

## STRUCTURED INNOVATION IN CONSTRUCTION VALUE ENGINEERING THROUGH LLM-ASSISTED TRIZ REASONING

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### Abstract

This study proposes an integrated framework that enhances idea generation in construction VE by leveraging LLMs to facilitate the application of TRIZ. The framework systematically incorporates project-specific contextual information into an LLM-driven TRIZ reasoning process. It enables context-aware abstraction of technical contradictions, retrieval of relevant inventive principles, and generation of solution ideas. By bridging TRIZ-based structured ideation with VE context, this approach supports more relevant and feasible creativity without requiring deep TRIZ expertise, demonstrating the feasibility of integrating LLM-assisted TRIZ reasoning into VE workflows.

### Introduction

Value Engineering (VE) has been widely adopted in the construction industry as a structured method to maximize project functional value while minimizing cost and resource use (Chen et al., 2022). In current VE practice, the idea generation phase has been criticized for relying on unstructured brainstorming, limited reuse of innovation knowledge, and inconsistent solution quality, ultimately constraining the overall effectiveness of VE implementation (Park et al., 2017).

TRIZ (the Theory of Inventive Problem Solving) provides a systematic framework that introduces structured reasoning to enhance the creativity and consistency of generated alternatives during VE execution (Mao et al., 2009). Developed through the systematic analysis of over 200,000 invention patents, TRIZ aims to uncover repeatable patterns in resolving technical problems through innovation (Sheu et al., 2020). Its core tools include the Contradiction Matrix, the 40 Inventive Principles, the Separation Principles, and a series of Standard Solutions, all designed to guide engineers in reformulating specific problems into generalized structures that can be resolved through heuristic reasoning (Kalevi & Ellen R., 2007). This structured logic makes the TRIZ conceptually well aligned with the tasks during VE execution, particularly in developing alternative ideas. TRIZ has, therefore, been introduced into VE frameworks to support more systematic idea generation and reduce reliance on unguided brainstorming (Mao et al., 2009; Wu et al., 2020; Zhang et al., 2009). However, the integration of TRIZ into practical VE applications remains limited.

One of the major challenges lies in the high level of abstraction embedded in TRIZ guidance tools, such as the contradiction matrix and inventive principles (Spreafico, 2022). Though conceptually powerful, these tools are typically presented in a condensed and domain-agnostic format, requiring both deep familiarity with TRIZ logic and advanced abstraction skills for effective use (Chen et al., 2024). These requirements are rarely met in typical VE teams. As a result, the cognitive effort required to map project-specific problems to usable TRIZ models has hindered its broader adoption in construction-related VE practice (Jiang et al., 2025).

Recent advancements in large language models (LLMs) offer promising avenues for addressing the cognitive and expertise-related barriers that limit the practical application of TRIZ. These models, exemplified by GPT-4 (OpenAI, 2023), DeepSeek (DeepSeek-AI, 2025), and similar architectures, exhibit strong capabilities in multi-step reasoning, analogical mapping, pattern recognition, and natural language generation. These competencies are well aligned with the analytical demands of TRIZ reasoning. In particular, LLMs can assist in abstracting technical contradictions, retrieving relevant inventive principles, and articulating generalized solution paths (Chen et al., 2024), thereby acting as intelligent assistants in the TRIZ reasoning process (Lee et al., 2024). Previous efforts have explored the integration of LLMs into TRIZ-based workflows. Relevant studies and prototype systems demonstrate that LLMs can automatically map problem statements to TRIZ contradiction models (Guarino et al., 2022), query inventive principles from pre-structured knowledge bases (Lee et al., 2024), and generate exploratory solution ideas (Chen et al., 2024; Jiang et al., 2025). These findings suggest that LLMs can reduce the reliance on expert-level TRIZ knowledge and make structured ideation more accessible.

However, while the feasibility of LLM-driven TRIZ reasoning has been preliminarily demonstrated, its application in the VE context remains underdeveloped. This is particularly significant given that prior attempts to integrate TRIZ into VE have struggled with practical adoption due to the abstract and domain-agnostic nature of TRIZ tools, which require considerable expertise to interpret and apply (Wu et al., 2020). With their capacity for abstraction, analogical reasoning, and guided knowledge retrieval, LLMs offer a viable solution to this

challenge by assisting non-expert users in applying TRIZ. Moreover, current work regarding LLM-assisted TRIZ remains largely confined to generic problem-solving scenarios, with limited consideration of domain-specific constraints (Lee et al., 2024). Existing approaches, such as AutoTRIZ and TRIZ-GPT, primarily focus on mapping problem descriptions to TRIZ models and generating solution ideas, but typically treat the input as standalone problem statements without systematically incorporating structured domain-specific information. Unlike general design settings, VE is inherently embedded in rich project-specific contexts (Gunduz et al., 2022). Before idea generation, VE involves extensive information gathering, including clearly defined objectives, requirements, constraints, and functional decompositions, among other things (Zu & Zhang, 2025). These are central to evaluating the feasibility and value of the proposed ideas. In contrast, this study explicitly integrates such VE-derived contextual information into the TRIZ reasoning process, enabling context-aware abstraction and idea generation aligned with project-specific constraints and value considerations.

Based on this, this study proposes an integrated framework that embeds project-specific contextual information, generated through the structured VE workshop, into LLM-driven TRIZ reasoning, to support the idea generation phase of VE practice. VE inherently clarifies project context through its early-stage activities, such as information gathering and function-cost analysis, providing a foundation for following idea generation (Zu & Zhang, 2025). By systematically incorporating this contextual information into the LLM-driven TRIZ reasoning process, the proposed framework aims to enhance the relevance and feasibility of the generated ideas while preserving the inventive rigor of TRIZ. In doing so, the framework bridges the gap between TRIZ-based systematic ideation and VE-oriented contextual understanding, offering a novel, LLM-powered approach tailored to the creativity phase of VE. This approach enables project teams to access structured innovation support without requiring in-depth TRIZ expertise, providing a context-aware pathway toward effective, value-driven VE practices in construction projects.

## Methodology

This section presents the proposed methodology to integrate LLMs into the TRIZ reasoning in the context of construction VE. It aims to enhance the idea generation phase by combining TRIZ innovation strategies with the intelligent reasoning capabilities of LLMs.

### Framework overview

As shown in Figure 1, the framework builds upon the traditional VE process, replacing the commonly used brainstorming approach with a structured, LLM-assisted TRIZ reasoning pipeline. In this way, it leverages the systematic innovation logic of TRIZ while addressing the expertise barrier that has historically limited its adoption in construction projects.

The process begins with the information and function analysis phases of VE, where project-specific information is collected, including project context (objectives, stakeholder priorities, and constraints, denoted as  $C$ ) and functions with value improvement potential (denoted as  $F$ ). This information serves as the foundation for defining the specific engineering challenge to be improved. Next, LLMs are engaged through prompt engineering techniques, leveraging few-shot examples and structured templates, to abstract the specific challenge into a formal TRIZ contradiction model. This abstraction translates domain-specific challenges into standardized TRIZ contradictions consistent with TRIZ theory. The contradiction model is then used to query the TRIZ matrix, producing a set of relevant inventive principles through structured retrieval. Finally, LLMs recontextualize these general TRIZ strategies into domain-specific, actionable alternatives. In this step, context-aware prompt engineering combined with a two-step process enables the LLM to fuse the retrieved TRIZ principles with detailed project context and functional descriptions. This ensures that the generated alternatives are inventive, feasible, targeted, and aligned with the project requirements, constraints, and stakeholder objectives. Through this, the framework not only addresses the expertise barriers in TRIZ application but also provides a scalable pathway for integrating AI-driven structured reasoning into VE practice.

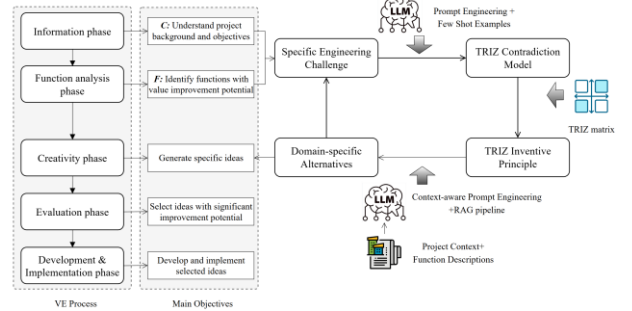


Figure 1: Framework of context-aware TRIZ reasoning supported by LLMs for VE

### LLM-Assisted abstraction of TRIZ contradictions

The first critical step in the proposed framework is to abstract engineering challenges into TRIZ contradiction models, bridging contextualized VE information with systematic TRIZ problem-solving tools. The objective is to identify pairs of engineering parameters representing the desired improvement and the accompanying negative trade-off, which define the row and column of the TRIZ contradiction matrix. Traditionally, this abstraction relies heavily on expert judgment, requiring practitioners to interpret specific challenges through the 39 standardized TRIZ parameters. In the proposed framework, this task is performed by LLMs guided through prompt engineering and few-shot learning techniques.

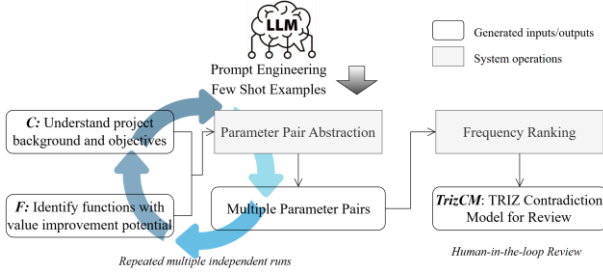


Figure 2: LLM-assisted abstraction and human-in-the-loop review of TRIZ contradictions

As depicted in Figure 2, to enhance LLM performance in TRIZ abstraction, the model is provided with carefully designed prompts and few-shot examples demonstrating how similar challenges have been mapped to TRIZ parameters. This enables the LLM to derive logical mappings from the input context, i.e., descriptions of project objectives and functional improvement targets, to appropriate technical contradictions. For example, the model may infer that enhancing structural durability at the cost of increased material use corresponds to a contradiction between “strength” and “production expense.” Recognizing that complex design challenges often admit multiple perspectives, the framework incorporates multiple independent reasoning cycles to explore this diversity. In each cycle, the LLM generates distinct improving-worsening parameter pairs, offering alternative interpretations of the current challenge. The generated pairs are aggregated, and the most frequent are identified as the outputs of this phase. To ensure transparency and alignment with the project context, the framework incorporates Human-in-the-loop Review. As depicted in Figure 2, the ranked outputs are presented to VE teams for validation or adjustment based on domain knowledge, practical feasibility, and stakeholder priorities. In this step, users are expected to assess whether the identified contradiction pairs accurately capture the core design trade-offs and remain relevant to the specific project context. When discrepancies arise, they are resolved through discussion within the VE team, following standard workshop practices, and the selected pairs are refined accordingly.

This approach balances automation and flexibility. While the LLM handles the complexity of abstraction, human oversight preserves contextual appropriateness and critical judgment, with users evaluating the relevance of contradiction pairs, resolving disagreements through structured discussion, and refining selections to improve their contextual suitability for subsequent reasoning. The number of parameter pairs per cycle and the number of cycles are configurable, allowing adaptation to specific VE workflows or project complexity.

### TRIZ principle mapping and recontextualization

The core objective of this stage is to transform the TRIZ contradiction model into domain-specific alternative ideas that align with VE objectives. This stage ensures that the systematic innovation strategies of TRIZ are effectively translated into practical design proposals that are inventive and also feasible within the specific context

of construction projects. The process consists of two integrated components: (1) retrieval of inventive principles from the TRIZ matrix and (2) context-aware recontextualization of these principles through LLM-supported reasoning, as depicted in Figure 3.

In the retrieval phase, the framework employs a rule-based procedure grounded in TRIZ theory. Since the improving and worsening parameters of the TRIZ contradiction model have been identified, they map deterministically to inventive principles via the TRIZ matrix. This ensures that for any given contradiction, the inventive principles retrieved are traceable to historically validated solutions for similar technical conflicts, preserving methodological rigor. In the generation phase, the framework employs LLMs enhanced with context-aware prompt engineering to adapt the abstract inventive principles to the specific project environment. The model receives three types of input: (i) the retrieved inventive principles, (ii) the project objectives and constraints, and (iii) the functional improvement targets. These inputs are synthesized through carefully designed prompts that introduce the TRIZ strategies while embedding key elements of the project context, as well as functional descriptions, into the reasoning process. While the inventive principles retrieved for each contradiction pair are defined by the TRIZ matrix, the number and diversity of recontextualized ideas generated per principle can be configured according to project complexity or preferences. In this study, for demonstration purposes, five alternative ideas are generated for each inventive principle, providing project teams with a manageable yet diverse set of options for evaluation and selection. This ensures that the generation phase remains flexible and adaptable to different VE contexts.

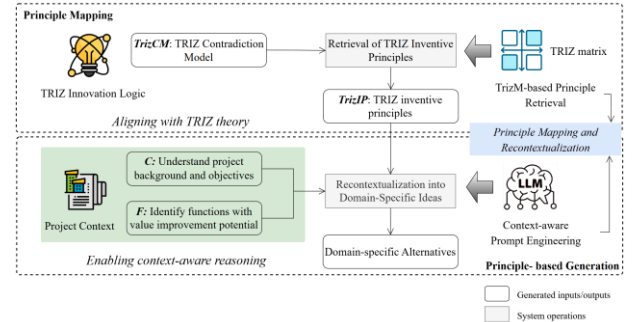


Figure 3: Two-step TRIZ reasoning and contextualized alternative generation

This framework integrates TRIZ-based retrieval with LLM-assisted recontextualization to systematically support the creativity phase of VE. By building directly on the outputs of the information and function analysis phases, it enables automated idea generation that aligns seamlessly with the VE workflow and reduces reliance on traditional brainstorming methods. At the same time, the framework ensures that the generated ideas are rooted in the structured logic of TRIZ and adapted to the specific goals, constraints, and functional requirements of the project, thereby enhancing their relevance, feasibility, and value for subsequent evaluation and decision-making. This offers a structured, scalable alternative to the

conventional creativity phase in the VE workshop, supporting more consistent, rigorous idea generation.

## Demonstration

This part presents the development of the proposed prototype and demonstrates its functional workflow through a representative case study.

### Prototype development

To demonstrate the feasibility of the proposed LLM-assisted TRIZ reasoning framework for construction VE, a prototype system is developed. The platform integrates LLMs, TRIZ theory, and human-in-the-loop validation to support automated, context-aware idea generation that aligns with the standard VE workflow.

As depicted in Figure 4, the system comprises four main components: (1) a user interface module implemented using Python Tkinter for structured input collection, human-in-the-loop review, and result visualization; (2) an LLM-assisted abstraction module for mapping project context and functional requirements to TRIZ parameter pairs; (3) a TRIZ knowledge base module that stores the 39 standard TRIZ parameters, the contradiction matrix, and inventive principles in structured JSON format; and (4) a context-aware idea generation module that implements the two-step process, combining principle retrieval with LLM-based recontextualization.

In the parameter pair abstraction phase, the system invokes ChatGPT-4o via Azure OpenAI to identify improving and worsening parameters from the user-provided project context and functional improvement targets. The prompt design for this phase follows a template-based structure. 39 TRIZ parameters and their definitions are embedded statically within the prompt, together with the designed few-shot examples relevant to the construction domain (e.g., balancing size v.s. performance, or durability v.s. maintainability). This structured design provides information for understanding and replicating the core prompting logic, although full prompt templates are not included due to space constraints. The project-specific inputs are inserted into this static template at runtime. This design ensures that the LLM reasons consistently within a defined framework while accounting for variations in project descriptions. To enable the LLM to generate multiple reasonable interpretations of the problem for frequency aggregation, the temperature is set to a moderate level (0.5-0.7). The system performs multiple independent abstraction cycles, aggregates the resulting parameter pairs, and ranks them by frequency for human validation, thereby enhancing robustness against individual model variances. In this study, five reasoning cycles were conducted, each generating three parameter pairs. The frequency of each contradiction pair was calculated based on its occurrence across the five cycles, and the two highest-ranked pairs were provided for subsequent analysis. When ties occurred, final selection was determined through human review based on project context.

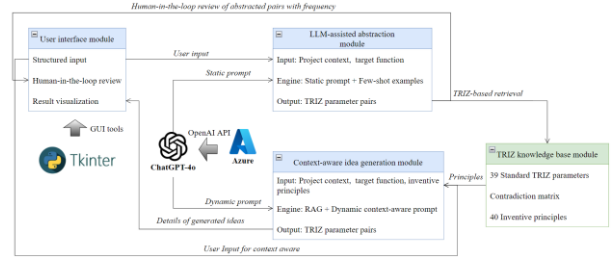


Figure 4: Architecture of the developed prototype

From a deployment perspective, multiple LLM calls introduce additional cost and latency, which are controlled in this prototype by limiting the number of reasoning cycles to 5 and outputs per cycle to 3. Each cycle completes within a few seconds, resulting in an overall response time suitable for interactive VE use. Potential failure modes include incorrect contradiction mapping and inconsistent or unsupported reasoning. To mitigate these risks, the system constrains the LLM using a fixed prompt structure embedding the 39 TRIZ parameters, incorporates domain-specific few-shot examples to guide mapping consistency, and applies frequency-based aggregation to filter unstable outputs across cycles. These measures complement the human-in-the-loop validation by reducing the likelihood of erroneous candidates being presented to users.

In the TRIZ strategy retrieval and idea generation phase, the recognized parameter pairs are used to query the stored contradiction matrix (in JSON format) to retrieve the associated inventive principles. The LLM is then engaged to generate domain-specific alternative ideas based on the retrieved principles and project context. The prompts for this phase are dynamically constructed in real time, designed to synthesize the inventive principles, project objectives, functional targets, and key constraints. The LLM is explicitly instructed in these prompts to reason how each inventive principle can be adapted to the specific project conditions and to articulate the rationale behind each generated idea, enabling context-aware reasoning that tailors idea generation to the unique conditions of the project. To encourage creative and diverse idea generation, the temperature is increased to a high level (0.8-1.0) at this stage. This configuration supports the generation of innovative alternatives that remain traceable to TRIZ theory and adapted to the specific realities of the VE project.

This architecture demonstrates the technical feasibility of embedding LLM reasoning and TRIZ logic into the VE process to systematically enhance the creativity phase, providing a system foundation for functional demonstration and evaluation in subsequent sections.

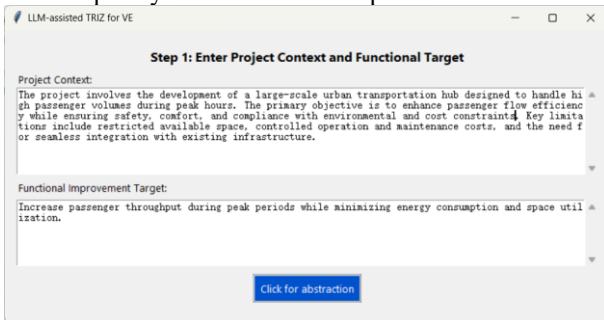
### Functional demonstration

To verify the functionality and practical feasibility of the developed prototype, a demonstration was conducted using a representative case study aligned with typical VE applications in construction projects. The case focuses on enhancing passenger throughput in an urban transportation hub during peak periods, while minimizing energy consumption and space utilization.

## Abstraction of TRIZ contradictions

The first step of the prototype corresponds to the information and function analysis phases of VE. As shown in Figure 5, the user provides structured inputs describing the project context and functional improvement target. These inputs are derived from typical VE artifacts, where the project context summarizes key constraints, stakeholder requirements, and system characteristics, while the functional improvement target reflects the prioritized functions identified through function analysis and function-cost evaluation. The project context specifies the development of a large-scale urban transportation hub designed to accommodate high passenger volumes while ensuring safety, comfort, and compliance with environmental and cost constraints. The functional improvement target focuses on increasing passenger throughput during peak periods with minimal energy consumption and space usage.

Once the input is submitted, the system engages the LLM-assisted abstraction module to identify potential contradiction pairs. ChatGPT-4o (via Azure OpenAI) is invoked multiple times, with each reasoning cycle leveraging a static prompt that embeds the 39 TRIZ parameters, their definitions, and domain-relevant few-shot examples. The project-specific input is dynamically inserted into this template at runtime. To promote diverse interpretations of the problem, the temperature is set to a moderate value of 0.5 in the demonstrated case. The system executes five independent abstraction cycles, with each cycle generating three candidate contradiction pairs. The resulting pairs from all cycles are aggregated, and their frequency distribution is computed.



LLM-assisted TRIZ for VE

**Step 1: Enter Project Context and Functional Target**

Project Context:

The project involves the development of a large-scale urban transportation hub designed to handle high passenger volumes during peak hours. The primary objective is to enhance passenger flow efficiency while ensuring safety, comfort, and compliance with environmental and cost constraints. Key limitations include restricted available space, controlled operation and maintenance costs, and the need for seamless integration with existing infrastructure.

Functional improvement Target:

Increase passenger throughput during peak periods while minimizing energy consumption and space utilization.

[Click for abstraction](#)

Figure 5: Interface for specifying project context and functional improvement target

As shown in Figure 6, the system visualizes the top-ranked pairs in a bar chart along with textual explanations of their origins. At this point, a human-in-the-loop review is conducted. The user examines the generated contradictions and their contextual explanations, and selects two pairs for further analysis. This interactive step ensures alignment of the automated abstraction results with domain knowledge and project-specific priorities, enhancing the transparency and adaptability of the process.

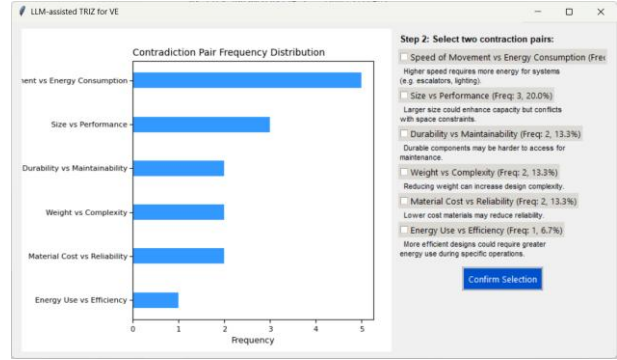


Figure 6: Interface for human-in-the-loop review.

## Retrieval of TRIZ principles

After the user confirms their selection, i.e., Speed of Movement vs Energy Consumption and Size vs Performance, the system queries the embedded TRIZ contradiction matrix to retrieve the associated inventive principles. The context-aware idea generation module then dynamically constructs prompts combining the retrieved inventive principles, project objectives, functional targets, and key constraints. The LLM is explicitly instructed within these prompts to reason how each inventive principle can be adapted to the specific project conditions and to articulate the rationale for each proposed idea. The temperature is raised to a higher range, 1.0 in this case, to foster creativity and encourage diverse solution pathways.

## Context-aware idea generation

As illustrated in Figure 7, the system generates multiple domain-specific alternative ideas for each inventive principle. Each idea is accompanied by a clear rationale demonstrating how the principle is contextualized within the specific VE problem. For example, under the Preliminary Action principle, the system suggests deploying smart signage that activates before peak periods to proactively guide passenger flow, thus reducing reactive energy demand. Under Mechanics Substitution, proposals such as AR-based wayfinding and virtual queuing are generated, offering innovative alternatives that minimize reliance on physical infrastructure. These generated ideas, together with their reasoning logic, form structured and traceable outputs that can seamlessly feed into the subsequent VE evaluation phase, where design alternatives are assessed for value contribution, feasibility, and alignment with stakeholder objectives. The human-in-the-loop review at this stage further supports the collaborative refinement and selection of the most promising alternatives.

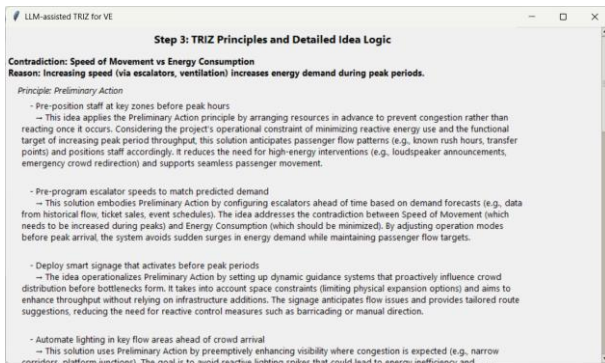


Figure 7: Interface for context-aware TRIZ idea generation with principle-specific rationales

## Conclusions

This study presents a framework for integrating LLM-assisted TRIZ reasoning into construction VE. The results demonstrate its feasibility in supporting structured, context-aware, and traceable idea generation during the creativity phase. Its main contributions can be summarized in three dimensions. From a methodological perspective, the proposed framework demonstrates how LLMs can function as structured reasoning assistants, guiding the mapping of project-specific challenges to standardized TRIZ contradictions and supporting context-aware generation of alternative ideas. This advances the theoretical foundation for enhancing the creativity phase in VE by combining AI reasoning with established innovation models. From a technical standpoint, the prototype demonstrates the feasibility of the proposed framework. It supports TRIZ-inspired reasoning in identifying contradictions and generating alternative ideas. These ideas span both technological solutions and operational considerations, such as space optimization and energy efficiency. The inclusion of clear, traceable reasoning chains linking the identification of contradictions, the retrieval of principles, and the rationale for solutions supports subsequent evaluation and decision-making in VE phases. Finally, in terms of practical relevance, this study highlights how LLM-assisted innovation reasoning can be embedded within real-world VE workflows. The tool can serve as a supportive aid in group discussions, providing structured suggestions and reasoning cues that participants can iteratively review and refine. The integration of human-in-the-loop ensures that automation is balanced with expert oversight, making the system adaptable to collaborative and time-constrained workshop settings across varied project contexts.

Despite these contributions, there remain limitations. Specifically, the prototype is developed as a standalone tool and has not yet been integrated into a comprehensive VE management platform. It focuses on demonstrating methodological feasibility and does not include a systematic evaluation of the quality of generated ideas. Future work will incorporate user studies and expert-based comparisons with conventional brainstorming and expert-led TRIZ processes. In addition, the mapping of project-specific challenges to TRIZ parameters relies on

LLM-based reasoning, which may introduce inconsistencies across contexts and therefore requires human validation; improving the reliability of this process remains an important direction for future work.

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