AI-Enhanced TRIZ: Integrating 9 Windows Model with Large Language Models and Automatic Speech Recognition for Systemic Problem-Solving in Desertification Mitigation"

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Abstract– Engineering projects in desertification-affected regions like Valparaíso, Chile, must address complex environmental, technical, and socio-economic challenges such as water scarcity and soil degradation. Traditional Root Cause Analysis (RCA) methods often fall short in these dynamic contexts due to limited scalability and adaptability. This study presents a novel methodology integrating Artificial Intelligence (AI), Large Language Models (LLMs), and Automatic Speech Recognition (ASR) to enhance RCA in environmental adaptation and mitigation efforts. The approach leverages the 9 Windows Model from the TRIZ methodology for multi-level, time-scaled problem analysis. It involves three stages: (1) collecting and transcribing environmental discussions via ASR, (2) using LLMs to extract RCA insights aligned with the 9 Windows framework, and (3) generating automated reports with visualizations and strategic recommendations. A case study in Valparaíso examines the impact of desertification on water availability and agricultural productivity, demonstrating improved decision-making speed and quality. The approach reduces diagnostic time and supports more effective mitigation strategies. While AI-related challenges like bias and data dependency persist, the study emphasizes the importance of a human-in-the-loop model. This research offers a scalable, structured framework for applying AI to environmental management and supports innovation in multidisciplinary problem-solving.

Keywords--9 Window model, Root Cause Analysis, TRIZ, Large Language Models, Automatic Speech Recognition, Desertification.

I. INTRODUCTION

Engineering projects in regions affected by desertification, such as the Valparaíso region in Chile, present inherent complexity that requires the integration of environmental, technical, and socio-economic factors [1][2]. These initiatives must address challenges such as water scarcity, soil degradation, and impacts on local communities, demanding robust decision-making frameworks to manage uncertainties and conflicting criteria effectively [3]. While traditional methods such as Root Cause Analysis (RCA) have provided structured means to identify underlying problems, they face limitations in scalability, efficiency, and integration of unstructured data within dynamic environmental contexts [4]. Therefore, innovative approaches that integrate advanced technologies are required to optimize diagnostic processes and decision-making.

In this regard, the combination of Artificial Intelligence (AI), Large Language Models (LLMs), and Automatic Speech Recognition (ASR) represents a promising opportunity to enhance RCA in adaptation and mitigation projects related to desertification. LLMs, through Natural Language Processing (NLP), have demonstrated exceptional capabilities in analyzing unstructured textual data, enabling decision-makers to extract valuable insights from complex discussions [5][6]. At the same time, advances in ASR have significantly improved transcription accuracy, even in challenging environments, facilitating the conversion of verbal exchanges into structured formats for analysis [7]. By integrating these technologies, RCA can be optimized not only to identify root causes with greater precision but also to generate data-driven solutions in real time.

This study proposes a 9 Windows Model-based approach for integrating LLMs and ASR into RCA within the context of desertification in Valparaíso. The TRIZ methodology, which analyzes problems across different system levels and timeframes (past, present, and future), provides a structured framework for synthesizing information from both traditional and digital sources to improve environmental project planning and management. Traditional RCA methodologies, such as Ishikawa diagrams and the "Five Whys" technique, heavily rely on expert-driven processes and structured data inputs, often resulting in time-intensive and inconsistent outcomes [8][9]. In contrast, the proposed approach employs LLMs to analyze field discussions, transcribe environmental meetings via ASR, and structure problem hierarchies within the 9 Windows Model, identifying causal patterns and suggesting mitigation strategies.

The proposed methodology is structured into three key stages: (1) data collection and transcription of environmental discussions using ASR in interviews with communities and land management experts, (2) analysis of transcriptions by LLMs to identify causal relationships and generate RCA insights within the 9 Windows Model, and (3) generation of automated reports integrating visualizations and recommendations based on predictive environmental models.

This approach not only streamlines RCA but also addresses common limitations such as reliance on structured inputs and subjectivity in expert evaluations. Furthermore, LLMs' ability to analyze reactions provides an additional layer of understanding, enabling the identification of stakeholders' priorities and concerns during discussions [6].

To validate the applicability of this model, a case study in the Valparaíso region is presented, focusing on the assessment of desertification impacts on water availability and agricultural productivity. LLM-driven RCA was applied to analyze inefficiencies in water distribution across rural communities, using standardized evaluation tools such as the Technology Acceptance Model (TAM) to assess the feasibility and perception of adopting this methodology[10] (Murillo et al., 2021). Preliminary results suggest that this approach significantly reduces diagnostic time and enhances decision-making effectiveness.

Despite its promising potential, integrating LLMs and ASR into RCA is not without challenges. Issues such as model biases, dependency on high-quality training data, and the risk of over-reliance on AI-generated outputs must be carefully managed (Heaven, 2020)[11]. Therefore, this study emphasizes the importance of a human-in-the-loop approach, where environmental experts and territorial planners validate and contextualize AI-driven insights, ensuring robustness and relevance in decision-making [12]. This research contributes to the growing body of literature on AI applications in natural resource management by presenting a scalable and adaptable framework to enhance root cause identification and problem-solving in desertification contexts.

II. LITERATURE REVIEW

A. The 9 Windows Model in Problem-Solving Methodologies

The 9 Windows Model, a key component of the TRIZ methodology (Theory of Inventive Problem Solving), provides a systematic framework for analyzing and addressing problems across different system levels (super-system, system, and sub-system) and timeframes (past, present, future) [13][14]. This model is widely applied in engineering, manufacturing, and innovation management as a structured approach for problem decomposition and solution generation [15]. Unlike traditional root cause analysis (RCA) techniques, which focus primarily on immediate causal relationships, the 9 Windows Model expands the analytical scope by considering broader systemic influences and long-term evolution [14][15].

While conventional problem-solving frameworks, such as Ishikawa diagrams and the Five Whys, provide an immediate causative factors, they often fail to account for external system dependencies and future implications [16]. The 9 Windows Model overcomes these limitations by integrating a multi-dimensional perspective, enabling decision-makers to foresee challenges, adapt solutions to evolving conditions, and enhance innovation-driven outcomes [15].

In the context of desertification in the Valparaíso region, this model offers a holistic tool for analyzing the interdependencies between environmental degradation, resource management, and socio-economic factors over time. By mapping these elements across different levels, it becomes possible to predict future constraints, optimize land-use strategies, and develop long-term resilience frameworks [17].

B. Advances in TRIZ and Systematic Innovation

Recent research has expanded the applications of TRIZ and the 9 Windows Model beyond traditional engineering problem-solving, integrating these methodologies into sustainability, risk assessment, and environmental planning [15][16][17]. The systemic approach of the 9 Windows Model enables a more adaptive framework for decision-making, particularly in uncertain, data-intensive environments such as climate change mitigation and water resource management [18].

One of the key strengths of this model is its ability to identify contradictions and leverage inventive principles to resolve systemic challenges. Traditional RCA techniques focus on addressing single failure points, whereas the 9 Windows Model incorporates multi-layered problem structures to develop more robust and scalable solutions. In mining operations, for example, the model has been applied to optimize extraction processes, minimize environmental impact, and enhance operational efficiency through a structured problem-solving lens [19][3].

In the Valparaíso desertification scenario, the 9 Windows Model can systematically structure the analysis of how climate variability, land use policies, and water scarcity interact over time. By applying TRIZ inventive principles, it is possible to design proactive adaptation strategies, such as innovative water management techniques, drought-resistant agricultural practices, and community-driven mitigation initiatives [17].

C. Integration of AI and TRIZ for Enhanced Decision-Making

The evolution of Artificial Intelligence (AI) and machine learning has significantly enhanced TRIZ-based methodologies, particularly in the automation of problem analysis, pattern recognition, and predictive modeling[6] .Large Language Models (LLMs), such as GPT-4, enable the rapid processing of unstructured data, extracting meaningful insights from historical records, expert discussions, and real-time environmental data[20][21].

By incorporating AI into the 9 Windows Model, decision-makers can:

1. Analyze historical environmental patterns to identify long-term drivers of desertification.
2. Assess real-time data from meteorological and hydrological sources to understand current system conditions.
3. Simulate future scenarios based on projected climate and land-use trends, aiding in proactive policymaking [22].

Furthermore, the integration of AI-powered RCA frameworks has shown promise in multi-criteria decision-making (MCDM), providing structured insights into complex, interdependent environmental issues [21].

D. Combining Automatic Speech Recognition (ASR) and TRIZ for Field Data Collection

A major challenge in applying the 9 Windows Model to large-scale environmental projects is the collection and synthesis of expert knowledge, stakeholder feedback, and real-world observations [23]. Automatic Speech Recognition (ASR) technologies provide a means of automating field data collection, converting verbal discussions, interviews, and community input into structured datasets for TRIZ analysis[20]

E. Challenges and Future Research Directions

Despite its advantages, integrating AI-driven TRIZ methodologies presents several challenges:

1. Bias and reliability – AI models can introduce algorithmic biases, particularly when trained on domain-specific datasets with limited representation [23][24].
2. Human-in-the-loop validation – Ensuring AI-generated insights align with expert judgment requires a hybrid approach where TRIZ specialists refine AI-driven recommendations.
3. Scalability and real-time adaptation – The effectiveness of the 9 Windows Model in environmental planning depends on its ability to process evolving climate data and policy changes dynamically.

Future research should focus on i) Developing domain-specific AI training datasets for environmental TRIZ applications; ii) Enhancing ASR transcription accuracy for multilingual and dialectal variations in stakeholder interviews; iii) Creating adaptive, real-time AI-driven TRIZ systems for desertification mitigation planning.

III. METHODOLOGY

This study applies the 9 Windows Model of TRIZ to systematically analyze and address challenges related to desertification in the Valparaíso region. The methodology integrates Large Language Models (LLMs) and Automatic Speech Recognition (ASR) to process environmental data, extract causal relationships, and generate innovative solutions. The approach is structured into three key phases: systemic data acquisition, structured TRIZ-based analysis, and evaluation.

The first phase involves collecting multi-level data across different timeframes (past, present, future) and system levels (super-system, system, sub-system) as defined in the 9 Windows Model. Data sources include historical environmental records, climate data, and land-use changes to analyze past conditions, while current satellite imagery, meteorological data, and stakeholder interviews provide insight into the present state of desertification. Additionally, predictive models, climate projections, and policy scenarios help outline future trends. To enhance data collection, field interviews and discussions with local communities, environmental scientists, and policymakers are conducted. These verbal exchanges are transcribed using ASR technology (Whisper v2-large model), ensuring that spoken input is converted into structured text for further analysis (Li, 2022).

In the second phase, the structured TRIZ-based analysis is carried out using GPT-4 to process transcribed discussions, reports, and environmental data with Natural Language Processing (NLP) techniques [5]. The 9 Windows Model of TRIZ is applied at three levels. At the super-system level, external influences on desertification, including climate change, regional policies, and economic drivers, are identified, while comparisons of historical, current, and future trends in land use and vegetation loss are analyzed. At the system level, key processes contributing to land degradation, such as water scarcity, soil erosion, and deforestation, are examined alongside assessments of existing mitigation strategies and their effectiveness. At the sub-system level, specific technological solutions such as drought-resistant crops, sustainable irrigation techniques, and AI-based resource monitoring are evaluated, focusing on their feasibility within the Valparaíso environmental context. Using TRIZ principles, contradictions within existing mitigation strategies, such as the trade-off between water conservation and agricultural productivity, are identified, and solutions inspired by TRIZ inventive principles are generated.

The final phase evaluates the effectiveness of the AI-driven 9 Windows Model application through multiple assessment criteria. Usefulness and accuracy of AI-generated RCA insights are validated through expert review, while stakeholder feedback on AI-generated solutions is collected via structured TAM (Technology Acceptance Model) questionnaires [10]. Additionally, case studies on water resource management, soil restoration, and afforestation projects are conducted to validate AI-generated TRIZ recommendations. A case study on adaptive water management in rural Valparaíso communities is included, where responses from 24 stakeholders, including local farmers, policymakers, and environmental scientists, assess the feasibility and scalability of the proposed solutions.

By integrating AI-enhanced RCA, the 9 Windows Model, and TRIZ inventive principles, this study proposes a systematic and data-driven framework to address the complex environmental challenge of desertification in Valparaíso. The methodology ensures that both quantitative environmental data and qualitative stakeholder insights contribute to a scalable and actionable problem-solving model capable of guiding long-term climate adaptation strategies.

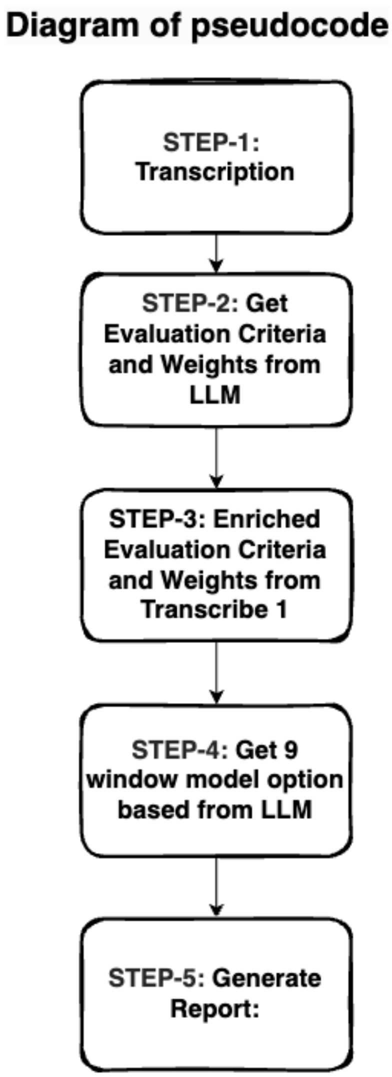

Figure 1: Step by step description of pseudocode.

Finally, the pseudocode below shows the core steps of the analysis pipeline:

Input: Path file ("9_window.mp3")
Output: 9_window_ report.pdf

Steps:
1. Transcribe 1
- Audio: Transcribe audio file using ASR.
- Store transcription.

2. Get Evaluation Criteria and Weights from LLM:
- Send transcription to LLM, ask for:
- Definition of expected answers structure for different 9 window model based on RCA approach
- Define super-system, system and sub-system to analysis data transcription with main ideas based on RCA

3. Enriched Evaluation Criteria and Weights from Transcribe 1:
- Audio: Transcribe audio file using ASR based on step 2..
- Store transcription 2.

4. Get 9 window model option based from LLM:
- Send transcription and classification to LLM, ask for:
- Redefinition of super-system, system and sub-system based on Transcription 1.
- Each variable option past, present, past in 9 window model
- Use TRIZ-classification resources and RCA(Ishikawa categories) to understand better each variable
- Enriched 9 window model of TRIZ with GAI
- Store LLM response

5. Generate Report:
- Combine transcription, LLM results (Model, variables, definition and solutions) into a structured report.
- Include:
- Executive Summary
- Explanation of Multiscreen process
- Detailed Analysis (criteria, solution, justification)
- Decision recommendation
- Export report as a PDF.

IV. Case Study and Results: Addressing Desertification in Valparaíso

STEP 1 : The problem description phase was completed within a concise ten-minute timeframe, during which participants provided a detailed overview situation.

STEP 2:
##Super-System (Region and Broad Context)##

Past (10 years ago or more):

- The climate in the Valparaíso region was more favorable, with more regular rainfall, although structural issues in water resource management and storage persisted.
- The desertification process was beginning to become noticeable, but with less intensity than today.
- Water was less scarce, but inadequate management practices, such as illegal diversion by farmers, were already observed.

Present:

- Desertification and climate change have intensified drought in the region.
- Water scarcity has increased, exacerbated by the lack of adequate infrastructure, such as reservoirs needed for water retention.
- Illegal practices to access water continue; however, some technological advances have slightly improved water sourcing.

Future (next 10 years):

- Predictions indicate that the water situation will worsen even further if adequate solutions are not implemented.
- Potential social conflicts due to unequal access to water, especially between mining companies and farmers.
- Urgent need for sustainable water management solutions, such as desalination or improvements in hydraulic infrastructure.

System (Water Network in the Valparaíso Region)
Past:

- The water network mainly depended on rainfall; however, this dependency was less critical due to more frequent precipitation.
- Reservoirs were scarce, which already posed a challenge in resource management during periods of lower rainfall.

Present:

- There is low water availability in the region due to the lack of snow (rain-fed watersheds) and reduced precipitation.
- High projected costs for transporting water from the coast to inland areas, limiting the economic viability of alternatives such as importing ocean water.

Future:

- Natural water resource availability is expected to continue decreasing without substantial intervention.
- Potential development of desalination and water redistribution infrastructure based on sustainable models.

Subsystem (Local Community and Current Practices)
Past:

- Local communities based their agricultural practices on traditional methods, with fewer water restrictions.
- Reliance on the limited reach of natural water systems to meet basic needs.

Present:

- Agriculture is the most affected activity, accounting for 70-75% of water consumption.
- Local communities and farmers resort to short-term, sometimes illegal, solutions to secure water supply.
- Initiatives such as agreements with mining companies to reduce water costs are emerging but remain insufficient.

Future:

- Potential shift toward more sustainable or less water-dependent agricultural practices in response to current restrictions.
- Communities may take part in efforts to adopt advanced water management technologies (e.g., drip irrigation, rainwater harvesting).
- Possible development of partnerships with industries (such as mining) to ensure sustainable water supply, provided favorable agreements are reached.

In summary, each level of the system reflects a series of challenges that have historically evolved into the current critical situation, requiring proactive solutions in public policy, technology, and infrastructure to improve water management in Valparaíso.

STEP 3: The problem description phase was enriched within a concise five-minute timeframe, during which participants provided a detailed overview previous analysis.

STEP 4:
Super-System (Global Trends and Systemic Solutions)

Past (Material, Energy, Information):

1. (EXP) Material: Overreliance on local resources without considering long-term impacts.
2. (EXP) Energy: Use of non-renewable sources increased costs and affected sustainability.
3. (IAG) Information: Lack of convergence in international policies on sustainable water use.
4. (IAG) Material: Unexplored potential of biodegradable materials for water infrastructure.
5. (IAG) Energy: Missed opportunities to integrate renewable energy into water systems.

Present (Material, Energy, Information):

1. (EXP) Material: Challenges in implementing water-saving technologies across multiple sectors.
2. (EXP) Energy: Advances in energy efficiency are still not widely adopted.
3. (IAG) Information: Improved interconnection thanks to smart platforms.
4. (IAG) Material: Development of advanced polymers for water purification systems.
5. (IAG) Energy: Trends toward cogeneration in treatment plants.

Future (Material, Energy, Information, Time):

1. (EXP) Material: Integration of desalination technologies with low environmental impact.
2. (EXP) Energy: Development of decentralized energy networks to support water infrastructure.
3. (IAG) Information: Collaborative platforms for sharing innovations in water usage.
4. (IAG) Material: Advanced materials to improve water collection and storage.
5. (IAG) Energy: Application of AI to optimize energy resource use in water processes.

System (Water Management in Urban Infrastructure)
Past (Material, Energy):

1. (EXP) Material: Historical dependence on outdated water transportation infrastructure.
2. (IAG) Energy: Lack of adaptation to incorporate renewable energy solutions in water systems.

Present (Material, Energy, Space):

1. (EXP) Material: Lack of investment in water infrastructure renewal.
2. (IAG) Energy: Untapped potential in local self-generation of energy.
3. (IAG) Space: Expansion of urban areas without proper planning for water resources.

Future (Material, Energy, Information):

1. (EXP) Material: Innovations in leak-proof materials for water networks.
2. (IAG) Energy: Implementation of real-time renewable energy systems for water treatment.
3. (IAG) Information: Use of AI to model future consumption and optimize water infrastructure.

Sub-System (Community Practices and Environmental Education)
Past (Material, Information):

1. (EXP) Material: Traditional community practices without resource optimization.
2. (EXP) Information: Insufficient knowledge transfer in water management.

Present (Material, Information, Time):

1. (EXP) Material: Emerging technologies are still not adopted at the community level.
2. (IAG) Information: Unlocked potential through environmental education programs and new technologies.
3. (IAG) Time: Medium-term strategies to educate on sustainable practices.

Future (Material, Energy, Information):

1. (EXP) Material: Integration of efficient water-use farming practices.
2. (IAG) Energy: Microgrids of renewable energy for communities.

3. (IAG) Information: Digital connections to share optimal water management techniques.

This analysis proposes ways to evolve water resource management by integrating both traditional solutions and the opportunities offered by Artificial Intelligence to achieve more efficient, sustainable, and innovative management.

The Technology Acceptance Model (TAM) questionnaire was employed to students' perceptions regarding the usability and effectiveness of the AI-driven and 9 windows model proposed in this research. The results indicated high levels of satisfaction among students perception, with average scores of <5.27 out of 7> for perceived usability and <5.18> for perceived effectiveness. These findings highlight relatively ease of use and practical utility of the proposed approach in addressing a multilevel analysis.

The high usability score underscores the intuitive design of the ASR and LLM integration, which facilitated seamless interaction about specific situation knowlegde with minimal learning curves. This reflects the effectiveness of the transcription and analysis processes in reducing cognitive load during 9 window model. Similarly, the strong rating for perceived effectiveness emphasizes the tangible benefits realized, such as quicker identification of root causes and actionable solution generation. This analysis reinforces the value of combining AI technologies with user-centric approaches to achieve robust and efficient problem-solving frameworks in engineering contexts.

Table 1: Technologic Acceptance Model used in 18 students to understand usability of author proposal.

Usefulness	**N**	**Media**	**s.d**
Using 9 Window-ASR in my job would allow me to accomplish my tasks faster.	18	5,48	0,79
Using 9 Window -ASR would improve my job performance.	18	5,55	0,45
Using 9 Window -ASR in my job would increase my productivity.	18	5,90	0,63
Using 9 Window ASR would enhance my work effectiveness.	18	5,20	0,72
Using 9 Window -ASR would make my job easier.	18	4,93	0,64
I would find 9 Window -ASR useful in my job.	18	4,53	0,90
Ease of Use	**N**	**Media**	**s.d**
Learning to use 9 Window -ASR would be easy for me.	18	4,55	0,58
I would find it easy to make 9 Window -ASR do what I want it to do.	18	6,02	0,76
My interactions with 9 Window ASR would be clear and understandable.	18	4,50	0,72
I would find 9 Window -ASR flexible to interact with.	18	4,60	0,98
It would be easy for me to become skilled at using 9 Window -ASR.	18	6,24	0,82

III. DISCUSSION

This study ilustrate the potential of combining Automatic Speech Recognition (ASR), Large Language Models (LLMs), and the TRIZ 9 Windows framework to enhance Root Cause Analysis (RCA) in environmental contexts. The case study in Valparaíso provides a useful benchmark, but the broader discussion points to issues of validation, scalability, benchmarking, bias, and accessibility that must be considered for real-world deployment.

A key requirement for AI-assisted RCA is the validation of outputs and ASR performance. In this research, transcription of stakeholder interviews and community discussions was performed using the Whisper v2-large model, which has shown strong accuracy across diverse acoustic environments. Critical paths were manually checked to further ensure reliability. Once transcribed, data were processed by GPT-4, which was instructed to map content into the TRIZ 9 Windows framework. Validation occurred in two steps: first, through structural consistency with predefined categories of super-system, system, and sub-system across past, present, and future; and second, through expert review and user evaluation. The use of the Technology Acceptance Model (TAM) confirmed both usability and effectiveness, with scores above 5 on a 7-point Likert scale, underscoring that the outputs were not only technically coherent but also practically useful. This multi-layered process highlights the importance of human-in-the-loop validation in preventing blind reliance on AI-generated insights. Aditionally, the framework also show scalability beyond the Valparaíso case. While the pilot centered on water scarcity and desertification in central Chile, the methodology is domain-independent and transferable. Similar processes could be applied in mining operations in northern Chile, agricultural systems in Argentina, or wildfire mitigation in Australia, with only minor adaptations to the input data. The modular pipeline—ASR transcription, LLM processing, and TRIZ structuring—provides flexibility, enabling adoption across different industries and geographies. This scalability underlines the model's potential to become a generalizable decision-support tool.

Comparisons with traditional RCA methods reveal significant advantages. Ishikawa diagrams and the Five Whys technique, though widely used, are limited by their dependence on structured data and expert-driven facilitation. They often result in slow and subjective outcomes. User surveys further confirmed increased perceptions of productivity and effectiveness, suggesting that the method not only speeds up RCA but also provides deeper and more systemic insights.

Nevertheless, the integration of AI raises concerns about bias, data quality, and oversight. LLMs may reproduce biases embedded in their training data, such as privileging institutional narratives over community voices. Likewise, ASR, although robust, can misinterpret dialects or low-quality audio. These risks were mitigated by hybrid intelligence strategies, where environmental experts validated AI-generated outputs, ensuring contextual accuracy and fairness. Such an approach emphasizes that AI should augment rather than replace human judgment.

IV. CONCLUSIONS

This research explored the transformative potential of integrating Large Language Models (LLMs) and Automatic Speech Recognition (ASR) technologies into the 9 Windows Model, particularly in addressing environmental challenges such as desertification in the Valparaíso region. Traditional problem-solving methodologies, while effective in structured engineering applications, often struggle with scalability, integration of unstructured data, and systemic complexity. By leveraging the advanced capabilities of LLMs and ASR, this study introduces an innovative, structured, and AI-enhanced approach to the 9 Windows Model, optimizing decision-making in environmental planning and sustainability initiatives.

The proposed methodology integrates ASR to transcribe unstructured verbal discussions into structured text, followed by the application of LLMs to analyze causal relationships, identify systemic dependencies, and propose actionable solutions. Through the 9 Windows Model and TRIZ principles, the approach enables multi-level analysis of environmental, technical, and socio-economic factors, enhancing the accuracy and efficiency of decision-making. Findings from the case study in Valparaíso demonstrate the effectiveness of this framework, particularly in diagnosing inefficiencies in water resource management and suggesting sustainable interventions. The high satisfaction scores from the Technology Acceptance Model (TAM) assessment further validate the usability and applicability of this AI-driven problem-solving methodology.

Key advantages of this approach include its adaptability to various environmental and engineering contexts, the ability to process and analyze large volumes of unstructured data, and its potential to improve decision-making processes. Stakeholders benefit from a streamlined workflow, reduced cognitive load, and data-driven insights that enhance policy development and resource allocation. These attributes are crucial in dynamic and resource-intensive sectors such as environmental management, where rapid and informed decision-making is essential. However, the integration of LLMs and ASR into the 9 Windows Model also presents challenges, including the potential for AI biases, reliance on high-quality training data, and the necessity of human oversight to contextualize AI-generated insights. Addressing these limitations requires continuous refinement of AI models and the development of domain-specific datasets to ensure robust and contextually relevant outcomes.

Future research should focus on enhancing domain-specific training datasets, refining hybrid intelligence frameworks, and integrating real-time environmental monitoring tools to further advance AI-driven applications of the 9 Windows Model. In conclusion, this study contributes to the growing body of knowledge on AI applications in engineering and environmental sciences by presenting a practical, validated, and scalable approach to systemic problem analysis. By addressing the limitations of traditional methodologies, this research lays the foundation for future advancements in AI-enhanced decision-making frameworks, offering a powerful tool for tackling complex environmental challenges.

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