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Integrating Automatic Speech Recognition and Natural Language Processing with Root Cause Approach to Improve Mining Projects.

Christopher Nikulin
Universidad Alberto Hurtado, Facultad de Ingeniería, Chile.
E-mail: cnikulin@uahurtado.cl

Eduardo Piñones
Universidad Técnica Federico Santa María, Departamento de Diseño en Ingeniería, Chile.
E-mail: Eduardo.pinones@usm.cl

Carolina Carreño
Universidad Alberto Hurtado, Facultad de Ingeniería, Chile,
E-mail: carocarrenoc@gmail.com

Pablo Viveros
Universidad Técnica Federico Santa María, Departamento de Industrias, Chile.
E-mail: Pablo.viveros@usm.cl

Fredy Kristjanpoller
Universidad Técnica Federico Santa María, Departamento de Industrias, Chile.
E-mail: Freddy.kristjanpoller@usm.cl

This research explores the integration of Large Language Models (LLMs) and Automatic Speech Recognition (ASR) technologies into Root Cause Analysis (RCA) to enhance decision-making in complex engineering environments, particularly mining operations. Traditional RCA methods, such as Ishikawa diagrams and the "Five Whys," often face limitations related to scalability, reliance on structured data, and the labor-intensive nature of manual processes. By leveraging advanced AI capabilities, this study presents a novel step by step approach that combines ASR for accurate transcription of unstructured verbal data with LLMs for automated causal analysis and solution generation towards to provide an structured RCA analysis. A specific case study was introduced to validate the novel proposal in real scenario. Moreover, a test with different mining operators was developed to evaluate novelties of research proposal by using the Technology Acceptance Model (TAM) questionnaire, which showed high operator satisfaction and usability. The findings emphasize the potential of AI-driven RCA frameworks in streamlining workflows, reducing cognitive load, and improving decision-making processes.

Keywords: Root Cause Analysis; Artificial Intelligence; Automatic Speech Recognition; Natural Language Processing.

1. Mining Projects.

Mining engineering projects are inherently complex, requiring the integration of diverse technical, economic, and operational factors to ensure efficiency and reliability (Viveros et al., 2012; Nikulin et al., 2024). These projects often involve extensive data analysis and multi-stakeholder collaboration, demanding robust decision-making frameworks to navigate uncertainties and conflicting criteria effectively (Taherdoost & Madanchian, 2023). Traditional methods such as Root Cause Analysis (RCA) have provided structured approaches to identifying underlying problems, but they face significant limitations in scalability, efficiency, and the integration of unstructured data sources (Medina et al., 2012; Wang & Wu, 2024).

Addressing these challenges requires innovative approaches that leverage advanced technologies while preserving the core principles of structured decision-making. One promising advancement in this field is the integration of Artificial Intelligence (AI), particularly Large Language Models (LLMs) and Automatic Speech Recognition (ASR), into RCA methodologies. LLMs, powered by Natural Language Processing (NLP), have demonstrated exceptional capabilities in synthesizing insights from unstructured textual data, allowing decision-makers to extract actionable knowledge from complex discussions (Dwivedi et al., 2023; Krugmann & Hartmann, 2024).

Concurrently, ASR technologies have significantly improved in transcription accuracy, even in challenging environments, facilitating the seamless conversion of verbal exchanges into structured formats for analysis (Li, 2022). The synergy of these technologies seems to enable a more efficient RCA process, enhancing both the precision of root cause identification and the generation of data-driven for companies. In specific, traditional RCA methodologies, such as Ishikawa diagrams and the "Five Whys," rely heavily on expert-driven processes and structured data inputs, often resulting in time-intensive and inconsistent outcomes (Yu & Deng, 2016; Ma et al., 2021). In contrast, LLMs can process transcribed maintenance discussions to extract critical information, establish causal relationships, and generate RCA insights with minimal human intervention. For example, ASR can capture maintenance discussions, creating a textual dataset that LLMs analyze to identify problem hierarchies, prioritize failure causes, and propose tailored mitigation strategies (Wang & Wu, 2024).

In this context, this article a novel structured approach that integrates LLMs and ASR to automate RCA applied in mining industry. To validate the proposed approach, an illustrative case study was conducted in a mining environment, analyzing operational inefficiencies in SAG mills. The system's usability was assessed using standardized evaluation frameworks such as the Technology Acceptance Model (TAM) questionnaire (Murillo et al., 2021).

This research contributes to the growing field of AI applications in engineering by presenting an structured approach by using ASR and RCA technique for mining projects.

2. Literature Review

2.1 Methodology in Root Cause Analysis

Root Cause Analysis (RCA) is a systematic approach employed to identify the underlying causes of failures or inefficiencies in various domains, including engineering, healthcare, and manufacturing (Andersen & Fagerhaug, 2006). RCA methods are instrumental in reducing the recurrence of issues by addressing the root rather than the symptoms of problems (Gano, 2007). Traditional RCA frameworks, such as the "Five Whys" technique, Ishikawa diagrams, and Failure Mode and Effects Analysis (FMEA), have long been applied to analyze causative factors systematically (Barberá et al., 2012; Medina et al., 2012). These methods are widely regarded for their ability to deconstruct complex problems into manageable components, aiding decision-makers in identifying causative chains effectively (Rasmuson & Kelly, 2008).

Despite their advantages, traditional RCA methods are not without limitations. Manual execution of these approaches is labor-intensive and prone to subjectivity, especially in cases where significant expertise is required to interpret data and prioritize causes (Li & Gao, 2010). Moreover, the scalability of these methods in large, data-intensive projects is constrained by their reliance on structured data and expert input (Medina et al., 2012). Addressing these challenges requires innovative approaches that integrate advanced tools capable of processing unstructured data, reducing manual intervention, and enhancing the accuracy of cause identification.

2.2 Advances in RCA Methods

Recent advancements in RCA methods have sought to address these limitations by incorporating quantitative techniques and digital tools. For instance, methods such as Bayesian Inference and Fault Tree Analysis (FTA) provide quantitative frameworks to model the probability of failures and their interdependencies (Medina et al., 2012). Similarly, HAZOP and Ishikawa diagrams are often enhanced with software tools to streamline data processing and visualization, improving their applicability in complex systems (Rossing et al., 2010). At the samte time, emerging approaches also emphasize integrating RCA into broader operational frameworks, such as Reliability-Centered Maintenance (RCM) and Proactive Maintenance. These approaches leverage RCA to enhance equipment reliability, minimize downtime, and optimize resource allocation (Gano, 2007; Crespo, 2007). However, even with such advancements, the challenge of effectively analyzing unstructured data, such as maintenance logs or stakeholder discussions, persists. Traditional RCA frameworks often fail to capitalize on the wealth of information embedded in natural language inputs, which are increasingly common in real-world scenarios (Latino & Latino, 2002; Pietsch et al., 2024).

2.3 Large Language Models in RCA

The advent of Artificial Intelligence (AI), particularly Large Language Models (LLMs), has introduced transformative potential in addressing the limitations of traditional RCA methods (Pietsch et al., 2024). LLMs, such as GPT-4, leverage advanced Natural Language Processing (NLP) capabilities to process and analyze unstructured text data with remarkable accuracy (Dwivedi et al., 2023). These models can synthesize information from diverse sources, identify patterns, and provide insights that are both contextually relevant and actionable (Krugmann & Hartmann, 2024).

One of the primary advantages of LLMs is their ability to process natural language inputs, such as meeting transcripts or maintenance discussions, enabling them to extract critical information for RCA (Wang & Wu, 2024). By employing reaction analysis and contextual understanding, LLMs can identify stakeholder priorities, quantify the relative importance of causative factors, and propose data-driven mitigation strategies (Krugmann & Hartmann, 2024). This capability significantly reduces the reliance on manual interpretation and expert-driven analyses, enhancing the scalability and efficiency of RCA processes.

2.4 Integration of ASR and LLMs in RCA

The integration of Automatic Speech Recognition (ASR) and LLMs represents a significant advancement in RCA methodologies. ASR technologies have achieved notable improvements in transcription accuracy, enabling the conversion of verbal discussions into structured text formats for analysis (Li, 2022). When combined with LLMs, ASR facilitates the automated analysis of maintenance discussions, towards to enable real-time RCA execution.For instance, the transcription of maintenance team discussions using ASR provides a dataset that LLMs can analyze to identify causative hierarchies and propose solutions (Wang & Wu, 2024; Pietsch et al., 2024). This approach not only reduces the time required for RCA but also enhances the consistency of results by minimizing human biases and errors. Additionally, the use of AI-powered RCA frameworks has demonstrated significant potential in multi-criteria decision-making (MCDM), providing structured analyses of complex, data-intensive problems (Taherdoost & Madanchian, 2023; Pietsch et al., 2024).

3 Methodology

This study employs step by step approach that integrates Large Language Models (LLMs) and Automatic Speech Recognition (ASR) to enhance the Root Cause Analysis (RCA) in mining engineering projects. The methodological approch is structured into three key phases: data acquisition, automated RCA execution, and evaluation.

3.1 Data Acquisition

The first phase involves collecting audio recordings of maintenance and operational discussions from mining projects. These recordings are transcribed using ASR technology, specifically the Whisper v2-large model, known for its high accuracy in transcribing unstructured audio data (Li, 2022). The transcription process ensures that all verbal inputs are converted into a structured text format suitable for analysis.

3.2 Automated RCA Execution

In the second phase, the transcribed data is processed using GPT-4, a state-of-the-art LLM with advanced Natural Language Processing (NLP) capabilities (Dwivedi et al., 2023). The model identifies causal hierarchies, prioritizes root causes, and proposes actionable solutions. By employing techniques such as reaction analysis and contextual understanding, the LLM provides insights that align with the principles of traditional RCA methods like Ishikawa diagrams and the "Five Whys" approach.

3.3 Evaluation

The final phase evaluates the effectiveness of the LLM-ASR-driven RCA process. Metrics such as time easy to use and usefulness of RCA-ASR are assessed through standardized tools like the Technology Acceptance Model (TAM) questionnaire (Murillo et al., 2021). An illustrative case study involving a critical mining systems was included as SAG mill. Moreover, raw material transportation networks, are utilized to validate the proposed research proposal with 24 operators answer using TAM. This questionnaire aims to understand advantage and disadvantage towards to LLM-ASR-driven RCA as intrinsical company practice. Moreover, this analysis aims to validate the potential of integrating AI technologies to address the limitations of traditional RCA frameworks, providing a scalable, efficient, and data-driven approach to problem-solving in complex engineering contexts.

3.1 Step by step approach

The figure 1 presented step by step approach leading with usability evaluation, consisting of five steps.

STEP-1: Discussion on potential causes. This step involves a conversation focused on identifying possible causes of a problem or issue. Participants discuss various factors that might have contributed to the problem.

STEP-2: Discussion on relevant criteria and parameters. In this step, participants refine their discussion by focusing on key criteria and parameters that should be considered for further analysis. This helps narrow down the factors that are most relevant for Root Cause Analysis (RCA).

STEP-3: Automated RCA Using Transcriptions. The recorded discussion is transcribed, and an automated Root Cause Analysis (RCA) process is applied to extract meaningful insights. This step leverages speech-to-text technology and analytical tools.

STEP-4: Results reporting. After the automated RCA, the findings and insights are compiled into a report. This report summarizes the identified causes and relevant parameters discussed in the previous steps.

STEP-5: Usability Evaluation. The final step involves evaluating the usability of the results, ensuring that the findings are actionable and meaningful for decision-making.

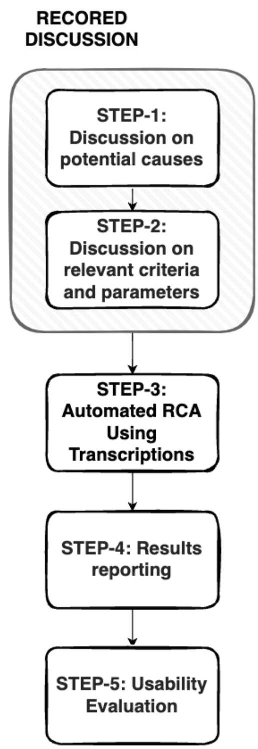

Fig. 1. Step by step approach.

For instance, the pseudocode below shows the core structure of code for this analysis:

Input: Path file ("RCA.mp3")
Output: RCA report.pdf

Code stages:
1. Transcribe
- 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 RCA methods.
- Define RCA method to analysis data transcription: Five Why and Ishikawa

3. Get RCA option based from LLM:
- Send transcription and classification to LLM, ask for:
- Each variable option on each criterion behind classification
- Justification for RCA-causes from LLM
- Final RCA proposal according problems identified.
- Store LLM response

4. Maintenances solutions proposal base on Stored LLM response:
- Audio with brainstorming solutions.
- Send transcription and classification to LLM, ask for:
- Each variable option(solution) for RCA classification
- Justification for RCA-causes toward solutions.
- Final RCA proposal with solutions according problems identified.
- Store LLM (model and solutions) response

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

4 Case study and results

In this section, the authors attempt to illustrate the effectiveness of the proposed approach by discussing its application within the RCA process of a Chilean mining company. In more detail, Chile is one of the largest exporters of copper worldwide, contributing significantly to the world production of copper mining. In specific case study is related to SAG mill problem, which had to be stopped due to potential contamination of lubrication system. This problem produced several operational issues that operators need to identify and solve. Based on recorded discussion the results are presented below.

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

Practical STEP 2:
The method used was Five whys and Ishikawa model and main parameter was time production.

Autonomous STEP 3 from recorded audio and transcription:
****Problem Statement**:**
The mill was stopped due to potential contamination of the lubrication system.

###Five-Why Analysis###:

1. **Why was the mill stopped?**
- Potential contamination of the lubrication system.

2. **Why was there potential contamination in the lubrication system?**
- Manipulation of the water valve was added to the chute, and the closure was delayed.

3. **Why was the water valve closure delayed?**
- Inadequate post-alarm actions and process controls.

4. **Why were the post-alarm actions inadequate?**
- Lack of proper review and adjustment procedures for the crushing process and interlock systems.

5. **Why were procedures lacking?**
- Insufficient routine checks and process adjustments, leading to a lack of elasticity in the lubrication system.

RCA Ishikawa (Fishbone) Analysis

****Problem Statement**:**
Potential contamination of the lubrication system leading to mill stoppage.

****Main Causes (Ishikawa Variables)**:**

- **Methods:**
- Inadequate handling procedures for water valve manipulation.
- Ineffective post-alarm procedures for chute blockages.

- **Machines:**
- Non-optimal interlock settings for the needle valve closure.
- Insufficient thermographic inspections of the chute.

- **Materials:**
- Possibility of material contamination due to delayed valve closure.
- Potential for contamination from chute blockages.

- **Manpower:**
- Insufficient training on handling valve operations and recognizing alarm conditions.
- Inappropriate actions taken after an alarm is triggered.

- **Measurements:**
- Inability to measure the exact amount of contamination.

- Lack of clear guidelines on acceptable oil level thresholds.

- **Environment**:
- Reduced volumetric capacity due to water supply issues affecting the mill operation.

Autonomous STEP 4:
Reported andMitigation Actions
Mitigation actions for each identified Ishikawa variable:

- **Methods**:
- Establish clear standard operating procedures (SOPs) for water valve operation.
- Develop and train on a comprehensive post-alarm checklist for chute blockages.
- **Machines**:
- Review and optimize interlock settings for the needle valve to ensure timely closure.
- Implement a schedule for daily thermographic inspections of chutes and lubrication systems.
- **Materials**:
- Introduce a contamination monitoring system to promptly detect any foreign material in the lubrication oil.
- Regularly clean and inspect chutes to prevent and promptly address blockages.
- **Manpower**:
- Conduct training sessions focused on alarm response procedures and correct valve operations.
- Set up a feedback mechanism for operators to report on alarm conditions and corrective actions taken.
- **Measurements**:
- Establish clear guidelines for lubrication oil levels and incorporate these into routine checks.
- Implement a tracking system to record and analyze any deviations from normal oil levels for prompt action.
- **Environment**:
- Monitor changes in volumetric capacity and integrate these observations into mill operation adjustments.
- Ensure a redundant water supply system to prevent disruptions that could cause material blockages.

According to case study, the integration of LLM-ASR-driven RCA in mining operations, as showed in the case of mill stoppage due to potential lubrication system contamination, offers a transformative approach to problem-solving. By automating Step 3—root cause analysis from recorded discussions—this method simplifies the identification of critical issues, such as delayed water valve closures and inadequate alarm responses. The automation ensures structured knowledge transfer, reducing time on manual transcription and subjective analysis.

Additionally, by leveraging recorded audio and transcriptions, LLMs can efficiently extract recurring patterns, categorize root causes, and propose targeted mitigation strategies. This enhances operational efficiency, minimizes downtime, and promotes proactive risk management. Additionally, the structured documentation of failures and corrective actions contributes to continuous improvement, ensuring that lessons learned are effectively integrated into SOPs, training programs, and equipment optimization. Finally, this approach strengthens knowledge retention, enhances decision-making, and fosters a culture of operational excellence in the mining industry.

4.1 Technology Acceptance Model(TAM) test

In this subsection, the Technology Acceptance Model (TAM) questionnaire was used to evaluate operators' perceptions of the usability and effectiveness of the LLM-ASR-driven RCA proposed in this research. According to Table 1, the results indicated high levels of satisfaction among operators, with average scores of **6.13 out of 7** for perceived usability and **5.92**for perceived effectiveness. These findings highlight the ease of use and practical utility of the proposed approach in addressing operational inefficiencies.

The high usability score underscores the intuitive design of the ASR and LLM integration, which facilitated seamless interaction for operators with minimal learning curves. This reflects the effectiveness of the transcription and analysis processes in reducing cognitive load during RCA execution. Similarly, the strong rating for perceived effectiveness highlights the tangible benefits realized, such as faster identification of root causes and the generation of actionable solutions. These attributes likely contributed to improved decision-making and workflow optimization in critical mining systems.

Despite the overall positive feedback, slight variations in individual scores suggest areas for further refinement. For instance, enhancing the adaptability of the AI framework to accommodate a broader range of operational scenarios could further improve user satisfaction. This analysis reinforces the value of combining AI technologies with user-centric approaches to develop robust and efficient problem-solving frameworks in engineering contexts.

Table 1: Technologic Acceptance Model used in 24 Operators results.

Usefulness	N	Media	s.d
Using RCA-ASR in my job would allow me to accomplish my tasks faster.	24	6,58	0,50
Using RCA-ASR would improve my job performance.	24	5,92	0,78
Using RCA-ASR in my job would increase my productivity.	24	6,13	0,85
Using RCA-ASR would enhance my work effectiveness.	24	5,63	0,77
Using RCA-ASR would make my job easier.	24	5,83	0,82
I would find RCA-ASR useful in my job.	24	6,00	0,93
Ease of Use	**N**	**Media**	**s.d**
Learning to use RCA-ASR would be easy for me.	24	3,88	0,68
I would find it easy to make RCA-ASR do what I want it to do.	24	4,04	0,81
My interactions with RCA-ASR would be clear and understandable.	24	4,00	0,83
I would find RCA-ASR flexible to interact with.	24	5,50	1,06
It would be easy for me to become skilled at using RCA-ASR.	24	5,46	0,98

Despite its advantages, integrating LLMs and ASR into RCA presents challenges, including potential model biases, dependence on high-quality training data, and the risk of over-reliance on AI-generated outputs (Heaven, 2020). To address these concerns, this study emphasizes a human-in-the-loop approach, ensuring that domain experts validate and contextualize AI-driven insights, maintaining robustness and relevance in decision-making (Chiang et al., 2024).

5 Conclusions.

This research explored the potential of integrating Large Language Models (LLMs) and Automatic Speech Recognition (ASR) technologies into the Root Cause Analysis (RCA) process, particularly in complex operational environments such as the mining industry. The study presented in this paper integrates ASR to transcribe unstructured verbal data into analyzable text, followed by the application of LLMs to extract insights, prioritize causes, and propose actionable solutions. This approach significantly reduces the time required for RCA while enhancing the accuracy and consistency of the results. The findings from the case study validate the effectiveness of this framework, demonstrating its ability to identify multiple root causes of operational inefficiencies and propose tailored solutions.

Regarding operator testing, the high satisfaction scores from the Technology Acceptance Model (TAM) questionnaire underscore the usability and practical benefits of this AI-driven RCA methodology. Specifically, key advantages of this approach include its adaptability to various operational contexts, its ability to process and analyze large volumes of unstructured data, and its capacity to improve decision-making processes. Operators and decision-makers benefit from a simplified task flow, reduced cognitive load, and actionable insights that are both timely and data-driven. These attributes are critical in dynamic and resource-intensive sectors such as mining, where operational efficiency is paramount.

However, integrating LLMs and ASR into RCA is not without challenges. The potential for AI-generated biases, reliance on high-quality training data, and the necessity of a human-in-the-loop approach remain important considerations. These limitations highlight the need for ongoing refinement of AI models and methodologies to ensure robust and contextually relevant outcomes. Future research should explore domain-specific training datasets, hybrid intelligence frameworks, and the integration of additional AI tools to further enhance RCA processes.

In conclusion, this research contributes to the growing body of knowledge on AI applications in engineering by presenting a practical, innovative, and validated approach to RCA. The integration of LLMs and ASR has shown significant potential for advancing decision-making frameworks in mining and other complex engineering fields. By addressing the limitations of traditional RCA methods, this study lays the foundation for future advancements in AI-driven problem-solving methodologies. Specifically, the authors consider this research a initial step toward developing a software application capable of guiding RCA analysis using LLMs and ASR in maintenance, following a systematic approach.

References

Andersen, B., & Fagerhaug, T. (2006). Root cause analysis. Quality Press.

Barberá, L., Crespo, A., Viveros, P. & Nikulin, C.(2012a "Methodological Proposal for Problem Resolution in Industrial Activities Based on Failure Mode Analysis. Case Applied in the Cellulose Industry, Chile" 2nd IFAC Workshop on Advanced Maintenance Engineering, Services and Technology,Spain.

Chiang, C.-W., Lu, Z., Li, Z., & Yin, M. (2024). Enhancing AI-Assisted Group Decision Making through LLM-Powered Devil's Advocate. Proceedings of the 29th International Conference on Intelligent User Interfaces, 103–119. https://doi.org/10.1145/3640543.3645199

Crespo Marquez, A. (2007). "The maintenance management framework: models and methods for complex systems maintenance". Springer-Verlag London Limited. ISBN: 9781846288203

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023). Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. International Journal of Information Management, 71, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Gano, D. (2007). Apollo Root Cause Analysis - A New Way of Thinking (Third ed.).

Heaven. (2020). How to make a chatbot that isn't racist or sexist. MIT Technology Review. https://www.technologyreview.com/2020/10/23/1011116/chatbot-gpt3-openai-facebook-google-safety-fix-racist-sexist-language-ai/

K. C.(2002) Root cause analysis: Improving Performance for Bottom-Line Results. 2nd. ed. CRC Press LLC.

Krugmann, J. O., & Hartmann, J. (2024). Sentiment Analysis in the Age of Generative AI. Customer Needs and Solutions, 11(1), 3. https://doi.org/10.1007/s40547-024-00143-4

Li, D., & Gao, J. (2010). Study and application of Reliability-centered Maintenance. Journal of Loss Prevention in the Process Industries, 23: 622-629

Li, J. (2022). Recent Advances in End-to-End Automatic Speech Recognition. APSIPA Transactions on Signal and Information Processing, 11(1). https://doi.org/10.1561/116.00000050

Ma, Q., Li, H., & Thorstenson, A. (2021). A big data-driven root cause analysis system: Application of Machine Learning in quality problem solving. Computers & Industrial Engineering, 160, 107580.

Medina Oliva, Iung, B., Barberá,L. & Viveros, P.(2012). Root Cause Analysis to Identify Physical Causes. PSAM 11 & ESREL 2012.

Murillo, G. G., Novoa-Hernández, P., & Rodriguez, R. S. (2021). Technology Acceptance Model and Moodle: A systematic mapping study. Information Development, 37(4), 617-632.

Nikulin, C., Arrieta, C., Valdés, C., & Madariaga, L. (2024). Replanteamiento de la planificación de proyectos mineros: uso de NASA-TLX para medir una novedosa integración entre OTSMTRIZ y DSM. *DYNA-Ingeniería e Industria*, *99*(6).

Pietsch, D., Matthes, M., Wieland, U., Ihlenfeldt, S., & Munkelt, T. (2024). Root Cause Analysis in Industrial Manufacturing: A Scoping Review of Current Research, Challenges and the Promises of AI-Driven Approaches. Journal of Manufacturing and Materials Processing, 8(6), 277.

Rasmuson, D. M. & Kelly, D. L.(2008). Common-cause failure analysis in event assessment. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 222(4):521-532.

Rossing, N., Lind, M., Jensen, N., & Jørgensen, S. (2010). A functional HAZOP methodology. Computers and Chemical Engineering , 244-253.

Taherdoost, H., & Madanchian, M. (2023). Multi-Criteria Decision Making (MCDM) Methods and Concepts. Encyclopedia, 3(1), Article 1. https://doi.org/10.3390/encyclopedia3010006

Viveros,P., Zio, E., Nikulin, C., Stegmaier, R. & Bravo, G. (2012). Integration of root cause analysis and theory of inventive problem solving. PSAM 11 & ESREL 2012.

Wang, X., & Wu, X. (2024). Can ChatGPT Serve as a Multi-Criteria Decision Maker? A Novel Approach to Supplier Evaluation. ICASSP 2024 - 2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 10281–10285. https://doi.org/10.1109/ICASSP48485.2024.10447204

Yu, D., & Deng, L. (2016). Automatic speech recognition (Vol. 1). Berlin: Springer