases like WordNet), in a way that avoids path dependencies, validity and usability could additionally be improved.

5 | DISCUSSION AND CONCLUSION

In this paper, we explored new perspectives for data-supported foresight by exploring the possibilities for foresight created by AI to detect emerging topics. To do so, we introduced the hybrid AI-expert foresight framework and explored the different steps in foresight processes and the role both experts and AI might play within those steps. Our discussion of the theoretical considerations and practical implementation of such a hybrid approach indicates that the hybrid AI-expert-based approach holds great potential to add value to current foresight practices to identify emerging topics, and our hybrid AI-expert foresight framework offers a guideline on how to achieve this in a meaningful way at the same time. The experiences from two projects of TNO and Fraunhofer ISI further illustrate this in practice.

Both projects show that introducing automatized AI-based data analysis within the scoping, scanning, and trend analysis phase of a foresight project broadens the range of hypotheses of emerging changes that can be fed into a sense-making process within subsequent futures dialogues. It is important to note that due to the inherent uncertainty in the evolution of complex systems there is no "data from the future." Accordingly, neither the automatized nor the "manual" human analysis of present data has a predictive value. Rather the scoping, scanning, and trend analysis phases of our hybrid approach serve to support the questioning of anticipatory assumptions that frame our perception of the present by subjecting a wider range of (emerging) aspects into our conceptualization of the future and thereby improves our capacity to deal with uncertainty and emergence (Miller, 2018, Rossel, 2012, Warnke & Schirrmeister, 2016).

In light of this, it is important to consider that how such findings from the previous phases can become of value for the impact assessment and strategy phase has yet to be explored in more detail. Specifically, as our hybrid approach serves to support the questioning of anticipatory assumptions, results might not necessarily duplicate or extend users' intuition, but rather challenge it by subjecting a wider range of (emerging) aspects into our conceptualization of the future. Especially when resulting insights become more distant and deviate from the status quo (Lehr et al., 2017), it might remain a challenge for decision makers to alter existing strategies, mental models, intuition, and assumptions (cf. Lehr et al., 2017) based on such insights.

Thus, the projects show that to fully leverage the potential of the hybrid AI-expert foresight approach and establish best practices, more research is needed. Based on shared discussions between the various co-authors, we identify the following major points within our approach that need special attention: validity and the interplay between experts and AI, relevance and acceptance of the output (e.g., depending on the type of sources used), and longevity of efforts (e.g., financial support, access to databases). Future research can address not only these overarching challenges but also specific shortcomings we identified within the projects.

5.1 | Challenges and requirements: A future research agenda

Despite the promises the hybrid AI-expert foresight approach holds, several challenges remain. We identify three points for attention: (1) validity and the role of the expert, (2) relevance and acceptance, and (3) longevity.

5.1.1 | Validity (or trustworthiness or reliability) and the role of the expert

While descriptive validity refers to the factual accuracy of the information provided, interpretative validity refers to the degree to which the researcher actually portrays the meaning behind the data (Tashakkori & Teddlie, 2003). Interpretative validity is a high concern in a hybrid AI-expert foresight approach. Although human minds easily interpret texts and find the relation with another word (or group of words), the output of data-supported models can place words out of their context. What is more, models and algorithms can easily misrepresent the meaning of the text. It thus requires background information and most likely expertise in the field to make a valid interpretation (Himanen et al., 2019). The involvement of experts thus guarantees that the added value generated throughout the process does not stay within the data. What is more, the participation of experts and stakeholders is key to ensure the buy-in of decision-makers (Lehr et al., 2017).

At the same time, experts bring along certain idiosyncratic experiences, norms and values, background information, and viewpoints, which too can bias their interpretation in a way that is misleading (for various views on this topic, see i.e., Baker et al., 2020; Geurts & Raaijmakers, 2020; Hilkamo et al., 2021; Lehr et al., 2017; Schirrmeister et al., 2020). Think, for instance, about dominant representations, sources of inertia, or the inability to legitimize new strategies that could influence the ability of strategists and policy makers to follow up on identified strategic futures (Lehr et al., 2017).

The combination of both – expert and AI –has great potential to address these concerns but what is still needed are deeper insights into possible synergies between AI and expert input. To address this validity challenge, two areas for future research can be identified. First, it is important to explore the AI-bias side or the extent to which data-supported models place developments out of context. Expert judgment can play a role to address this issue. Comparative analyses and case studies that are deliberately designed to assess such influences could provide knowledge of human or data/modeling bias that could advance not only the field of foresight but also the field of data-driven science in general. Second, future research could explore the expert-bias side by exploring various hybrid approaches to determine how to enable a hybrid AI-expert-based approach in the best way to overcome strategizing bounds (cf. Lehr et al., 2017). For this, we encourage the exchange of experiences on which steps can be (semi-) automated and what are the needs and requirements to enable actors to validate, correct, and interpret the outcomes. The outcome of such analyses could indicate the context and the chosen research questions most suitable for various AI methodologies.

5.1.2 | Relevance and acceptance

The added value of a hybrid AI-expert-based approach is determined by the relevance of the data and the information acquired from that data. Different communities (i.e., science, industry, government, policy makers, citizens, etc.) will have different specifications of what is considered "relevant," which makes it challenging to draw conclusions and make decisions based on the output (Amanatidou et al., 2012; Himanen et al., 2019). The resulting information gap (see i.e., Himanen et al., 2019)—the fact that stakeholders require different information sources and data output than what might be currently used and produced—provides further strain on the acceptance of insights based on hybrid AI-expert approaches. What is needed, therefore, are comparative insights into the capacity of such different information and data sources to answer different questions from or for different stakeholders. Systematic analyses of the information needs of various stakeholders, and the way various data sources meet those needs should be conducted (see e.g., Amanatidou et al., 2012). Such analyses can further support the widespread acceptance of the hybrid AI-expert foresight approach, as it would increase trust in the data, models, and outputs and help providing information where and when it is needed. Hence, keeping the experts in the loop is not only necessary for a valid outcome, but also for an acceptable outcome.

In addition to the assessment of informational needs, an assessment of the added value of different data sources is needed. In foresight, various attempts can be identified to use data-supported approaches, largely drawing upon various data sources (i.e., bibliometrics, web data, social data—see e.g., Porter, 2019; Ranaei et al., 2020). A systematic analysis of the differences in results from those various data sets has yet to be made. Only by providing this kind of analysis, the question which data is important to acquire which information can be addressed. In addition, it is worth exploring whether such different data sources should be compiled together to provide holistic insights, or whether they should be systematically compared to identify what types of questions a certain source can address best. Finally, a comparison of different data sources would provide the opportunity to identify important sources of bias stemming from these data sources.

Finally, it should be taken into account that to produce relevant and acceptable results, it is important to consider the challenge of multidisciplinary collaborations, wherein experts with different backgrounds (i.e., computer scientists, technologists, industry or sector representatives, or policy makers) collaborate. The experiences from the two illustrative projects indicate that each of those actors has different interests and aims with a project, and might consider different outputs as result. In those instances, we found that the development of a common language and shared understanding are important to increase the relevance of the project to all stakeholders. Future research could provide more insights into how such common ground can be established among different types of multidisciplinary collaborations.

5.1.3 | Longevity

A final constraint to any data-supported science projects are concerns around longevity (see Himanen et al., 2019). Due to the current hype of big data and AI, many platforms, databases, and other open science initiatives proliferate. However, long-term financial support for sustained operation and timely updates of such platforms, databases, or other formats are rarely guaranteed. As a result, initiatives to enable data-supported science, including the hybrid AI-expert foresight approach, run the risks of duplication of efforts and loss of valuable data and insights. To exploit big data and AI for new perspectives on data-supported foresight, institutions thus need to begin to consider how to strategically deploy big data collection and storage management solutions. Part of the challenge will be how to combine data from various disparate sources in a meaningful way. Some form of interoperability or interfacing is also essential for the widespread adoption of a new approach or ways of doing research (Himanen et al., 2019). That is, stakeholders can only participate in the development of technology if they speak a common language, for instance in the form of ontologies or metadata. Such approaches enable researchers from the same field to transform various dialects into a common language.

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CONFLICT OF INTERESTS

The authors declare that there are no conflict of interests.

DATA AVAILABILITY STATEMENT

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

ENDNOTES

[1]For more information on ontologies/knowledge graphs, see Background Section 1.

[2]Depending on the context, our understanding of domain experts encompasses a variety of potential groups in participatory processes, including, for example, citizens who can be considered experts on issues that affect their everyday lives.

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