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APPLYING GENERATIVE ARTIFICIAL INTELLIGENCE TO SUPPORT INVENTION PROCESSES: AN ANALYSIS OF THE SYSTEMATIC INVENTIVE THINKING (SIT) METHODOLOGY

Paweł WAWRZAŁA

Silesian University of Technology, Faculty of Organization and Management; Pawel.Wawrzala@polsl.pl,
ORCID: 0000-0001-9974-7689

Purpose: This paper aims to explore the integration of Systematic Inventive Thinking (SIT) methodology with Large Language Models (LLMs) to enhance innovative processes. It seeks to assess how LLMs can support analytical and creative processes in design teams and how hybrid human-LLM collaboration can contribute to more dynamic and unconventional problem-solving approaches

Design/methodology/approach: The study employs a theoretical analysis of SIT methodology and LLM capabilities, synthesizing existing literature on both topics. It proposes a framework for integrating SIT with LLMs, including structured prompt patterns for each stage of the SIT process. The approach includes a comparative analysis of human and LLM capabilities in inventive processes.

Findings: Research reveals that LLMs can significantly enhance the SIT process by providing rapid information synthesis, generating diverse ideas, and systematically applying SIT principles. However, human creativity, intuition, and holistic assessment remain crucial for breakthrough innovations. The study identifies specific prompt patterns and techniques for effective human-LLM collaboration within the SIT framework.

Research limitations/implications: As this is an initial theoretical framework, empirical validation through case studies or experimental research is needed to assess its practical effectiveness.

Practical implications: The proposed framework offers practitioners in the fields of innovation and design a structured approach to integrating AI into their creative processes. Provides specific guidelines for the use of LLM to enhance each stage of the SIT methodology, which could lead to more efficient and innovative outcomes.

Social implications: Integration of SIT with LLM could significantly influence public attitudes toward AI, potentially increasing its acceptance as a collaborative tool in creative and problem-solving processes. This approach may lead to more efficient and sustainable innovation practices in various industries, potentially addressing social challenges more effectively. However, it may also raise concerns about job displacement in creative fields, necessitating a focus on reskilling and education to prepare the workforce for collaboration with AI systems.

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Originality/value: This paper presents a novel approach to integrating SIT methodology with state-of-the-art AI technology, offering new perspectives on increasing human creativity with machine capabilities in structured innovation processes. It contributes to the emerging field of AI-assisted design thinking and provides a foundation for further research in this area.
Keywords: Systematic Inventive Thinking, Large Language Models, Innovation, Human-AI Collaboration.
Category of the paper: Conceptual paper, Research paper.

1. Introduction

In November 2022, a new entity emerged in our world, the first general-purpose artificial intelligence system, designed to pass as human and perform creative, innovative work previously exclusive to human capabilities. Direct inspiration for this article was Ethan Mollick's influential book 'Co-Intelligence' (Mollick, 2024), in which the author advocates collaboration with AI in the roles of co-worker, co-teacher, and trainer.

Systematic Inventive Thinking (SIT) is a methodology developed to support the innovation process by utilizing creative techniques and tools that aid in generating new ideas. This methodology is based on five fundamental principles that allow a systematic approach to problem solving and the creation of innovative solutions. While there is already a considerable body of scientific literature on integrating Design Thinking methodology with generative artificial intelligence, the SIT approach has not yet been considered in this context, creating new opportunities for researchers and practitioners in the field of innovation.

The main objectives of this paper include assessing how Large Language Models (LLMs) can support the analytical and creative processes of design teams, and how hybrid human-LLM collaboration can contribute to more dynamic and unconventional thinking about problems. In this way, the article contributes to the development of theoretical and practical foundations for the use of AI in SIT methodology, offering new perspectives and tools for practitioners in the field of innovation.

In the remainder of this article, Section 2 presents the SIT methodology and its distinctiveness from other design approaches. Section 3 presents the necessary knowledge about large language models and a selection of reports on the integration of AI technology with design processes. Section 4 presents structured patterns of design prompts. Section 5 describes in detail a design experiment that examines the impact of different rapid syntheses on the effectiveness of LLMs in generating concepts. Section 6 contains conclusions and future work.

2. Systematic Inventive Thinking (SIT)

The Systematic Inventive Thinking (SIT) methodology, and its later variant ASIT (Advanced Systematic Inventive Thinking), originate from the TRIZ theory (Theory of Inventive Problem Solving), which was developed by Soviet engineer and inventor Genrich Altshuller in the 1940s. TRIZ was originally created to identify regularities and patterns in innovative technical solutions (based on existing patent descriptions), making it possible to take a systematic approach to creating new inventions (Horowitz, 1999).

SIT was developed in the 1990s by a group of Israeli researchers and consultants who decided to simplify and adapt TRIZ for applications beyond the technical industry. They aimed to create a tool that would be easier to implement in various fields such as marketing, management, and product development. The key goal was for the SIT methodology to be simple, understandable, and universal, so that it could be used by individuals with varying levels of technical understanding (Horowitz, Maimon, 1997).

Systematic Inventive Thinking (SIT) is a methodology that distinguishes itself from other approaches to problem-solving and innovation design, such as Design Thinking, Lean, Six Sigma, or TRIZ, through its unique structure and principles. While other methodologies focus on identifying problems or optimizing processes, SIT concentrates on creatively utilizing available resources and assumes that creativity stems from restrictions and limitations, rather than infinite freedom, as posited by Design Thinking, which is oriented towards empathy and user understanding. Lean and Six Sigma methodologies focus on process optimization and waste elimination, often through data analysis and precise metrics. SIT differs from them in that it focuses on creative exploration of the constraints and available resources, promoting thinking “inside the box’ instead of striving for process excellence. In the case of the approach from which SIT evolved, TRIZ, it is based on a systematic approach to innovation, but uses a knowledge base of previously solved technological problems to inspire new ideas. SIT is more intuitive and universal, focusing on transforming existing resources without referring to external patterns.

Although SIT is not as widespread as Design Thinking, which has reached the stage of solid critical analyses (Verganti et al., 2021), it appears to be an important candidate for wider application not only in organizations but also in education (Barak, 2013; Barak, Albert, 2017).

2.1. Structure of the SIT Methodology

The Systematic Inventive Thinking methodology consists of several key stages that ensure the systematic generation of innovative ideas, based on the application of five thinking patterns that are intended to lead to non-obvious but effective solutions. The process is similar to many problem-solving approaches, such as Design Thinking, Lean, Six Sigma, or TRIZ; it is structured and iterative (Barak, Bedianashvili, 2021).

For the purposes of this paper, the following stages of the SIT process have been adopted based on the publication by Barak & Bedianashvili (2021) and materials from SIT – Systematic Inventive Thinking Ltd. (2024).

Stage 1. Problem Definition

The first step is to thoroughly understand and define the problem to be solved. It is important to define both the goal and the context of the problem, which in SIT terminology we call the ‘closed world’, and further steps will be ‘thinking inside the box’. At this stage, it is also necessary to define the constraints and resources available to the team.

Stage 2. Functional Analysis

This stage involves analyzing the system, product, or service in terms of its functions. The aim is to identify what functions the individual elements perform and how they affect the whole. This analysis helps to understand which aspects are crucial and what potential starting points there are for innovation.

Stage 3. Application of SIT Patterns

At this stage, specific SIT thinking patterns are applied to generate innovative ideas. SIT is based on five main patterns that serve as tools for creative thinking.

1. **Division** - breaking down an object or system into parts and then reassembling them in a new way.
2. **Multiplication** - replicating an element of the system with certain modifications that lead to a new function or effect.
3. **Subtraction** - removing an essential element of a product or system to identify new applications or functions.
4. **Task Unification** - combining two or more elements in one system, leading to new functions or capabilities.
5. **Attribute Dependency** - changing the relationship between different attributes of the system, which can lead to new solutions.

Stage 4. Evaluation and Selection of Ideas

Generated ideas are evaluated in terms of their feasibility, innovativeness, and potential value. The team selects the best solutions that align with the project goals and can be implemented. Visualization of the new configuration is often recommended, imagining how the product or process looks after applying the chosen technique. This leads to the identification of potential benefits: analysis of what new values or functions have emerged as a result of the transformation, considering who might be interested in such a solution, and why.

Stage 5. Implementation

Selected ideas are further developed and prepared for implementation. It starts with assessing feasibility and identifying potential obstacles and ways to overcome them. At this stage, it may be necessary to develop prototypes, conduct tests and prepare a plan to bring the innovation to market.

Stage 6. Evaluation and Optimization

After implementing the solution, its effectiveness is evaluated. The team analyzes whether the intended goals have been achieved and identifies areas for further optimization.

These stages are iterative, meaning that if necessary, the team can return to previous steps to refine their solutions. This approach helps SIT in searching for innovative solutions systematically and organizedly in various fields.

2.2. Key Differences of SIT from Other Methodologies

SIT focuses on finding solutions within the ‘closed world’, or the immediate environment of the problem, instead of seeking external solutions. This approach contrasts with the idea of ‘thinking outside the box’, which often leads to less practical and less innovative solutions.

SIT emphasizes reversing the traditional problem-solving process, where a solution concept is first created and then a problem it solves is sought. This approach, known as ‘function follows form’, often leads to more innovative solutions than the traditional ‘form follows function’ approach.

The structural and systematic approach to problem-solving allows for increasing the chances of finding creative and practical solutions compared to methods based on spontaneity and randomness.

Advantages of SIT over other problem-solving methodologies

SIT does not focus on finding compromises, but on discovering new, surprising, and valuable problem solutions.

SIT offers a systematic and systematized approach to idea creation, introducing a sense of structure and order, in contrast to brainstorming, which often leads to chaos.

The ‘closed world’ principle in SIT encourages finding solutions using existing elements, which is particularly valuable with limited budgets or time.

SIT methods help identify and overcome the tendency to perceive problems and solutions in traditional ways.

The effectiveness of SIT is based on the analysis and manipulation of elements of the ‘closed world’. If a problem does not have clearly defined boundaries or components, applying SIT may be difficult, although collaboration with LLM can introduce new perspectives and simulations still within the concept of the ‘closed world’.

Although SIT can be applied in various fields, most of the problems analyzed require deep expert knowledge that the methodology itself cannot provide. SIT can be a support for experts but will not replace their knowledge.

The Systematic Inventive Thinking methodology is the right choice for the following tasks:

- Creating new products and services.
- Improving existing products and services.
- Solving technical and engineering problems.

- Generating innovative marketing and advertising ideas.
- Optimizing business processes.
- Solving complex organizational problems.
- Breaking thought patterns and overcoming functional fixation.
- Creating new business models.
- Solving product design problems.
- Generating creative solutions with limited resources

Problems that should not be solved with the help of SIT include:

- Ethical and moral issues, SIT is not a tool for making ethical decisions.
- Problems requiring extensive scientific research or gathering new data; SIT relies on using existing knowledge.
- Crisis situations requiring immediate action; SIT requires time for thought and application of techniques.
- Purely logical or mathematical problems; SIT is more suitable for conceptual and practical problems.
- Interpersonal issues and conflicts - SIT is not a tool for solving social or psychological problems.
- Problems requiring a radical paradigm shift or complete departure from existing frameworks - SIT works best within existing constraints.
- Simple problems with obvious solutions: SIT is most effective for complex challenges requiring a creative approach.

Of course, Systematic Inventive Thinking, like any tool (SIT can be treated as a set of tools), in the hands of an experienced moderator, can also be used for quick solutions, including those of a social nature.

3. Large Language Models (LLM)

Large language models, one of the main achievements in the field of artificial intelligence (AI), have transformed the way we process natural language. Generative artificial intelligence (GenAI) using LLMs now forms the foundation of many applications, ranging from natural language processing and machine translation to supporting creativity and innovation in inventive processes. The development of LLM technology since 2018, when the *transformer architecture* was presented (Vaswani et al., 2017), has allowed for an enormous increase in the capabilities of these models, both in the context of data processing and content generation. LLMs are models trained on enormous text datasets, using neural networks to analyze data sequences, which allows for predicting subsequent words in sentences. Due to the advanced architecture and the availability of vast data resources, these models are able to understand and generate text in a way that resembles human language, making them useful in a wide range of applications.

3.1. Specifics of GenAI Models

One of the most well-known examples of applying this architecture is the GPT (Generative Pretrained Transformer) model, developed by OpenAI, whose successive versions, from GPT-3 to GPT-4, have revolutionized the approach to generative artificial intelligence. The basic mechanism of LLM operation is the so-called next token prediction, where 'token' means the smallest linguistic element (on average, one token is about 3/4 of a word in English). The model, based on previous tokens, tries to predict what should appear next. To achieve this, the model relies on its knowledge gained during training on enormous text datasets, which include diverse sources such as books, scientific articles, blog posts, or comments on internet forums.

In practice, LLMs do not possess semantic understanding in the traditional sense, as humans do. Instead, they use statistical associations between words and phrases that occur in the training data. Despite the fact that these models do not 'understand' text, their ability to model natural language is impressive. Correct content generation is based on the analysis of language patterns and contexts, which allows LLMs to create both short answers and long and complex texts.

Although LLMs are presented as autonomous reasoning engines, there is much research showing that they reliably fail in reasoning when left to their own devices (Kambhampati et al., 2024). These systems are best viewed as gigantic, approximate sources of knowledge that use incredible pattern-matching abilities to generate the next token, resulting in words and sentences.

3.2. The Concept of Context Window

The context window defines how many tokens the model can analyze at a given time, which affects its ability to understand and generate coherent and contextual responses. For example, if a model has a context window of 4096 tokens, only these tokens will be taken into account when generating a response, and any earlier information outside this range will be ignored. The size of the context window can significantly affect the performance of a language model. A larger context window allows the model to consider more information, potentially leading to more accurate and context-relevant results. Currently, the largest values are offered by the Gemini 1.5 Flash model – 1 million tokens, and Gemini 1.5 Pro has a context window of 2 million tokens. The most popular ChatGPT-4 model offers a context window of 128k tokens, while Llama 3 and Mistral allow the use of only 8,192 tokens, but it should be remembered that they can be run locally on a computer, ensuring data confidentiality. However, it should be noted that this parameter is not directly related to the quality of the response of the model.

3.3. Model Parameters

In AI-based language models, the key parameters affecting the quality and character of generated responses are temperature and top-p. Adjusting these parameters allows for precise control over the style and creativity of the response models, which is applicable in tasks that require coherent and predictable results, as well as those that need more diversity in the generated content. *Temperature* is a parameter responsible for controlling the degree of randomness in responses. Higher values, such as 1.0, lead to more diverse and creative responses, whereas lower values, for example 0.2, result in more predictable and repetitive answers. Lowering the *temperature* makes the model generate more conservative content, while raising this parameter increases the potential risk of less coherent but more original responses. *Top-p*, also known as nucleus sampling, regulates how 'deep' a pool of tokens the model can consider when generating responses. In this mechanism, the model selects tokens with the highest probability until their cumulative sum exceeds the value specified by the parameter *top-p*, for example, 0.9. This means that the higher the *top-p* value, the wider the set of potential responses is considered, which can lead to more diverse but less coherent results. On the other hand, lower *top-p* values limit the choice to the most probable tokens, which increases the predictability of responses.

Unfortunately, these parameters are set in the API (Application Programming Interface - a set of rules and protocols that allow different applications to exchange data and integrate functions) interface, not directly in the prompt content. However, by using the API (which is widely described on the internet), users can adjust the parameters of the LLM models to the specific needs of their applications, gaining control over the behavior of the model when generating responses.

3.4. Hallucinations

In the context of language models and generative artificial intelligence, 'hallucination' refers to the phenomenon where the model generates information that is not based on input data or factual reality. This can manifest in several ways. Fabricated information - the model may include details or facts that are completely made up, which can mislead users if considered accurate. Non-existent references - the model indicates data, suggests importing packages or libraries that do not exist. Contextual errors are content that is contextually inappropriate or irrelevant.

Addressing the problem of hallucinations is crucial to ensuring the accuracy and reliability of AI-generated content, especially in applications where precision is critical, and this can be achieved through specific prompting techniques. However, in this human-LLM collaboration model, whether the system response is correct or not is not such a big problem because if the LLM system hallucinates, humans will fairly easily detect it. Hence, any erroneous paths that generative artificial intelligence may take do not negate the sense of using it in the entire process of systematically supporting inventiveness. Therefore, it is advisable to create prompts according to a model that contains examples. Of course, without examples, the currently functioning largest language models can perfectly function giving desired answers. However, examples make it easier for the system to orient itself through analogy to what we demand in more complex situations. Removing examples from prompts can be effective when we want a more open statement from the model and when the used model handles too low a context window in relation to the assumed needs.

3.5. Specific Applications of LLM

LLMs have found wide application in many fields, from automatic translation, summarizing long content, to business analytics. The following publications can help the reader deepen their knowledge about the integration of AI technology into organizations and processes that lead to innovation.

The authors (Gama, Magistretti, 2023) in a systematic literature review distinguish 6 stages of AI introduction in organizations, from making AI available in the organization (basic competencies and procedures required for effective technology implementation), to automating basic tasks and expanding decision-making processes. This work refers to the integration of AI technology and design processes, indicating the possibilities of including generative artificial intelligence in teamwork in a way that puts user needs first and does not aim to automate the design process.

In the context of this work, supporting creative and inventive processes, large language models can provide new ideas and solutions that were previously difficult to imagine. And so, generating novel and useful concepts is one of the important stages of design, the authors (Zhu, Luo, 2023) defined three concept generation tasks to utilize different knowledge and reasoning: domain knowledge synthesis, problem-based synthesis, and analogy-based synthesis. Evaluation experiments conducted on humans and data showed good performance in generating new and useful concepts.

Group ideation processes were studied in the work of (Shaer et al., 2024), which proposed forms of collaboration with GenAI at the stage of idea generation and evaluation. Researchers suggest that LLMs can support idea evaluation and improve the results of the ideation process. This indicates the potential to integrate LLM with design thinking processes to enhance creativity and decision making.

Another noteworthy example of integrating LLM with the Design Thinking process is the work of (Asadi, 2023), in which the author discusses the benefits, challenges, and transformative potential of ChatGPT and Google Bard in facilitating idea creation, prototyping, and user-centered design.

AutoTRIZ is an idea creation tool that uses LLM to automate and enhance the TRIZ methodology (Jiang, Luo, 2024). Using the broad knowledge and advanced reasoning capabilities of LLMs, AutoTRIZ offers an innovative approach to design automation and interpretable ideation with artificial intelligence. The system takes a problem description from the user as the initial input and automatically generates a solution report upon completion of the reasoning process.

Unprecedented possibilities are provided by the use of GenAI for information analysis. In his work, (Buehler, 2024) transformed a dataset covering 1000 scientific articles devoted to biological materials into a comprehensive ontological knowledge graph. Through in-depth structural analysis of graphs, useful frameworks for innovation open up by revealing hidden connections.

There are also works that introduce generative artificial intelligence to applications for many users (He et al., 2024), pointing to concerns of several participants regarding the transparency of content ownership, private digital spaces, and specialized AI capabilities.

4. Prompt Patterns for Working in SIT

It should be emphasized that a necessary step for satisfactory cooperation with large language models is a brief information for team members about what they are, how they generate responses, how to build commands, and how to continue the dialogue. Sometimes, indicating even more technical details, such as context window size and response temperature, allows for breaking fears of using LLM. Using a few entertaining examples of using generative artificial intelligence, showing surprisingly precise responses from GenAI, seems to be an essential step to initiate team work with this technology.

Six families of use cases for artificial intelligence to support design teams have been identified:

1. Intelligent assistance, using artificial intelligence for quick information retrieval, explaining concepts, to creating specialized assistants (i.e., bots) for various tasks or design stages.
2. Research and analysis - using artificial intelligence to quickly gather and synthesize information on the topic we are designing for, from a huge number of sources, including those attached as local documents.
3. Creative ideation - using artificial intelligence to evoke novel ideas and challenge assumptions.
4. Data-Driven Insights - using artificial intelligence to extract meaningful patterns and forecasts from datasets, including multimedia ones.
5. Content generation, i.e., using artificial intelligence to design, write, and create multimodal materials, ranging from simple conversation with LLM, through generating complex reports, to graphic visualizations, including video.

6. Adaptation and localization, that is, using artificial intelligence to adapt content to different cultures and individual needs.

By applying these use cases, the moderator and/or members of design teams can unlock an unprecedented level of both efficiency and effectiveness.

4.1. Prompt Construction for LLM

Generative artificial intelligence systems are being implemented in many industries and environments. Developers and end-users interact with these systems using prompts or prompt engineering. The quality of prompt input into LLMs has a significant impact on the relevance and accuracy of their responses in terms of answering general purpose questions and problem solving (Liu et al., 2023). Currently, the most comprehensive meta-analysis (Schulhoff et al., 2024) summarizes knowledge about prompt techniques, introduces a taxonomy of prompt techniques, and analyzes their use.

4.2. Basic Prompt Structure for Generative AI Models

When designing basic prompts for commonly used models such as Gemini, Claude, LLaMA, or ChatGPT, the following elements should be considered.

Clear instructions. The prompt should clearly define the task or question. For example,

"Explain the component removal technique in SIT methodology".

Contextual information. Providing context can help the model generate more relevant responses.

"You are a human resources management consultant in a technology company undergoing restructuring. Propose a strategy to improve internal communication, taking into account the growing number of employees working remotely and the need for integration of international teams".

Output format. Describe the desired output format; you can include it as an example file.

"To evaluate ideas, use a rating scale of 1-5 (1=strongly disagree, 5=strongly agree), present the summary in a table".

Style instructions. To obtain a specific tone or style, include style instructions. For example:

"Use clear, concise, and jargon-free language understandable to nontechnical audiences.

Maintain an objective and data-driven approach, avoid personal opinions or interpretations.

British spelling".

Examples and templates - using model text can help in getting the model’s response. For example, providing a marketing email template can help the model generate content that fits the desired structure.

One of the somewhat surprising capabilities of LLM is the ability to ask the model to write its own prompt. Example prompt:

"I want you to [provide details of what we want GenAI to do for us]. Write an optimal prompt to instruct a large language model to perform this task in the best possible way. Make sure that the prompt has the following structure: Role, Recipients, Goals, Style".

Moreover, we can be quite imprecise in our request, as artificial intelligence is good at working out what we want and creating the best prompt. If we run the prompt it creates and the result is not what we wanted, we should send this result back to the AI and ask the LLM to redo the prompt, explaining why the result was not appropriate, trying to explain doubts in a similar way as we would to another person.

Another important technique helpful in clarifying our needs is to add a request for questions to the prompt.

"Then ask me [number of questions here, usually three to five] questions that will allow you to better [understand e.g. the problem, do your job]".

4.3. Sample Patterns for SIT

It is worth starting work with the chosen model by presenting the role that the LLM will fulfill:

"You are an experienced Systematic Inventive Thinking (SIT) facilitator and will be working with a team of people. Remember that you are a specialist in the SIT method and serve as an advisor and helper - you provide knowledge, accumulated experience, and are curious by asking the team questions that can improve the SIT process. At the same time, you are a large language model (LLM), and your analytical capabilities are very important".

The system's response will assure us that the chosen GenAI technology understands the assigned role, and we can proceed to the actual work.

Stage 1 - Problem Definition

There are many techniques for defining a problem, but in the case of LLM, you can start with a simple prompt:

"Present a problem description consistent with the first stage of the SIT method (closed world definition), which is a wheelchair being too heavy for a person with low physical ability, but with a large mass. This wheelchair should not be electrically assisted due to problems with maintenance and battery charging. Ask me three questions that will allow you to better perform the task".

As shown in the above example, the initial description can be quite incomplete and may even be unclear. However, dialogue with LLM will allow for specifying requirements and generating a problem definition with a description of the goal, context, constraints, scope, and key success indicators.

Another approach to this stage is to treat LLM as a system that guides the team step by step.

"Guide the design team through the problem definition stage (thinking inside the box), step by step, asking individual questions. At the end, summarize the problem definition in points".

Of course, nothing prevents (except for the time that needs to be devoted to dialogue with LLM) from using both versions, as the results can be significantly different.

Stage 2. Functional Analysis

Here is an instruction on how to give me information so that we can collaborate effectively.

"Let’s move on to the product world analysis for our wheelchair. Here is the information we have previously established:

[Here we place the entire text from the previous answer, containing the problem description]

Taking into account this information, please help me conduct a product world analysis. Let’s start by listing all the main components of the wheelchair in points, and then analyze their functions, mutual relationships, and potential areas for improvement".

Of course, the prompt can be more elaborated by instructing it to generate descriptions of elements, reminding about the possibility of asking questions to the team, specific formatting of the answer, etc.

Stage 3. Application of SIT Patterns

Here are proposals for patterns to use SIT tools.

Prompt for **Subtraction**:

"Identify the key components of [product]. Which of them can be removed while maintaining or improving the main function? How will this change affect [project goal]?"

Prompt for **Multiplication**:

"Choose one element of [product]. How can we replicate or increase its number in an unusual way? What new functions or benefits could this bring?"

Prompt for **Division**:

"Consider the main functions of [product]. How can we separate them into smaller, more specialized elements? What new possibilities does this create?"

Prompt for **Task Unification**:

"Identify unique features of [product]. Which of them can we combine in a non-obvious way? How can this combination solve [problem]?"

Prompt for **Attribute Dependency**:

"What are the key attributes of [product]? How can we create new, beneficial dependencies between them to better address [user needs]?"

For each SIT tool, the following process is proposed, referring to **Stage 4 - Idea Evaluation and Selection**:

a) Application of prompt to [product].

b) Generation of at least 3 ideas.

c) Evaluation of each idea in terms of [goal] realization and project constraints.

d) Selection of the most promising idea for further development.

These universal prompts can be adapted to different products and problems, while maintaining the structure of the SIT method. It's worth remembering about the possibility of using the knowledge accumulated in the language model itself and treating LLM as a facilitator of the process.

4.4. Techniques Improving Results in Prompting

Knowledge of rapid prompt engineering allows for more precise control of LLM, and hence familiarity with the following techniques can greatly enhance human-LLM collaboration.

Zero-shot is a technique used in natural language processing, in which the model receives a task without prior examples or task-specific training, which can help in shaping results for open-ended tasks.

Rephrase and Respond (RaR) in the zero-shot technique, instructing the model to rephrase and expand the question on its own before providing an answer. This method can lead to better results, as demonstrated in many comparative tests.

Least-to-Most Prompting - this technique involves dividing the problem into sub-problems and solving them sequentially. It is particularly effective in tasks that require symbolic manipulation and mathematical reasoning.

Chain of Thought (CoT) involves constructing a reasoning path that leads the model through a series of logical steps to arrive at an answer. This can be done in various ways, for example using natural language or symbolic languages such as Python, depending on the task requirements. Example variants:

- Zero-Shot CoT - this variant does not use any examples. It typically involves appending a thought-provoking phrase to the prompt, such as "Let's think step by step" to encourage the model to generate its own reasoning path.
- Few-Shot CoT - this approach presents the model with multiple examples that include chains of thought, significantly improving performance by providing examples of problem-solving reasoning.
- Self-criticism and self-improvement - encouraging models to critique their own outputs and iteratively refine responses based on feedback can increase accuracy and confidence in results.
- These techniques are systematic approaches that take advantage of the strengths of language models to improve the quality of their outputs in various tasks.

5. Risks and Problems

This paper will not develop the issue of risks associated with the use of AI, and there are many. A detailed list is contained in a paper developed by a team of researchers mainly from MIT and The University of Queensland (Slattery et al., 2024) - a comprehensive living database of over 700 AI risks categorized by their cause and risk domain.

From a business point of view, the confidentiality of information is important. Many problems can be avoided by using locally run models (the most popular are LLaMa, Minstral), which can generate responses at an acceptable pace on personal computers with efficient graphics cards. It is also a great technique to be able to analyze confidential documents; a locally run LLM model can work without an internet connection.

However, another element of human-LLM collaboration that needs to be considered is the sense of psychological safety among team members using generative artificial intelligence. Although the direct impact of GenAI on psychological safety has not yet been widely studied, the existing literature on emotional and psychological safety provides valuable insights. The sense of safety is subjective and can vary depending on individual perceptions and experiences. Therefore, supporting a sense of safety in interactions with artificial intelligence requires considering both real threats and psychological factors that affect users' perceptions. An interesting approach is presented in the work of (Li et al., 2024) that maps patterns of human interaction with GenAI. The study identified four main areas of human-LLM interaction: processing tool, analysis assistant, creative companion, and processing agent. These categories help to understand the different roles that LLMs can play in human interactions.

6. Future Research Directions

The integration of LLM systems with SIT methodology opens several promising research directions, although designing empirical studies presents significant methodological challenges. Three key areas emerge as particularly valuable for future investigation:

- Team Dynamics and Creativity Assessment:
    - Investigating how LLM integration affects individual and collective creativity in SIT sessions.
    - Examining changes in team members' perception of their creative capabilities when working with AI.
    - Analyzing the impact of AI collaboration on team dynamics and innovation processes.

- Acceptance and Adaptation Studies:
  - Evaluating team members' acceptance of LLM systems in creative processes.
  - Studying the evolution of human-AI interaction patterns during SIT sessions.
  - Assessing how different levels of AI literacy affect collaboration effectiveness.
- Process Effectiveness Measurement:
  - Developing metrics for evaluating the quality and innovativeness of solutions generated through human-AI collaboration.
  - Comparing problem-solving efficiency between traditional SIT and AI-enhanced approaches.
  - Creating frameworks for measuring the impact of different prompt patterns on solution generation.

These research directions require careful consideration of multiple variables that can influence outcomes, including team composition, prior experience with AI systems, and problem complexity. Future studies would benefit from developing specialized agent-based systems using LLM with standardized prompt sets, allowing for more controlled measurement of collaboration effects while maintaining the flexibility inherent in creative processes.

The challenge lies in balancing the need for standardized measurement with the inherently unique nature of creative problem-solving processes. This suggests a mixed-methods approach combining quantitative metrics with qualitative assessment of team experiences and solution quality.

7. Conclusions

This paper presented a comprehensive framework for using generative artificial intelligence (AI) in the context of supporting inventive processes, with particular emphasis on the Systematic Inventive Thinking methodology.

Due to the initial stage of work on integrating SIT methodology with LLM systems, no research was conducted, e.g., on the effectiveness of the developed framework. This was also not the intention of the author, who at this stage does not see the need to look for ways to prove the effectiveness of integration but rather sees the need to support people than create automatic systems designing innovations. Of course, we should appreciate the efforts of researchers to provide more automated solutions that, however, will not limit human creativity. For example, (Tian et al., 2024) provides an OpenAI-based assistant called the ‘Design Prompt Assistant’ (Liu, 2024).

One of the potentially important applications is the role of LLM as a tool to support facilitators in working groups. It can provide suggestions for team management, helping to eliminate tensions and avoid stagnation. Additionally, GenAI can support the building of a sense of safety in the team by providing appropriate inspiration in real time. Although LLM can partially replace facilitators in terms of access to knowledge and familiarity with moderation techniques, it is not able to fully recreate human relationships, which are crucial in building an atmosphere of trust. GenAI generates excellent content, but relationships based on emotions, empathy, and deep interpersonal understanding remain the domain of humans.

One of the significant limitations of generative artificial intelligence is its dependence on the quality of the input data. If users do not specify or force an analysis of the emotional state of people working on solutions, AI may show ‘deafness’ to these subtle signals. It must be remembered that LLMs are trained mainly on textual data and their ability to analyze moods and emotions is based solely on what can be inferred from linguistic data, although recently we can use multimodal models.

A comparative analysis of human and LLM system capabilities in inventive processes reveals both complementarity and areas of potential advantage for each side. Humans demonstrate an unmatched ability to contextually understand problems, using intuition, and combining seemingly unrelated fields of knowledge in an innovative way. This ability to ‘think outside the box’ is crucial in the initial stages of the inventive process, where defining the problem and identifying potential directions for solutions requires a deep understanding of the social, economic, and technological context.

Moreover, humans possess a unique ability to understand user needs and empathy, which is invaluable in designing human-centered innovations. Their ability to adapt to unforeseen circumstances and deal with ambiguity allows for a flexible approach to the inventive process, often leading to breakthrough discoveries.

However, LLM systems demonstrate impressive effectiveness in certain aspects of the inventive process. Their ability to quickly process large amounts of data and identify patterns exceeds human capabilities. In the context of SIT methodology, LLMs can be particularly effective in generating a large number of potential solutions based on principles such as unification, multiplication, or division.

LLMs also show an advantage in systematically applying heuristics and creative thinking methods. They can generate hundreds of solution variants in a short time, consistently applying SIT principles to various aspects of the problem. This ability to ‘exhaustively search the solution space’ can lead to the discovery of non-obvious but potentially revolutionary ideas.

However, the advantage of LLMs in generating a large number of ideas must be balanced with the human ability to assess their real value and feasibility. Humans are better at assessing the practical, ethical and social implications of proposed solutions, which is crucial for the effective implementation of innovations.

Ultimately, optimal utilization of potential in inventive processes requires a synergistic combination of human and machine capabilities. While LLMs can significantly expand the range of possibilities considered and accelerate certain stages of the process, human creativity, intuition, and the ability to evaluate holistically remain essential for truly breakthrough innovations. The key to success is therefore not so much replacing human invention with AI, but rather its augmentation, leading to new, hybrid forms of creativity and innovation.

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