Proceedings of the Design Society, Volume 5: ICED25
https://doi.org/10.1017/pds.2025.10101

Case study: is there a space for TRIZ in the era of ChatGPT?

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ABSTRACT: This study investigates the integration of Large Language Models with the TRIZ to improve problem solving and innovation in industrial product development. By combining the structured problem-solving framework of TRIZ with LLMs to process large amounts of data and generate ideas, this hybrid approach seeks to overcome the limitations of traditional TRIZ and optimize solution generation. In a case study conducted in an industrial setting, the effectiveness of this integration was investigated by comparing team-generated solutions with those derived using LLMs and TRIZ-enhanced LLMs. The results show that while LLMs accelerate idea generation and provide practical solutions, the additional structure of TRIZ can provide unique insights, however depending on the application context.

KEYWORDS: TRIZ, large language models, design methodology, conceptual design, design engineering

1. Introduction

The rapid development of Large Language Models (LLMs) in recent years, has opened new ways to support and improve decision making, problem solving and innovation in various fields (Zhu & Luo, 2023). These models, based on huge amounts of data and sophisticated natural language processing techniques, have shown great promise in everything from natural language understanding to creative idea generation. However, despite their potential, LLMs often lack a structured framework for systematic problem solving in complex, technical environments.

The TRIZ (Theory of Inventive Problem Solving) method, on the other hand, has long been recognized as a powerful tool for structured innovation and overcoming technical challenges. Altshuller provided a systematic approach to solving inventive problems by identifying and eliminating contradictions and applying inventive principles (Orloff, 2020). However, traditional TRIZ methods can be difficult to use as they require expert knowledge and extensive manual input, which limits their scalability and accessibility.

The integration of Artificial Intelligence (AI) with TRIZ holds significant potential for transforming problem-solving and innovation. AI's ability to process vast amounts of data and identify patterns could automate certain aspects of TRIZ, speeding up the problem-solving process and making inventive thinking more accessible. This shift could democratize innovation, enabling a broader audience to apply TRIZ principles (Cavallucci, 2023). Moreover, AI has the potential to enhance TRIZ by augmenting human creativity. Machine learning algorithms, trained on past inventive solutions, could suggest novel approaches to new challenges based on identified patterns, effectively evolving TRIZ into a more powerful tool for innovation. However, it is important to recognize that AI should complement, not replace, human creativity. While AI excels at pattern recognition, it lacks the deeper understanding and inspiration that human inventors bring to the table (Cavallucci, 2023).

Recent research is investigating the integration of TRIZ with AI to improve innovation and problem-solving processes. Ni et al. (2021) investigated the replication of TRIZ reasoning through deep learning, demonstrating the potential of AI to reproduce TRIZ-like insights. Ghane et al. (2023) conducted a systematic review of Semantic TRIZ (S-TRIZ) applications in technology development and emphasized the need for further research into the integration of AI with specific TRIZ components. Giordano's research clarifies the definition of key semantic relationship concepts and prioritizes key semantic relationships relevant to design knowledge, focusing on those that directly improve the engineering design process rather than more general or abstract relationships (Giordano, 2024).

Sojka & Lepší. (2020) explored the use of TRIZ in combination with other process improvement tools, pointing out its potential benefits but also the complexity of implementation. Ba. (2005) provided an example of the application of TRIZ methods to AI problems and suggested ways to incorporate TRIZ into computer science curricula. Overall, these studies show the growing interest in using AI to improve TRIZ methods, while recognizing the challenges in practical implementation and the need for more user-friendly approaches.

This paper explores the synergies between LLM models and TRIZ methodology and proposes that their combination can improve and streamline the product development process. By integrating the rich information processing capabilities of LLMs with the structured problem-solving framework of TRIZ, this hybrid approach can strengthen both methodologies and make the inventive problem-solving process more efficient, accessible and scalable in industrial settings. The study presented in this paper focuses on the application of this combined methodology in an industrial environment where the challenges of product design and development are complex and multi-layered.

Through a series of case studies and tests conducted in a real industrial context, this paper aims to demonstrate the practical benefits of using LLMs together with TRIZ to drive innovation and solve engineering problems. The results suggest that the hybrid approach accelerates the search of specific solutions in product development. The literature research has identified a gap between the promising features of TRIZ-LLM approach and practical applications. This paper is trying to fill the gap with details the methodology, results and implications for future applications of TRIZ-LLM integration in industrial product development.

1.1. Literature review

The integration of AI and TRIZ has the potential to automate and accelerate the invention process so that it can keep pace with rapid technological change. This intersection is leading to the emergence of NeoTRIZ or TRIZ-X, a new paradigm expected to drive significant breakthroughs in innovation (Brad, 2023). However, the development of this integration remains uncertain, contingent on factors such as AI' evolving capabilities, integration challenges, and the broader adoption of TRIZ methodology.

Several studies have explored how can Large Language Models (LLMs) enhance TRIZ-based innovation and design processes. Chen, Song, et al. (2024) introduced a workflow that uses LLMs to reformulate concrete problems into TRIZ problems and generate inventive solutions through structured reasoning. Similarly, Jiang and Lu. (2024) presented AutoTRIZ, an AI-driven tool that automates ideation within the TRIZ framework by leveraging LLMs' knowledge and reasoning capabilities to generate automated solution reports. Despite these advancements, industrial implementation remains untested, with comparisons mainly limited to textbook solution (Jiang & Luo, 2024; Chen, Song et al.,2024). In controlled settings, such as university trials (Chen, Tsang et al., 2024), LLM-driven approaches have shown promise, but their effectiveness in complex, real-world industrial scenarios remain uncertain.

Beyond TRIZ, LLMs have been employed to enhance various aspects of product design. For example, Trapp & Warschat (2023) explored the application of LLMs in identifying TRIZ contradictions in patent texts, while Dunnell et al. (2023) demonstrated how interactive AI tools facilitate large-scale data analysis and collaboration. Chen, Tsang, et al. (2024) propose an LLM-driven morphological analysis approach to conceptual design that guides designers through a controlled, step-by-step process that encourages innovation. According to Arjomandi et al. (2024) datasets are defined as structured collections of data specifically tailored for testing new processes and validating methodologies and processes. Mas'udah & Livoto. (2024) investigated the potential of combining nature-inspired approaches with AI, further demonstrating AI's capacity to support design processes. The studies by Wang et al. (2023), and Zhu & Lu. (2023) emphasise the role of LLMs in conceptual design and show that they are able to generate creative and feasible solutions in the early stages of design and bio-inspired design. El Hassani (2024) demonstrated the application of LLM for reusing an existing knowledge for risk analysis.

However, real-world implementation faces numerous challenges. One primary issue is the interpretability of AI-generated TRIZ solutions. Studies on the efficiency of LLMs in generating design ideas, such as that of Girotra et al. (2023), show that LLMs such as GPT-4 can outperform human idea generation in both speed and quality, suggesting that AI can be a valuable tool in product development. While LLMs can rapidly generate ideas, translating these into actionable innovations requires human expertise (Chiarello, 2024). Additionally, AI-generated solutions often prioritize feasibility over novelty, as seen in studies comparing AI and crowdsourced solutions (Ma et al., 2023). Ensuring the practicality of AI-driven TRIZ solutions requires addressing issues of contextual understanding, domain-specific knowledge, and integration within existing innovation workflows.

Another challenge is industry adoption. Gmeiner et al. (2023) highlighted that the designers often struggle to collaborate effectively with AI-driven tools, requiring new learning approaches to maximize AI's potential in innovation. Furthermore, Xu et al. (2024) found that while AI excels in knowledge extraction, its limitations in decision-making necessitate human oversight. Similarly, Gomez et al. (2024) and Ege et al. (2024) underscored the importance of balancing AI-generated insights with human creativity in technical design.

In summary, the literature shows that, while LLMs and AI hold great promise for improving TRIZ and engineering design processes, their integration is still in its infancy. Combining the computational power of AI with the structured problem-solving approach of TRIZ offers exciting opportunities to accelerate innovation, although the balance between human expertise and AI-generated solutions will remain an important consideration as the field evolves.

2. Research objectives and methodology

In recent decades the TRIZ method have spread throughout the world and have been used more or less successfully in the context of product development. When using a contradiction matrix, the problem at hand must first be converted into a general problem and described by contradiction parameters (Orloff, 2020). The contradiction matrix, which is a collection of innovative approaches that were extracted from hundreds of thousands of patents, suggests which inventive principles should be used (Figure 1). The next step is to find a concrete solution to the problem at hand, which is the weak point of the method. This step is left to the creativity of the development team. In principle, this is fine - TRIZ serves as an inspiration to propose a broader field of possible solutions. However, proposed general solutions presented with four inventive principles for each contradiction in abstract form are often not enough to inspire the developer to come up with a new innovation.

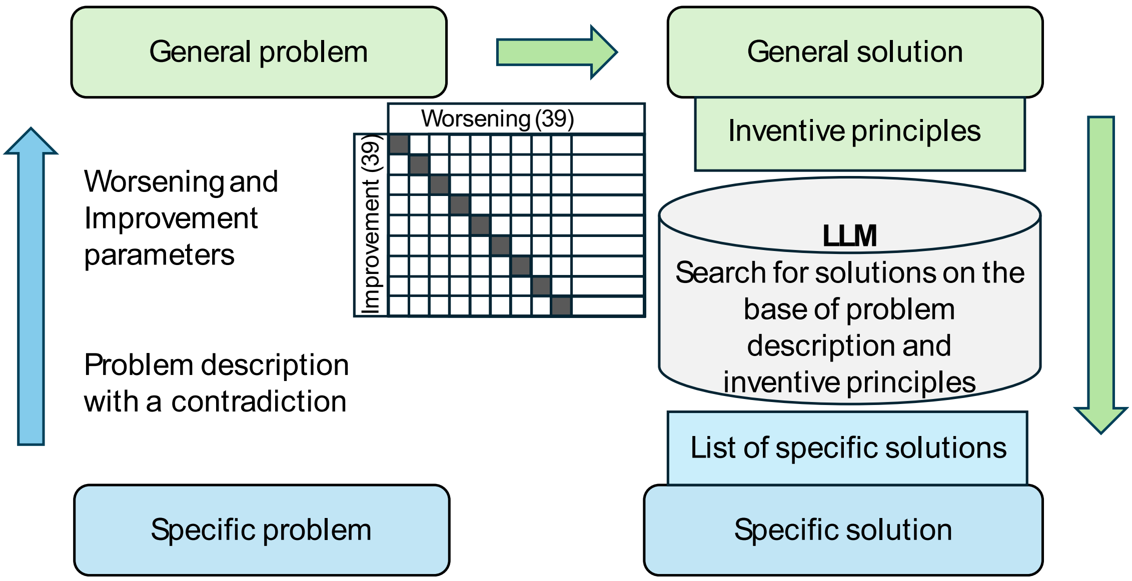

Figure 1. Integration of TRIZ and LLM in the problem-solving process

However, with the advent of LLM models, we have a very powerful tool to generate these concrete solutions. An LLM that captures knowledge from a very broad information base is perfect for this step. Even possible hallucinations of GPT outputs are not critical. The LLM suggestions are merely input for an engineer, whose task is to filter them and use them as an inspiration. So, we think that the combination of TRIZ and LLM as presented in Figure 1 is a very powerful new tool that needs to be explored. TRIZ with the contradiction matrix does a good job in the search and at the same time captures from the patent database. We expect TRIZ and LLM to complement each other well and achieve better results together. As there is a lack of recent studies on the efficiency of using TRIZ with ChatGPT, we decided to perform a comparison of the following steps where performance was observed and measured. According to Girotra et al. (2023), LLMs are efficient in generating ideas at a general level with a large solution space. In this context, we wanted to compare the performance of engineers and TRIZ/ChatGPT in their environment on the tasks given by the industrial company. The test was conducted in the following steps (Figure 2):

- **Step 1:** Finding solutions within a team without any additional tools (Teamwork 1)The team members were specialists in the technical problem. A brainstorming session was held and the team took notes on the board.
- **Step 2.1:** An introduction to LLM and prompt designThe introduction to LLM was conducted by two experts from academia for all teams simultaneously. A short discussion followed and the teams tested whether the prompts worked.
- **Step 2.2:** Finding solutions with LLM (ChatGPT) (Teamwork 2)The teams exchanged tasks with each other. The main task was to formulate a problem in a few sentences and use the right keywords to tell LLM to search through contradictions.
- **Step 3.1:** An introduction to TRIZ and contradiction matrixThe expert from the academic field used several examples to introduce the contradiction matrix and the principles of invention to all teams at once.
- **Step 3.2:** Finding solutions with TRIZ keywords, contradiction matrix and LLM (Teamwork 3) The problem was supplemented with keywords from TRIZ: inventive principles, contradiction matrix. The search was carried out in two steps, first for inventive principles and in the second step for specific solutions.
- **Step 4:** Assessment of results and critical review of the conducted experiment.Self-assessment by the team members. External evaluation by experts.

The main objective of these steps is to investigate the potential of the LLM with using TRIZ method for searching design/manufacturing solutions.

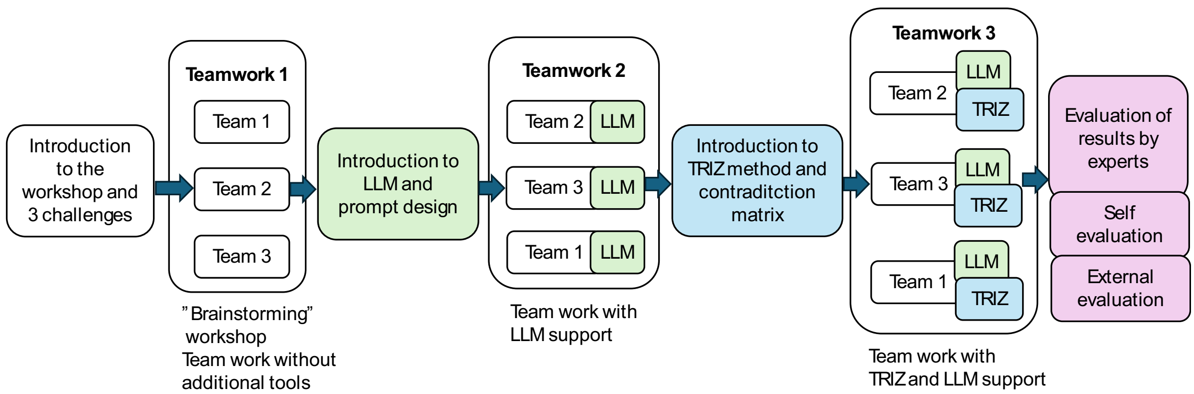

Figure 2. Flow-chart of the conducted experiment: search for design/manufacturing solutions

3. Case study

The case study was conducted as a workshop in the research and development department of a Domel company that manufactures electric motors in Slovenia, EU. The workshop took place during the week on Tuesday at 1 pm and lasted 3 hours until 4 pm. The workshop was attended by 4 academic experts and 11 engineers (development engineers, application engineers, etc.) as well as the R&D director. All participants were highly qualified experts and all had a bachelor's, master's or doctorate in engineering. They had extensive experience with product development. Most of them had previously used ChatGPT for technical challenges, with the exception of three people who used it for other purposes. They predominantly rated their knowledge of ChatGPT as 'average' to 'good'. When asked whether they had ever heard of the TRIZ method, seven participants answered 'yes', while five answered 'no'. With regard to previous use of the TRIZ method, ten participants stated that they had never used it, while two participants stated that they already had experience with it. Due to the confidentiality agreement, the technical details of the problems discussed are not presented. They all relate to the products manufactured by the company. The company is an established developer and manufacturer of electric motors for professional, automotive and consumer products. New demands for extended product life and cost reduction require a continuous product improvement process. The study focused on improving the company's existing products by addressing challenges related to welding, fatigue, and component life cycles. The mature products are automotive auxiliary drives, electric drives for garden equipment and vacuum cleaner motors.

In the introduction it was explained that the workshop would take place in three phases (Figure 2). First, solution finding, i.e. generating ideas without any tools, second, using ChatGPT to find solutions, and third, using the TRIZ contradiction matrix notion or TRIZ module in ChatGPT to find additional solutions to the technical challenge. The technical challenges were solved in Teamwork 1 by the team members that were familiar with the technical domain. That is, the teams consist of the experts in the technical challenge. The teams have switched the technical problem between each other in Teamwork 2 (Figure 2). That is, the engineers were not specialist in the problem domain. In this way, we wanted to eliminate bias. However, all the participants were development engineers, working in the same company. All of them had good knowledge of the technical challenges in Teamwork 2 and 3. In the search for solutions with LLM and TRIZ support (Teamwork 2 and 3) advanced expertise is less important than in Teamwork 1 without any tools. The final evaluation of results of Teamwork 2 and 3 and comparison with Teamwork 1 was performed by experts for each technical problem. We used both quantitative and qualitative methods to collect the data and answer the research question in a sound way. Participants' background and familiarity with LLM was assessed using a questionnaire. The data was collected using qualitative methods by recording feedback and self-reports on the usefulness of the two search methods (ChatGPT only, TRIZ + ChatGPT). The software used in the study were OpenAI's ChatGPT 4o, and custom ChatGPT module "TRIZ problem solver" (Author: Phiani Chandra Sekha) both accessed through web browser. The TRIZ module was selected by the experts from the academic field after a lengthy comparison based on the criteria that best fit the original steps of the TRIZ method.

4. Results

The results of the questionnaire in which the participants were asked about the usefulness of the TRIZ and ChatGPT method are as follows: 8 participants (72.73%) found this method "useful", while 2 (18.18%) of them wrote "I do not know this method well enough to judge it", one participant (9.09%) found this method "partially useful" and one participant (9.09%) did not answer to this question.

The solution finding process was characterized by the following time distribution over the iterations: The first iteration took exactly 15 minutes, while the second iteration took over 17 minutes due to the increased cognitive load caused by the abundance of potential solutions and the need to identify the most promising ones.

The third iteration was completed in less than 15 minutes. However, additional time would have been beneficial to perform a more thorough evaluation of the solutions and allow for further refinement in line with TRIZ principles.

The initial verbal feedback from the engineers was positive. The engineers' first impression was that solutions were found faster with ChatGPT than previously in a few months or years of work. TRIZ provided out-of-the-box solutions and led to a greater variety of solutions. The engineers said that it would have been easier for them if they could have continued working on a problem, they were familiar with and had started with in Teamwork 1. This suggests that they had to solve problems from a different, unfamiliar technical area, which would have made it easier to compare the relevance/performance of the solutions for the second and third tasks). One week after the workshop each team reported with a short feedback statement about their experiences with the individual steps taken in a guided workshop. They were asked to make their feedback as honest and objective as possible. Their feedback was following:

- **Engineers from Team 1:** "We looked at the suggestions made by ChatGPT. The suggestions made are reasonable and good. However, all the proposed solutions are already known to us. Either we already know these solutions or we cannot implement them (e.g. due to geometric constraints, welding machine limitations, etc.)."
- **Engineers from Team 1:** "In the ChatGPT answers, I am missing some key factors that are essential for a better performance. E.g.: at least a mention of parameters, which have a significant impact on the process. So, ChatGPT's answer is not complete and therefore perhaps a little misleading in the sense that: we ask him about colors of the rainbow and he talks a lot about shades of purple but forgets red. But we have no doubt that with a more elaborate prompt we would also get better suggestions. But the results with and without the TRIZ method are very similar and it would be hard to say which is better, just worded slightly differently."
- **Engineers from Team 2**: "ChatGPT has not proposed anything revolutionary or that we do not know about in terms of improving the dynamic strength of the system. The only novelty that we have not thought about is whether we would really gain anything from "heat treatment". We will probably try to test it. Even if we did, it is a question of actual feasibility for series production.
- **Engineers from Team 2**: "In our case, the TRIZ/LLM method has provided a number of ideas that are difficult to implement or they are out of the question due to the size of the component. In general, we prefer the ChatGPT-only more than the TRIZ/LLM method. With the TRIZ/LLM method, the proposed ideas would come into play with larger components."
- **Engineers from Team 3:** "The results of the ChatGPT suggested several solutions that are already known within the company. The solutions proposed by the TRIZ/LLM method (Teamwork3) are comparable to the ChatGPT results. However, ChatGPT and TRIZ/LLM proposed some interesting solutions that were not identified by Teamwork 1 and that seem promising. The nature of the problem is such that the practical applicability and degree of improvement cannot be assessed without extensive testing."
- **Engineers from Team 3:** "ChatGPT has shown that AI is able to find suggestions and ideas that are very similar in content to those of domain experts. The limitation of these ideas is that, just like the ideas generated by experts, they need to be verified and validated through testing. In the industry we work in, this accounts for at least 95-99% of the work until a final solution is found. So, most of the work still needs to be done. ChatGPT helps you brainstorm, maybe gives you an extra confirmation that you are thinking in the right direction, or brings up another idea that you may have neglected or left out. In our particular case, I would say that for the design example, the ChatGPT put a little more emphasis on temperature, which we have not paid much attention to in the past. We did take it into account, but we did not give it as much importance as ChatGPT. So, one of the main conclusions was that we will take a closer look at this parameter in the future. As for the TRIZ/LLM upgrade, we would say that we have not seen much added value. The responses from TRIZ/LLM and the classic ChatGPT just seemed quite similar to us."
- **Engineers from Team 3 comments on ChatGPT results:** "If we compare the results of this group with the results of ChatGPT, we can say that ChatGPT has given a lot of importance to a certain type of welding. This could be a good compromise between price and quality.

To summarize, I would say that the workshop encouraged us to use more AI in our search for solutions. It has stimulated discussion and increased interest."

In addition to the self-assessment by the engineers who participated in teamwork 1, 2 and 3, the search results were evaluated by two experts. The first expert was the R&D director, while the other expert is the previous employee of the company and know the products and technical issues well. The evaluation of the experts:

- **R&D director:** "After sifting through the solutions generated with the help of AI and the TRIZ method, we get a qualitative expansion of ideas, which are then filtered and evaluated more quickly and probably more correctly by experts. The first impression is that the daily use of these tools could effectively support and accelerate development activities."
- **The former employee expert:** "The results of the ChatGPT suggested several solutions that are already known within the company. The solutions proposed by the TRIZ/LLM method (Teamwork3) are comparable to the ChatGPT results. However, ChatGPT and TRIZ/LLM proposed some interesting solutions that were not identified by Teamwork 1 and which seem promising. The nature of the problem is such that the practical applicability and degree of

> improvement cannot be assessed without extensive testing. The practical and innovative value of the technical solutions to Problem 3 is considered to be better than the solutions to the first two problems. Problem 3 is not a pure design problem but is closely related to the manufacturing process. Various technologies that are applicable expand the search space. The proposed technology is currently not used in the company. This means that ChatGPT and TRIZ/LLM went beyond the thinking of the company's specialists."

Teams 1, 2, and 3 found that the AI tools (ChatGPT and TRIZ/LLM) provided useful yet familiar solutions, with some promising ideas not previously considered. The engineers emphasized that many suggestions were limited by practical constraints and required extensive testing. The teams preferred pure ChatGPT over TRIZ/LLM. Experts noted that AI tools could speed up development by extending ideas, but the practical value needed further evaluation. Overall, AI encouraged more innovation and deeper exploration, especially for manufacturing-related challenges.

5. Discussion

The literature suggests that LLM have promising potential for product development (Ege et al., 2024; Girotra et al., 2023). However, the workshop conducted as part of this study highlighted some important limitations of LLM, especially when applied to products that have been continuously improved for decades. In these cases, LLM was in competition with domain experts who had specialized knowledge and experience. As expected, LLM is based on existing knowledge and therefore had difficulty proposing truly innovative solutions to problems that were already well established and continuously optimized. Improvements in such highly competitive areas usually require extensive experimentation and testing. Even if the LLM produces good ideas, these cannot be implemented immediately —the solutions need to be verified, especially for durability and reliability issues. In addition, some good proposals may not be recognized as feasible by the evaluators, further complicating the path to practical application.

The combination of LLM and the TRIZ/LLM method did not show significant benefits in this industrial setting. Participants had mixed opinions on the results, and although familiarity with the TRIZ method could have improved the results, it appears that the method is more effective for open problems with fewer constraints. Therefore, while LLM is valuable for synthesizing existing solutions, it may not be the best tool for developing entirely new innovations.

Most engineers prefer ChatGPT instead of TRIZ in combination with LLM. The main reason for this is that ChatGPT is easy to use and provides quick, relevant answers to questions. In contrast, the TRIZ/LLM method follows a structured process: First, the user defines the problem, which leads to the identification of key contradictions and solution principles. Specific solutions are then generated for each principle, resulting in a wider range of possible answers. While this increases the chance of finding a good solution, it also requires more effort to check multiple options. This extra effort can be time-consuming and less convenient, so engineers are less likely to choose this approach. An alternative is to integrate multiple steps into a TRIZ/LLM application and simplify the process for the end user.

LLM and TRIZ are most beneficial when applied to new areas that are known but relatively unexplored, such as the development of a new product or the introduction of an existing technology into an organization. In these scenarios, the tools can quickly provide relevant, reliable information that can support decision-making and development efforts. However, to take full advantage of these tools, it is essential to know how to use them and when to use them.

The TRIZ contradiction matrix was developed several decades ago, and new technologies and patents have emerged since then. This raises the question of whether the matrix is still relevant today. The authors of this paper argue that the matrix still contains fundamental parameters and that the core principles have not changed significantly over time. However, advances in AI and the ability to process large amounts of data open up new possibilities. In the past, practical considerations led to the matrix being limited to 39 parameters in order to make it manually manageable. The challenge for research is now to explore an expanded set of parameters and utilize the full range of available patents.

The company's R&D director, who observed the workshop, expressed optimism regarding the future applications of LLMs. He highlighted that while the solutions generated by LLMs closely resembled those proposed by human experts, they were produced within minutes—a task that would typically require a multidisciplinary team several hours to accomplish. This positive outlook was further supported by the questionnaire results, which indicated that other participants (experts) found both methods useful.

This efficiency shows that LLM has the potential to speed up the ideation process, even if the final implementation still needs to be evaluated and tested by experts.

5.1. Limitations

Limitations of this study include the selection of open challenges in mature products for which no known solutions were available for comparison. Therefore, the evaluation relied heavily on expert judgment. In addition, the engineers involved had limited experience with the ChatGPT and TRIZ methods. It is likely that those with more experience would have achieved different — and possibly better — results. The experiment was conducted in a controlled environment with a limited time frame, which may have limited the depth of the investigation. Finally, the engineers' self-assessment could lead to psychological bias as they compared their brainstorming efforts with the results of TRIZ and LLM, making it difficult to objectively evaluate the superior method.

6. Conclusions

Despite the initial positive feedback, concerns were raised about the relevance and completeness of the solutions developed by ChatGPT and TRIZ. The teams noted that many of the proposed solutions were already familiar to them, and in some cases the proposals did not fully address the specific constraints of the problem. The solutions generated by LLM and TRIZ/LLM were similar in content but differed in wording. While LLM was considered more practical and user-friendly, the TRIZ/LLM approach offered more structured, though more complex, solutions. Neither method proved to be clearly superior; rather, each had particular strengths depending on the context.

Overall, the user experience was positive and the teams expressed their intention to continue experimenting with TRIZ/LLM and LLM. It was emphasized that understanding when and how to use each tool is critical to optimizing results. However, it is important to point out that the designer should remain involved in the selection of the final design solutions.

6.1. Future work

The findings from this study suggest several avenues for future research. One direction is to explore potential extensions of the TRIZ method when integrated with LLM. Future research could focus on refining this integration to enhance the specificity and applicability of the generated solutions.

When using LLMs to solve development tasks in an enterprise environment, several security concerns need to be considered. LLMs can process large amounts of data, including potentially sensitive or confidential business information. There is a risk that proprietary or private data entered into an LLM may be inadvertently leaked or used in subsequent queries, especially in cases where models are hosted by third parties, such as cloud providers. In the future, we plan to set up a local LLM model and update it with company-specific knowledge.

Another key area of future work involves understanding the acceptance of AI tools in the engineering field. It is essential to explore engineers' willingness to integrate AI-driven solutions into their daily workflows, as this represents a potential disruption to traditional methods of problem-solving. Investigating how engineers adopt and test AI-generated solutions will provide valuable insights into the broader application of AI tools in industrial settings. As AI and TRIZ integration advances, addressing these challenges will be crucial for real-world success. Future research should focus on industrial case studies, AI-human collaboration frameworks, and refining AI models to enhance both feasibility and novelty in TRIZ-driven innovation.

Acknowledgements

The activities and research were supported by the framework of the GREENTECH project, co-financed by the European Union – NextGenerationEU, and by the Slovenian Research and Innovation Agency within the research program P2-0425, 'Decentralized solutions for the digitalization of industry and smart cities and communities'.

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