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The Time Machine: Future Scenario Generation Through Generative AI Tools

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Abstract: Contemporary society faces unprecedented challenges—from rapid technological evolution to climate change and demographic tensions—compelling organisations to anticipate the future for informed decision-making. This case study aimed to design a digital system for end-users called the Time Machine, which enables a generative artificial intelligence (GAI) system to produce prospective future scenarios based on the input information automatically, proposing hypotheses and prioritising trends to streamline and make the formulation of future scenarios more accessible. The system's design, development, and testing progressed through three versions of prompts for the OpenAI GPT-4 LLM, with six trials conducted involving 222 participants. This iterative approach allowed for gradual adjustment of instructions given to the machine and encouraged refinement. Results from the six trials demonstrated that the Time Machine is an effective tool for generating future scenarios that promote debate and stimulate new ideas in multidisciplinary teams. Our trials proved that GAI-generated scenarios could foster discussions on +70% of generated scenarios with appropriate prompting, and more than half included new ideas. In conclusion, large language models (LLMs) of GAI, with suitable prompt engineering and architecture, have the potential to generate useful future scenarios for organisations, transforming future intelligence into a more accessible and operational resource. However, critical use of these scenarios is essential.

Keywords: scenarios; futures; generative AI; large language models (LLMs); prompt engineering

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1. Introduction

1.1. Scenario Planning

Since the latter half of the 20th century, organisations have increasingly sought methods to anticipate and navigate uncertainty. Scenario planning emerged as a pivotal strategic tool during this period, with companies like Shell pioneering its use to prepare for energy crises and unexpected geopolitical disruptions [1]. In a world where change remains the only constant, scenario planning has become an indispensable methodology for organisations striving to anticipate future developments and seize emerging opportunities. Constructing plausible future narratives grounded in current trends enables informed decision-making without resorting to overly deterministic predictions [1]. Beyond visualising diverse potential futures, scenario planning facilitates the development of adaptive strategies, equipping organisations to respond effectively and swiftly to dynamic challenges [2].

Moreover, scenario planning extends beyond predictive functions. It serves as a reflective tool that enables organisations to examine their core values and aspirations through narratives of what might happen and what the company might do, fostering a socially and ethically responsible direction [3,4]. This reflective dimension promotes decision-making that considers long-term consequences and emphasises social responsibility [5]. Identifying and evaluating trends, such as the rapid advancement of digital technologies, is critical in constructing robust and adaptive scenarios. Understanding these forces positions organisations to better prepare for future complexities [6]. Additionally, the collaborative nature of scenario planning strengthens organisational learning by creating a shared vision among participants and stakeholders [4,7]. Such collective engagement enhances the understanding of change dynamics, enabling adaptation to varied circumstances and fostering more informed decision-making [8].

However, traditional scenario planning methods often demand significant time and resources as they involve analysing multiple external forces and trends. These approaches may struggle to address contemporary complexities in rapidly evolving contexts and can prove excessively costly for smaller organisations and public administrations [9,10]. To this end, emerging technologies present new opportunities to overcome these limitations, offering innovative solutions that could make scenario planning more accessible and efficient for resource-constrained entities.

1.2. Generative AI

During the early evenings of November 2022, thousands of individuals experienced their first opportunity to "converse" with a seemingly intelligent machine. Following the launch of ChatGPT in November 2022, this technology rapidly captured public attention, achieving unprecedented adoption rates among digital consumers [11]. Generative artificial intelligence (GAI) represents one of humanity's most transformative technological advancements. GAI is artificial intelligence capable of creating original content—such as text, images, music, videos, and code—through instructions and input data provided to large language models (LLMs) [12]. These systems are trained on extensive datasets using sophisticated deep learning and natural language processing techniques.

In the coming years, GAI has the potential to significantly accelerate economic growth, with projections suggesting it could double recent GDP growth rates. Additionally, in the medium term, it may enable workers to reduce their task completion times by more than 50% [13]. The ability of GAI systems to engage in collaborative cognitive tasks suggests the possibility of profound transformations in numerous aspects of daily life [14]. However, while GAI offers significant opportunities, it also presents notable challenges, including the potential for heightened energy and water consumption. These concerns, particularly critical in the context of the global climate emergency, may emerge as pressing issues in the near future [15,16]. Nonetheless, such limitations and threats lie beyond the exploratory scope of this paper.

The application of GAI in generating compelling narratives is particularly relevant to the present discussion. LLMs have demonstrated remarkable proficiency in producing coherent and contextually appropriate texts—albeit not necessarily accurate or truthful, nor directly useful, as Newport notes for The New Yorker [17]. These systems have been employed to draft stories, scripts, and other narrative forms that align with user prompts. For instance, the experiment "*Language as Reality: A Co-Creative Storytelling Game Experience in 1001 Nights using Generative AI*" exemplifies how GAI can craft narratives that shape the storyline of an interactive role-playing computer game [18]. Research further suggests that GAI can positively influence writing skills and creative confidence. A study investigating undergraduate students' narrative intelligence and writing self-efficacy found that digital storytelling platforms powered by AI enhance students' abilities to construct narratives, thereby increasing their confidence in writing [19]. Consequently, GAI's potential extends beyond productivity, including enhanced customisation and communication.

1.3. The Potential of GAI in Future Scenario Generation

Owing to its proven narrative capabilities, GAI is poised to assume a more prominent role in the visualisation and conceptualisation of scenarios. AI-driven scenario generation enables a forward-looking perspective on potential futures through a collaborative dialogue between humans and machines, given structured interaction [20]. While general-purpose AI services like OpenAI's ChatGPT and Anthropic's Claude offer flexibility and deliver valuable results for experts across various tasks, more specialised tools may be essential for users who are not experts in scenario planning or GAI applications. Malakuczi et al. illustrate this need by examining the use of AI for design fiction among students familiar with scenario planning or the design process, from which user experience and previous knowledge can be seen on effective interaction of GAI applied to design and scenario planning [21]. Similarly, Finkenstadt et al. highlighted the limitation that AI scenario planning relies heavily on data, requiring prior knowledge of trends to supply GAI with appropriate datasets [22]. The authors created a custom GPT which follows certain instructions to generate scenarios based on multiple variables and conversational iterations with the user. Nonetheless, the reliance on the model itself can also introduce notable biases and hallucinations (i.e., in Finkenstadt et al.'s tests, no additional data were provided to the GPT), behaviours that should be minimised or, at least, clearly identified. As a result, effective scenario planning is often limited to foresight experts or those with specially designed AI tools for this purpose.

The gaps in the previous examples score on some challenges in human–AI collaboration, whether applied to scenario planning or other professional practices. The evolving landscape of human–AI collaboration is driving the creation of an augmented workforce, where the accessibility and suitability of AI tools can provide a significant competitive edge. GAI's capabilities offer an opportunity to those companies whose scenario planning is too resource-intensive and which could now benefit from including these approaches in their workflows. Seemingly, developing countries stand to benefit from AI technologies, provided they have the necessary infrastructure and conditions for effective access and utilisation [23]. However, merely having access is insufficient; the appropriateness of AI tools is equally important. GAI technologies offer speculative and generative capabilities that enhance human cognition, necessitating further investment in skill development to equip professionals for this transformation [13]. Unless these skills are democratically acquired, using GAI might only benefit those with a competitive advantage.

Despite the aforementioned challenges and perils, many opportunities exist for the intersection of GAI and scenario planning. GAI can be used in the early stages of design to create narratives and speculative solutions, providing speed and adaptability in exploring future scenarios. Additionally, it can potentially support the conception and exploration of alternative futures from a critical perspective [24].

Generative AI can significantly enhance scenario planning in several aspects:

- Scale Change: Generative AI allows for the rapid generation of future scenarios far beyond human capacity, efficiently processing large volumes of information and processes. Unlike traditional methods, AI can analyse massive datasets and develop adaptable narratives that facilitate the sharing and eventual acceptance of strategies within organisations [22]. GAI enables a parametric and iterative approach to exploring multiple scenarios, providing initial ideas that can be gradually refined [22].

- Personalisation: Generative AI allows for the adaptation of scenarios to each organisation's specific needs and preferences using particular data. It offers a new dimension in future studies, where created scenarios enable users to imagine and anticipate the impacts of these systems on their individual and collective realities [22] as experiments. This methodology promotes the inclusion of diverse perspectives, allowing participants to explore how AI might influence future values and impacts according to their specific needs and contexts. However, GAI has the potential for greater levels of personalisation when provided with custom data. It creates an augmented workforce that combines collaborative learning and anticipatory vision [25,26].
- Collaboration: Generative AI facilitates teamwork by sharing ideas and perspectives on scenarios, leading to potentially more cohesive strategies. AI-driven scenario generation offers a new perspective on collective intelligence when scenarios are constructed collaboratively, aligning AI proposals with human expert contributions. This process enriches the diversity of perspectives offered, making AI act as another group member capable of contributing new ideas that can broaden the collective vision [27] while also providing artefacts from which to generate debates. Although AI cannot replace the experience and tacit knowledge of human experts, its use as part of a collective team improves the quality of assessments and democratises access to knowledge, adding significant value to the scenario-creation process [28,29].
- Continuous Learning: Thanks to generative AI, participants in scenario-creation processes benefit from constant feedback and learning opportunities. Combining AI with human work enhances access to knowledge and creates inclusive spaces for collaboration in critical anticipation processes. This hybrid model offers a new perspective on collective intelligence, generating future scenarios that respond to educational and professional challenges more comprehensively and adaptively [30].
- Growth Mindset: Individuals with a growth mindset show a greater ability to anticipate and plan future scenarios, offer more optimistic responses, and are willing to learn new skills [31]. Participants with this mindset view AI as an opportunity to develop new competencies [14]. Combining positive mindsets and AI facilitates better preparation for future disruptions, helps identify organisational adaptation needs, and strengthens team bonds.

Despite these technological advancements, significant challenges persist in democratising GAI for scenario planning within organisations that lack the resources to employ expert planners. In the referenced cases, experts utilised generic tools, prompting a re-evaluation of the efficacy of designing specific-purpose tools for non-expert users, which is the field of the contribution of the present article. This involves designing and testing GAI tools to allow casual users with little to no experience in scenario planning to formulate and evaluate future scenarios, including determining suitable prompts and inputs for GAI models and ensuring the provision of accurate data regarding future trends.

This article describes the design process of a generative AI (GAI) tool developed to assist novices in creating future narrative scenarios. The Materials and Methods section outlines the research objectives and the authors' approach to scenario planning, detailing the design methodology and presenting the original design artefacts that informed the research and testing phases. The Results section reports the findings from the design testing sessions. Finally, the Discussion section addresses potential refinements to the tool, design, and philosophical challenges based on insights obtained through the testing process.

1.4. Foundational Concepts in Prompt Engineering

Prompt engineering is emerging as a key discipline for optimising the performance of large language models (LLMs). It involves a set of techniques and strategies for designing and refining the instructions given to LLMs, with the aim of obtaining more accurate, coherent, and relevant responses [32].

To perform AI experiments on future studies—or any sort of discipline for that matter—effective prompt engineering shall be considered to enable LLMs to generate useful content, even when only limited datasets are available. This is achieved by activating appropriate attention mechanisms, which help models focus on the most relevant parts of the input data and improve the interpretation of contextual information [33].

Some key prompt engineering strategies include the following:

- Few-shot prompting: Providing the model with a few examples to guide it in a specific task [34].
- Chain-of-thought prompting: Encouraging the model to think sequentially to respond more elaborately [35].
- Pattern structured prompting: Using specific structures or patterns in the prompt to obtain more consistent responses [36].
- Domain-Specific Knowledge Injection: Incorporating specialised information to enhance accuracy in specific areas.
- Iterative Prompt Refinement: Continuously adjusting instructions based on the model's previous responses [37].
- Self-consistency decoding: Generating multiple reasoning chains for the same question and selecting the most common response among them [38].
- Least-to-most prompting: Breaking down a complex task into simpler sub-problems and solving them sequentially [39].
- Generated knowledge prompting: Generating relevant knowledge before answering a question to provide a richer context for the response [40].
- Maieutic prompting: Generating recursive explanations to verify the logical consistency of responses [41].
- Tree-of-thought prompting: Generalising the "chain-of-thought" by allowing the model to explore multiple reasoning paths in a tree structure [42].

Understanding and applying these strategies is crucial for overcoming the current limitations of LLMs. The effectiveness of prompt engineering depends on understanding the models' internal mechanisms and combining different techniques to generate high-quality and reliable responses [34]. The technical development of digital systems based on prompts significantly differs from traditional software development, requiring new tools and methodologies. Nevertheless, prompt engineering is still in its early stages and requires significant scientific contributions. A recent survey highlights the lack of systematic organisation and understanding of the diverse prompt engineering methods and techniques, indicating the need for further research to illuminate open challenges and opportunities in this rapidly developing field [43]. Indeed, there is discussion about how advanced prompt engineering techniques are evolving towards constructing LLM-based agents capable of reasoning and acting more autonomously [44]. This transition implies that AI professionals will need to focus more on managing and orchestrating various models and agents, ensuring efficient collaboration among them to solve complex tasks.

2. Materials and Methods

This research project employs a research-through-design approach, treating the development and iterative refinement of prototypes—specifically, a generative AI-driven "Time Machine" (hereafter referred to as MdT)—as both a practical and epistemic endeavour.

By engaging directly with design artefacts, including software prototypes and tangible card decks, the project transcends traditional deductive or inductive approaches, instead leveraging abductive reasoning to generate insights and refine hypotheses throughout the design process [45].

Abductive reasoning, often called inference to the best explanation, offers a robust framework for iteratively proposing and evaluating design solutions in uncertain or complex contexts [20,45]. This is particularly pertinent in foresight exercises involving speculative future scenarios or general design methodologies. In this project, each iteration serves as a real-world testbed, where newly generated scenarios, participant feedback, and observed outcomes collectively inform subsequent refinements of the MdT. This cyclical approach aligns closely with design processes, often necessitating testing multiple ideas, hypotheses, and strategies before determining the most suitable solution for the final artefact.

By anchoring the methodology in research-through-design, the project underscores the co-evolution of prototypes [46]. The design of the Time Machine directs participant engagement, which, in turn, shapes and informs subsequent iterations of both the tool and the underlying conceptual framework for AI-supported futurisation. This approach is particularly advantageous for solution-oriented processes, where the goal is to arrive at an optimal design and produce knowledge along with it rather than merely validate a research hypothesis. This iterative process allows for the emergence of novel insights arising from the dynamic interplay between human expertise and machine-generated outputs [20]. Drawing from previous methodological analysis, we implement a triple approach: using software probes to assess the prototype design, exploring the interactions of people with the machine (i.e., how they draw on the outputs of the MdT to hold discussions), and reflecting on the experience with the community who took part in the experiments. This structure follows Brand and Binder's threefold approach to experimental design research [46].

2.1. Objective

The primary objective of this research project is to contribute to the design and evaluation of novel GAI tools for scenario planning, specifically tailored for non-expert users on scenario planning. The study also seeks to assess how these tools facilitate and stimulate reflections on future scenarios.

To this objective, the project employs GAI to automatically generate future scenarios based on hypotheses about the future and key drivers—defined as generic macrotrends, the data for which are provided to the AI. Central to this effort is the development of the MdT, which interacts with OpenAI's GPT-4 LLM to produce outputs in a structured future scenario format. Complementing the digital application, physical cards representing major macrotrends have been developed to foster engagement and facilitate discussions through analogue elements.

The project also addresses several secondary objectives that support the implementation and testing of the MdT:

1. Educating users and trial participants about fundamental concepts and methodologies in future studies.
2. Ensuring the system is accessible to end users by designing a simple and intuitive interface.
3. Evaluating the potential to improve the prompts upon which the Time Machine relies.

Figure 1 provides a visual overview of the project's phases, encompassing the initial research design, proof-of-concept development, and six iterative testing cycles. Insights derived from these test cycles informed the final service design and recommendations for integrating human and machine intelligence in future scenario generation. The project's core is applying GAI tools—specifically OpenAI's GPT-4 model—to enhance and extend traditional foresight methodologies. By iteratively designing, testing, and refining the MdT prototypes, the study embodies abductive logic: each trial reveals new possibilities and explanations that guide the subsequent design decisions cycle.

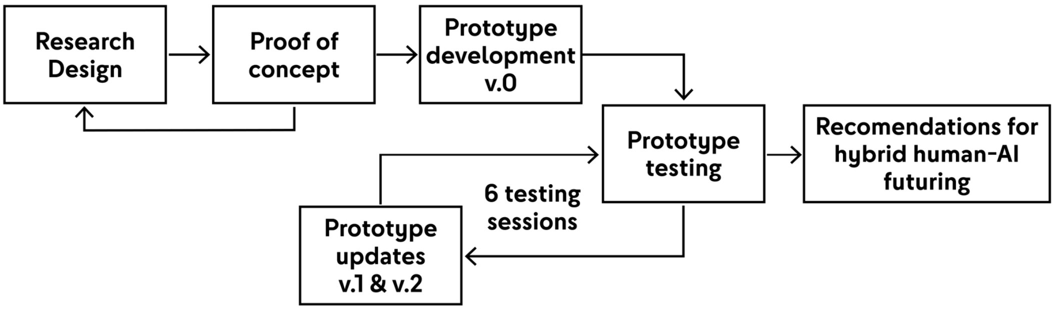

Figure 1. Project phases.

2.2. Future Scenario Generation Procedure

To test and iterate on the design of the MdT, the process illustrated in Figure 2 is followed throughout a series of 6 workshops (testing sessions in Figure 1). The futurisation process of the workshops follows a standard foresight approach in which weak signals and trends are first identified [47], leading to future hypotheses. In this design, scenarios were defined as narrative constructions incorporating both the initial hypotheses and up to four additional macrotrend "drivers".

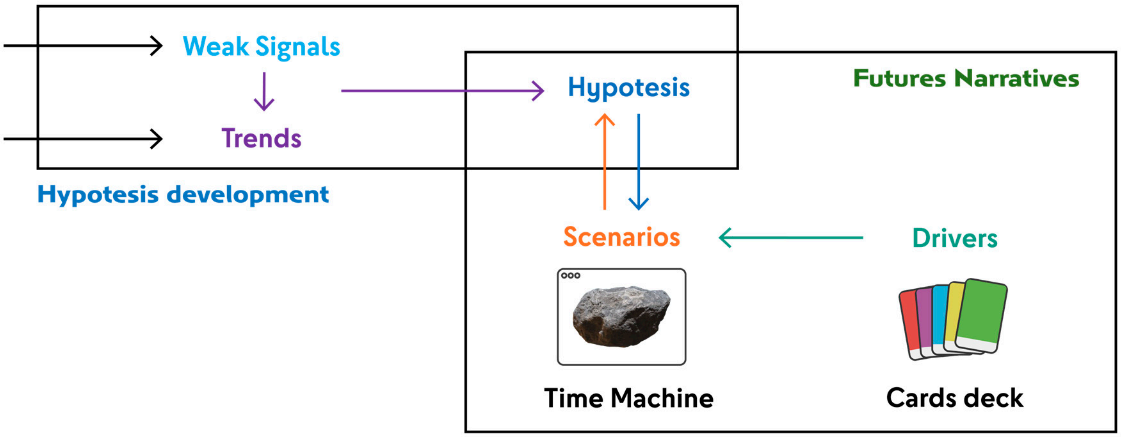

Figure 2. General scheme of the futurisation process.

2.2.1. The Time Machine, a Generative AI Tool for Future Scenario Development

The Time Machine (MdT) is a digital application that automates the scenario-writing process using OpenAI's GPT-4 model. Participants enter a hypothesis on the future and four selected macrotrends into a prompt form, which requests a structured scenario narrative, and the primary challenges associated with that scenario. These outputs are returned to the user for use and evaluation. This software is the basis of the design process and what the authors aim to test and iteratively design.

In parallel with the digital system, an analogue card deck of 80 macrotrend "driver" cards was created following the example of the UK's Trend Deck [48]. These cards were derived from an analysis of global macrotrends, drawing data from the European Commission's Joint Research Centre's Megatrends portal [49], and included a general title, a visual representation of the trend, and a textual explanation of the reverse (Figure 3). The contents of these cards are provided by the MdT to the GAI on the user's input before generating any future scenario. The drivers card deck does the following:

- Promotes participant education by highlighting real-world trends and stimulating discussion.
- Facilitates group dynamics by allowing experts to negotiate which drivers are most relevant, thereby fostering deeper collective intelligence and reducing the inference of individuals' subjectivity on trends selection [50].
- Provides a structured and validated source of global trends to be chosen due to their relevance (or irrelevance), diminishing participants' bias from the hypothesis.

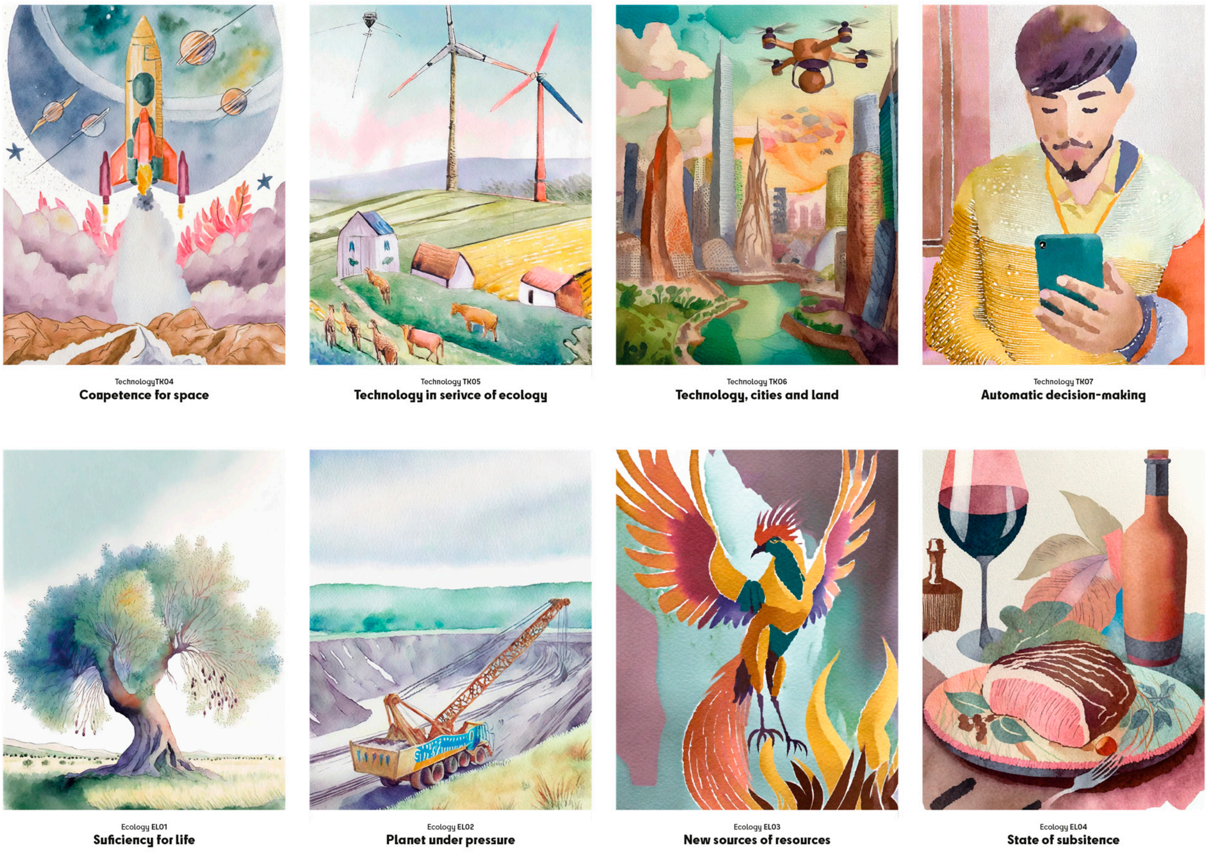

Figure 3. Sample of the collection of 80 megatrends card deck (translated to English from Catalan).

Although the MdT is designed for foresight practices, the system operates primarily within a predictive framework [51], aiming to generate the best possible assessments based on known data. Consequently, it does not explicitly address "black swan" events—rare and unpredictable occurrences with severe impacts [52]. By their nature, such events fall outside the purview of conventional predictive forecasting, as they are challenging to anticipate through weak signals or mainstream trends and might instead require other sources, such as fiction works [52].

The decision to exclude black swans reflects a pragmatic focus on leveraging observable, data-driven "drivers" that can be effectively integrated into generative AI prompts. While acknowledging that black swans have the potential to radically alter future trajectories, this study's primary objective is to evaluate how AI can enhance scenario planning grounded in known or reasonably inferred trends and hypotheses. Addressing genuine black swan events would require a fundamentally different methodological approach, more suited to wild-card analysis or risk-oriented frameworks—which are now usually employed in scenario-based planning.

That said, the MdT does not entirely rule out the inclusion of black swans. The decision to limit their consideration in this initial experiment was a deliberate choice to maintain focus on core objectives. Nevertheless, the system remains flexible, as black swan scenarios can still be incorporated into the MdT if explicitly stated in user-provided hypotheses, where more biased input can be introduced. In such cases, the MdT is given normative views of the future (i.e., those that align more with the emotion than the rationality of prediction) [51].

2.2.2. Workshop Design

Each workshop lasted approximately three hours and involved multiple working groups, each comprising 4 to 6 participants. Participants were professionals who had previously engaged in some sort of basic innovation-related training, ensuring a baseline familiarity with foresight concepts but not necessarily holding expertise on future scenario planning. During each workshop, participants did the following:

1. Proposed and refined future hypotheses based on salient trends.
2. Selected up to four drivers (i.e., macrotrends) for the MdT to integrate into scenario generation.
3. Evaluated the AI-generated scenarios, offering feedback to refine the scenario hypotheses and the MdT design and prompts.

2.3. Methodology for Generating Future Scenarios

Six iterative trials were conducted with different participant groups, each focusing on a specific foresight challenge (Table 1). The project team classified these trials into two blocks.

Refinement trials (Trials 1 to 3) are intended to optimise the tools and methods used for scenario generation. These trials focused on transitioning from prototype v.0 to prototype v.2 through incremental adjustments to key elements, including the prompt wording, user interface, and card deck design. Participants engaged in hypothesis creation by combining two or more trends relevant to their chosen domains—such as health, education, resource governance, or inequality. These hypotheses could be either generic (v.0) or geographically oriented (v.1 and onwards), providing a foundation for scenario generation and iterative tool refinement.

The validation trials (Trials 4 to 6) aimed to assess the final prototype (v.2) while exploring various strategies for hypothesis formation. During these trials, participants worked with three distinct types of hypotheses. The first type, generic-normative, consisted of broad or unstructured statements such as those from the previous trials. The second type, situational hypotheses, were designed to address specific problems or stakeholder groups, outlining the future context in greater detail. Lastly, interventional hypotheses introduce a policy, product, or service within a specific context to assess its impact on future scenarios. These trials helped validate the prototype's utility across diverse hypothesis frameworks.

Table 1. Overview of the trials, including the themes explored, participant profiles, methods of hypothesis creation, types of hypotheses, the number of scenarios generated, and the version of the Time Machine (MdT) prompt used.

Session	Work Themes	Participants/Groups	Profiles	Hypothesis Creation Method	Hypothesis Type	Scenarios	Prompt Version
1	The future of health and education services	25/5	Academics	Based on the combination of two trends	Generic hypothesis	32	v.0
2	The future of resource governance	15/3	Environmentalists and politicians	Based on the combination of two trends	Generic and geographic hypothesis	42	v.1

Table 1. *Cont.*

Session	Work Themes	Participants/Groups	Profiles	Hypothesis Creation Method	Hypothesis Type	Scenarios	Prompt Version
3	The future of inequalities	23/4	Third sector professionals	Based on the combination of two trends	Generic and geographic hypothesis	26	v.2
4	Challenges of the healthcare system	87/14	Hospital executives	Based on evaluating multiple trends	Generic and geographic hypothesis	35	v.2
5	Digitalisation of elderly health services	44/7	Professionals in the social-health sector	Based on designing innovative solutions using digital technologies	Situational and interventional hypothesis	52	v.2
6	Reversing negative predictions of health system outcomes	28/5	Healthcare professionals with clinical activity	Based on unfavourable predictions and proposed interventions	Interventional hypothesis	11	v.2

Total participants: 222 across 38 groups. Total scenarios created: 198.

The Iterative Approach to Hypothesis Formulation

In keeping with the abductive and iterative spirit of the research-through-design approach, the method for formulating hypotheses was intentionally altered across workshops. This progression allowed the research team to test the MdT under varying conditions and observe how changes in hypothesis formulation—from simplistic trend-pairing to designing an intervention—impacted the quality and relevance of the AI-generated scenarios, knowing that prompt structures impact the quality of GAI outcomes [44]. The shifting methods thus served as methodological probes, revealing new insights into how structured vs. unstructured hypotheses affect AI outputs and how participants deem these differences in group-based foresight exercises.

2.4. Evaluation Metrics

The study employed quantitative and qualitative metrics to measure the effectiveness of AI-generated scenarios, addressing key dimensions of perceived utility and scenario quality. By integrating these mixed methods—binomial metrics for immediate participant reactions and qualitative analysis for richer contextual insights—the team was able to abductively refine the MdT's design and tailor workshop procedures through activity-emergent and activity-learning feedback, as described by Wynn and Maier [53]. That is, a feedback system centred on the design activities allows for the emergence of insights and new designs. This iterative feedback loop is widely recommended in design practice as it enables researchers to generate new design ideas and theoretical explanations based on practical, real-world interactions [53].

2.4.1. Quantitative Utility Measures

After each AI-generated scenario was presented, participants answered two binomial questions:

- Did the scenario generate debate? (Yes/No)
- Did the scenario contribute new ideas? (Yes/No)

These responses, aggregated and expressed as percentages, provided a straightforward measure of whether the scenario content sparked productive discussion and offered novel insights.

2.4.2. Qualitative Observations

Facilitators used a fly-on-the-wall observation technique alongside unstructured inquiries to capture participant feedback and identify scenario limitations (e.g., excessive technocentrism or lack of depth). These insights were used to improve prompts and workshop facilitation in subsequent trials.

2.5. Use of AI in Writing

In addition to their research and analytical methods, the authors also incorporated GAI tools into the writing process of this paper. Specifically, ChatGPT-4o and ChatGPT-o1 were utilised following the low offloading approaches described by Knowles [54] (i.e., not assigning content decisions to the GAI models). This approach involved assigning the GAI tools specific writing tasks, such as generating content based on a predefined outline, suggesting potential arguments or structures for the authors to refine, and identifying relevant literature. Any literature suggested by the GAI tools was subsequently verified and assessed for suitability by the authors, who consulted the original sources and added additional citations through rather classic methods of research (e.g., databases, Google Scholar, and other scholarly search engines). These human–GAI–human interactions allowed for an iterative writing process in which the authors maintained full control over the paper's direction, content, and composition decisions at all times. Using these methods, human–GAI collaboration contributed to sections of the introduction and literature review, the tools and methods section, and the discussion.

3. Results

This section presents the results of the six trials conducted with various working groups. Table 2 summarises participants' responses to the questions posed after each generated scenario and the most relevant comments they provided.

Table 2. Participants' responses for each trial.

Session	Work Themes	Generated Debate	Contributed New Ideas	Participants' Comments
1	The future of health and education services	47%	52%	- "The scenario takes place in my village, Collbató. What a coincidence! Is it spying on me?" - "The geographic scope of the hypotheses is very repetitive and biased towards rural settings". - "There is a technological emphasis and a high techno-optimism. According to the machine, technology will save us". - Observation: The scenario narratives were considered familiar.
2	The future of resource governance	94%	71%	- "This is so realistic, isn't it? Gives me anxiety". - "We don't need a time machine for this. That's already happening". - "Okay, this is nice, but how do we get there? What must change to make this possible?"
3	The future of inequalities	73%	50%	- "It has no critical approach. It seems like everything will be quite nice". - "Technologies will be the solution to all inequalities, almost based on this". - "We added the most catastrophic hypothesis, and the result is still overly optimistic". - "I already know this. It gives me no insight".
4	Challenges of the healthcare system	84%	79%	- "We don't need to test any other scenario because this perfectly reflects what we want". - "These resources are essential for proposing future scenarios". - "We managed to discuss the hypothesis among all team members". - "We lacked time to test more scenarios".
5	Digitalisation of elderly health services	77%	69%	- Observation: Users often want to stick with the first scenario. - "The first scenario was exactly what we wanted". - "It shows what we proposed and gave us information through a clinical case we hadn't considered". - "Short-term scenarios seem highly unrealistic and do not fit the time frame well".
6	Reversing negative predictions of health system outcomes	82%	100%	- "The proposed scenario offers a systemic view of what needs to be done to promote the hypothesis". - "The drivers help to test many options". - "The scenario does not address the critical economic and investment aspects for our hypothesis". - "The scenarios turn out similar regardless of the timeframe we set".

4. Discussion

The study's findings indicate a positive perception of the Time Machine (MdT) among participants, particularly regarding its ability to foster debate and generate new ideas. These findings align with prior research [20,21] and highlight the potential of generative AI (GAI) to revolutionise, or at least augment, future-oriented processes within organisations. Notable benefits include rapid scenario generation, personalisation, and the promotion of collective intelligence, which can enhance strategic planning and adaptability in complex environments [2,8].

However, the study also uncovered several notable challenges. Despite advancements in prompt engineering, biases inherent in large language models remain a significant concern, potentially affecting the neutrality and diversity of generated scenarios. This issue was evident in participant observations, which pointed to biases in selecting scenario settings or an overarching optimism—specifically technopositivism. In response, additional parameters, such as geographical context and optimism level, were integrated into the MdT's design. While these adjustments yielded mixed results, the authors wish to highlight the dual sources of bias: the underlying model and the data provided to the GAI, including macrotrend inputs and user-driven selections. Addressing these issues may require employing more diverse data sources, refining prompt engineering techniques, and exploring multi-agent systems. Multi-agent frameworks, in particular, could facilitate more structured, iterative scenario generation while enabling robust validation procedures [55]. This approach could also integrate external knowledge, enhancing the tool's capacity to account for "black swan" events—a point insightfully raised by one of the article's reviewers.

Another observation identified by the participants is the MdT's tendency to generate long-distance narratives, whereas many users—possibly given the lack of long-term future visioning culture—preferred short-term projections (5–10 years or less in some cases). This challenge is compounded by the stronger results observed in tests where users introduced specific interventions as future hypotheses (test 6), leading to more actionable narratives. While adjusting the MdT to cater to short-term projections could improve accessibility and utility for scenario-planning novices, this approach risks diverting the tool from its intended purpose of strategic foresight. As noted by some philosophers, long-term thinking is to be preferred as short-term scenarios may merely represent incremental evolutions of the present [56]. Moreover, the MdT's reliance on extrapolation limits its capacity for radical reimagination of the future, confining it to predictive scenarios—just one aspect of the broader foresight discipline [51].

To address these challenges and enhance the MdT's efficacy, future research should focus on scalability, model refinement, and adaptation to different temporal needs and potentially different outputs—that is to say, the formalisation of scenarios, possibly in line with the field of speculative design and fiction [57], which leverages all sorts of artefacts to represent the future. Efforts should also include trials with more diverse participants and controlled profiles who systematically evaluate the accuracy of the results, further improvements in prompt design (including the sourcing of additional data), and techniques to fine-tune scenarios across various time horizons. Such advancements will ensure that the MdT remains a practical and valuable tool for strategic planning, capable of supporting organisations in navigating both near-term and long-term challenges.

5. Conclusions

This study confirms that the Time Machine (MdT) is valuable for generating future scenarios, particularly facilitating team discussions and fostering idea generation. It is especially effective as a complementary approach for refining potential future interventions and analysing their potential impacts. The iterative design highlights that GAI-driven scenario-making achieves the best results when inputs are parametrised—such as through specifying geographical locations or optimism levels—though no clear advantage was found in stipulating exact timescales. While these findings reinforce existing cases on the utility of AI integration in future-oriented processes, further research is needed to explore the application of GAI-driven scenario-making with unstructured inputs.

Despite its strengths, the MdT also has limitations that must be addressed to maximise its potential. These challenges are both practical and theoretical. On a practical level, reducing biases through model refinement and careful curation of input data is essential. Theoretically, a broader understanding of foresight is to be integrated into the MdT design, an understanding that moves beyond narrow reliance on weak signals and trends, including normative approaches and black swans. Addressing these issues will enhance the method's reliability and adaptability in various contexts.

Future research should focus on several key areas to further advance the MdT: refining the models to minimise biases and adapting the technique for varied temporal scopes. This includes tailoring the MdT to both shorter timeframes and long-term normative visions. By overcoming these challenges, the MdT can empower teams to make better-informed and adaptive decisions, ultimately fostering a proactive and resilient organisational culture.

Finally, this research contributes to the argument that collaboration between humans and AI in scenario generation holds great promise for strategic planning and change management. Such partnerships offer innovative solutions to help organisations navigate complex future challenges. To fully realise this potential, it is crucial to ensure these tools remain simple, accessible, and practical, enabling broader adoption and impact.

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