

Research Paper

Generative AI with prompt engineering in construction: Enhancing predictive slope stability modelling for safe, sustainable, climate-smart mining practices

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ABSTRACT

Generative AI (GenAI) and prompt engineering are rapidly advancing in industries such as construction and mining, leading to significant improvements in efficiency, accuracy, and decision-making processes. These technologies are transforming the construction sector by automating tasks and optimizing workflows, thereby enhancing productivity and risk management. This study explores the application of Google's Gemini AI tool, a notable breakthrough in GenAI, specifically for predictive modeling of slope stability. The Gemini AI tool is utilized within the Python programming language to generate prompts that incorporate key factors influencing slope stability, with the Google Colab interface facilitating prompt generation and testing. Initially, these prompts are employed for data analysis and visualization, followed by their application in both unsupervised and supervised machine learning approaches. The performance evaluation metrics indicate that the integrated approaches, which combine GenAI and prompt engineering, predict slope stability with a high level of accuracy. The model achieved 99% accuracy, with precision, recall, and F₁-scores ranging from 0.98 to 1.00 for both stable and unstable slope classes. This innovative methodology seeks to advance the implementation of GenAI in civil and mining engineering, offering more precise and efficient solutions for managing slope stability and supporting safe, sustainable, and climate-smart mining operations.

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1. Introduction

1.1. Generative AI and prompt engineering

Artificial Intelligence (AI) encompasses the ability of machines to perform cognitive functions traditionally associated with human intelligence, such as learning, reasoning, and problem-solving (Raisch and Krakowski, 2021). Key components of AI include machine learning, deep learning, and computer vision. A specialized subset of AI, termed Generative AI (GenAI), utilizes sophisti-

cated algorithms to autonomously produce novel outputs based on user-provided instructions (De Cremer et al., 2023). These outputs can take diverse forms, including code, text, audio, and digital images. Many GenAI systems are founded on Large Language Models (LLMs), which are developed using deep learning techniques applied to vast, unlabeled datasets (Krakowski et al., 2023; Kietzmann and Park, 2024). These models employ natural language processing and reinforcement learning to predict and generate content based on user prompts (Sundberg and Holmström, 2023). GenAI has demonstrated considerable promise in fields such as predictive modeling, where it aids in optimizing outcomes (Przegalinska et al., 2019; Desouza et al., 2020). However, despite its potential, GenAI remains in its early stages of development, with several challenges that require resolution.

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A major limitation of GenAI is the quality of its training data. The accuracy and diversity of the outputs generated by these models are closely tied to the precision and comprehensiveness of the datasets used during their training. Additionally, GenAI's ability to generate realistic and high-quality outputs is constrained by the significant computational resources required, making the process both time-intensive and costly.

The practice of designing inputs for GenAI systems, known as prompt engineering (also referred to as prompt design or prompting), is integral to the effectiveness of these models (Oppenlaender et al., 2023). Prompt engineering involves creating well-structured and clearly defined instructions to guide the AI's responses. As White et al. (2023) assert, a well-crafted prompt serves as a framework that directs the model's interpretation of the relevant information and shapes the form and content of the generated output. In contrast to traditional AI development, which focuses on the technical construction of models, prompt engineering is more concerned with human-AI interaction, emphasizing how individuals communicate with AI systems to achieve specific results (Oppenlaender, 2022).

GenAI models can be categorized into unimodal and multimodal types based on the types of data they process and generate, as illustrated in Fig. 1. Unimodal models are specialized in handling one type of data (Lv, 2023). For instance, GPT-4 is unimodal because it focuses on generating and understanding text, while DALL-E is designed exclusively to generate images from text inputs. On the other hand, multimodal models like Google Gemini are capable of processing and generating multiple types of data, such as text, images, and code, simultaneously. This versatility allows multimodal models to perform more complex tasks, such as interpreting an image and generating a text description or creating content that combines both text and visuals. Google Gemini, with its advanced multimodal features, is well-suited for diverse applications, ranging from creative projects to more sophisticated problem-solving and query-answering scenarios.

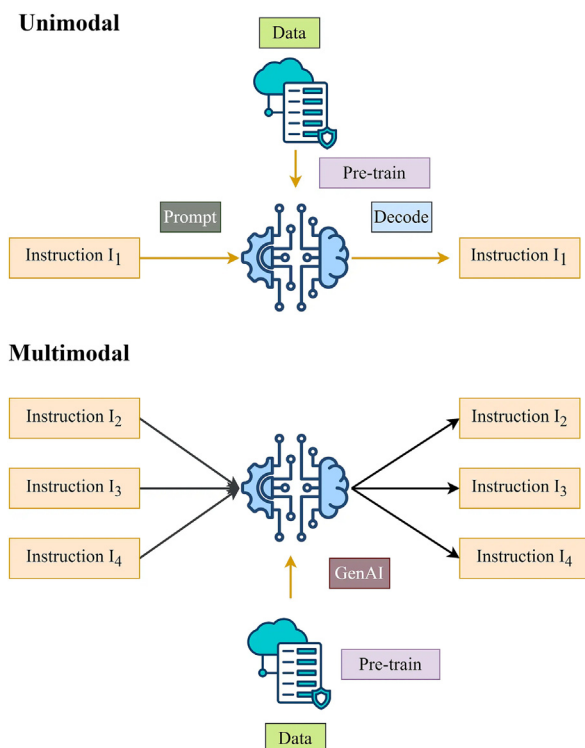


Fig. 1. Two different types of GenAI models (after Lv, 2023).

Despite the potential of LLMs, they present significant challenges (Bommasani et al., 2021), particularly in terms of the technical proficiency required to effectively engage with them (Dwivedi et al., 2023; Zamfirescu-Pereira et al., 2023). While traditional engineering methods focus on building models with annotated data and refining them with additional parameters, prompt engineering relies on carefully designed textual inputs to influence pre-trained models (Liu et al., 2023a).

Prompt engineering is an iterative process, requiring continuous interaction between human users and AI systems to enhance the quality of the generated outputs. As generative models become increasingly prevalent, research has focused on the significance of prompt engineering in human-AI collaboration (Dang et al., 2022a, 2022b; Hou et al., 2022). However, there is still a gap in understanding the intuitive prompting strategies employed by non-experts and the factors that could enhance their efficacy.

1.2. AI chatbots

In recent years, artificial intelligence (AI) has seen rapid advancements, significantly impacting both human productivity and creativity (Jahed Armaghani et al., 2020; Yari et al., 2023; Asteris et al., 2024). Among the notable developments, Large Language Models (LLMs) like OpenAI's GPT-3 have played a key role in transforming the capabilities of creative AI chatbots, with models such as ChatGPT-3.5 leading the way. Initially, LLMs were designed to handle unimodal inputs, restricting them to specific tasks. However, recent innovations have led to the creation of multimodal AI tools and models capable of interacting with a wide range of inputs, including data, text, images, audio, video, and PDFs. Some of the most prevalent multimodal AI models today include Google's Gemini AI, ChatGPT-4, ChatGPT-4 V, Inworld AI, Meta ImageBind, Runway Gen-2, and Google DeepMind's Gemini.

This study aims to investigate Google's Gemini AI, a multimodal AI model that marks a substantial advancement in GenAI technology. Gemini stands as one of the most advanced language models available, capable of simultaneously performing various tasks across different input types. Its design offers users sophisticated, accurate, and contextually relevant solutions, transforming the way information is accessed and processed. According to a report from Google's research team (Team, 2023), Gemini's visual coding builds upon foundational models such as Flamingo, CoCa, and PaLI (Alayrac et al., 2022; Chen et al., 2022; Yu et al., 2022). A key differentiator of Gemini, however, is its specific design as a multimodal model, tailored to manage complex and diverse tasks (Team, 2023).

Launched on December 6, 2023, Gemini by Google DeepMind employs Visual Language Model (VLM) technology, positioning it as a direct competitor to other leading AI tools like OpenAI's ChatGPT-4 and GPT-4 with vision capabilities (Coles, 2023; Perera, 2023). The tool incorporates multiple LLMs and advanced Natural Language Processing (NLP) techniques (Farrokhnia et al., 2024), and is available in three distinct versions: Gemini Nano, Gemini Pro, and Gemini Ultra. Each version is designed to meet the varied needs of users. For instance, Gemini Nano is optimized for mobile use, providing efficiency and accessibility. In contrast, Gemini Ultra harnesses the full potential of Google's cutting-edge AI technology, delivering unparalleled performance. Meanwhile, Gemini Pro strikes a balance between usability and power, offering a versatile tool for a broad range of applications (Team, 2023). Gemini's innovative design and its ability to handle multimodal inputs have revolutionized the field of AI chatbots. With its user-friendly interface and powerful processing capabilities, Gemini promises to significantly enhance productivity and creativity in various sectors, positioning itself as a leader in the evolving AI landscape.

1.3. Recent advances in applying GenAI and prompt engineering in construction industry

The application of GenAI and prompt engineering has seen rapid development in various industries, including construction and mining operation, where these technologies are being leveraged to improve efficiency, accuracy, and decision-making processes. The construction sector, known for its complexity and reliance on precision, is now embracing GenAI tools to automate and optimize several tasks, leading to significant improvements in productivity and risk management. For instance, Prieto et al. (2023) explored the use of ChatGPT in automating construction project scheduling. The study highlighted how AI could improve productivity, particularly in repetitive tasks, and noted positive user feedback concerning the quality of interaction and consistency of outputs. Similarly, Zhang et al. (2024) investigated the efficacy of ChatGPT-4 in energy management within building systems. Their findings underscored GPT-4's strengths in predictive modeling, enabling the implementation of data mining techniques in real-world scenarios, particularly for energy prediction and optimization. In a related study, Aladağ (2023) evaluated ChatGPT's potential to enhance risk management processes in construction operations. The study found that while ChatGPT demonstrated moderate overall effectiveness, it excelled in risk response and monitoring, though it faced challenges in identifying and analyzing risks. This suggests that while GAI has potential, further refinement is needed to improve its capabilities in more nuanced areas of project management. Naser et al. (2024) took the evaluation of advanced chatbots a step further by testing both ChatGPT-4 and Google's Bard on the Fundamentals of Engineering (FE) and Principles and Practice of Engineering (PE) exams. These AI models were assessed on civil and environmental engineering questions, and ChatGPT-4, particularly the October 2023 edition, achieved over 70% in both evaluations, indicating a high level of accuracy, pertinence, and clarity in its responses. Further applications of GenAI were explored by Ray et al. (2024), who analyzed the impact of ChatGPT and Bard on water research. Their study, which posed 50 questions on water treatment and 50 on water harvesting, revealed that these AI tools offered substantial advantages across various domains of water treatment, from conventional methods to more innovative techniques. Additionally, Rane et al. (2023) investigated the integration of ChatGPT and Bard in architectural design and engineering, highlighting the growing influence of these technologies in shaping design processes and decision-making in the construction industry. Although previous studies have focused on specific applications of ChatGPT in the construction industry, this study demonstrates the strong potential of GenAI for slope stability applications, with ongoing evaluations across broader scientific and engineering fields expected to further validate and enhance its effectiveness.

The implementation of GenAI and prompt engineering in the construction and mining industries is showing potential in areas such as project scheduling, risk management, energy optimization, and design processes. As these technologies develop, they are expected to play a crucial role in enhancing the efficiency and precision of civil and mining engineering projects, although further progress is needed to address challenges in complex decision-making. This study focuses on leveraging GenAI with prompt engineering to improve predictive modeling of slope stability for safe, sustainable, and climate-smart mining. Using Python programming, the study will generate prompts that incorporate key factors influencing slope stability, with the Google Colab interface integrated within the Gemini platform to facilitate prompt creation and testing. This innovative approach aims to advance the use of GenAI in civil and mining engineering, providing more accurate

and efficient solutions for managing slope stability in mining operations.

2. Developments in slope stability analysis: Current approaches and associated challenges

The development of structures on a variety of ground conditions is necessary due to the significant reduction in available land for construction subjected to population growth and urbanization (Fang et al., 2023). The construction of structures in sloped areas presents distinctive challenges, as mass movements and slope instability, which are now global concerns, pose substantial risks to the structural integrity, property, and life of humans. A slope is generally characterized as a landform inclined at an angle to the horizontal plane (Cernica, 1994). Consequently, slope stability analysis has emerged as a vital area of research in civil and mining engineering, with significant efforts dedicated to devising cost-effective and dependable solutions for construction on slopes.

Slope stability analysis techniques are mainly classified into two types. The limit equilibrium method, the first approach, is extensively utilized and assumes that the forces and moments inside the soil mass attain equilibrium along a potential slip plane. This method determines the critical slip surface and calculates the factor of safety (FS) for the entire slope by repeatedly assessing the soil's shear strength under static equilibrium (Atkinson, 1993).

The second category pertains to the finite element approach, employed to simulate soil stress-strain behavior. This sophisticated method facilitates accurate computations of capillary water pressures, displacements, and stress magnitudes. It facilitates the modeling of intricate geometries and boundary conditions through nonlinear stress-strain models. Nonetheless, both approaches possess constraints (Kurnaz et al., 2024). The limit equilibrium technique necessitates extensive iterative calculations over several assumed slip surfaces to ascertain the minimum factor of safety, which can be computationally intensive and fails to consider slope displacements. The finite element method, although proficient in modeling stress and deformation, necessitates partitioning the domain into several small elements and nodes, leading to substantial datasets and prolonged calculation durations. Furthermore, errors in input factors, including material qualities, boundary conditions, and slope geometry, might influence the reliability of slope stability evaluations.

In recent decades, artificial intelligence (AI) has gained prominence in civil and mining engineering, resulting in numerous models for slope stability evaluation. Initial investigations concentrated on utilizing artificial neural networks (ANNs) to create predictive models (Sakellariou and Ferentinou, 2005; Wang et al., 2005; Li and Wang, 2010; Asteris et al., 2022). Certain models focused on predicting slope stability status (i.e., stable or failure), whilst others assessed the slope's factor of safety (FS).

Numerous predictive models for slope stability, augmented by machine learning (ML) algorithms and optimization methods, have been suggested for both soil and rock slopes (Liu et al., 2018; Escobar-Wolf et al., 2021; Chen et al., 2022). Nonetheless, the implementation of machine learning techniques in slope stability analysis poses numerous obstacles. Lin et al. (2021) identified drawbacks include unexamined failure causes, the omission of external elements like as precipitation and seismic activity, and the computing demands of these methodologies. Gupta et al. (2022) emphasized the nonlinear intricacies of slope stability and the potential for overfitting resulting from insufficient training data. Zhang et al. (2022) addressed challenges in choosing appropriate machine learning models and identifying essential slip surfaces, whereas Mahmoodzadeh et al. (2022) recognized the intrinsic complexity of slope stability analysis utilizing diverse ML

methods. Liu et al. (2023b) emphasized the necessity of integrating all pertinent indications for enhanced precision, while Chen et al. (2023) underscored difficulties in modeling intricate soil strata. Nanehkaran et al. (2023) examined constraints associated with database size and the influence of hardware on ML model efficacy. Yang et al. (2023) highlighted the difficulties associated with conventional analytical techniques and the risk of overfitting in ML applications. The weighted ensemble learning algorithm from the AutoGluon package surpassed other algorithms, attaining an exceptional 97.5% accuracy in both testing and training, as indicated by the results. These findings highlight the intricacies of implementing ML techniques in slope stability analysis and reflect the continuous endeavors to enhance their dependability and accuracy in geotechnical engineering. ML approaches have shown considerable promise in providing more accurate and efficient solutions for slope stability analysis, addressing some of the limitations of traditional methods. Nevertheless, the application of ML in this domain is not without challenges, particularly related to data availability, quality, and the computational burden associated with complex modeling. As the field of artificial intelligence continues to advance, the emergence of GenAI introduces a new dimension to the analysis of slope stability.

The integration of GenAI, particularly through prompt engineering, offers the potential to enhance slope stability assessments by improving predictive models. This approach can extend the application by enabling automated code generation, interpretation, and decision support in natural language, making advanced analyses more accessible and transparent to practitioners and researchers. By exploring the contributions of prompt engineering and advanced AI techniques, this study aims to advance the development of safer, more sustainable, and climate-resilient mining practices. Ultimately, this work paves the way for the adoption of cutting-edge AI technologies in geotechnical engineering, offering innovative solutions to longstanding challenges in slope stability analysis.

3. Methodology

This study aims to integrate GenAI and prompt engineering to predict slope stability within the Python programming environment, using Google's Gemini platform. Initially, a comprehensive database was established, encompassing 404 slopes with documented failure risks from various countries. The primary stages of the research are outlined as follows:

- (1) Each slope was classified as either stable or failed based on available data.
- (2) Data visualization techniques were applied to gain insights into the influence of input variables on slope stability.
- (3) The dimensionality reduction algorithm i.e., *t*-SNE was implemented to isolate the most influential variables affecting slope stability.
- (4) The unsupervised machine learning algorithm, namely *K*-means clustering, was applied to categorize the data into stable and unstable groups, thereby facilitating pattern recognition within the dataset.
- (5) Finally, a supervised machine learning algorithm, specifically the Stochastic Gradient Boosting (SGB) algorithm, was used to predict slope stability and classify slopes as either stable or unstable.

3.1. *t*-distributed stochastic neighbor embedding (*t*-SNE)

Hinton and Roweis (2002) developed an enhanced version of the Stochastic Neighbor Embedding (SNE) algorithm, known as

t-distributed stochastic neighbor embedding (*t*-SNE). The SNE operates through two primary steps: (1) it initially transforms the distances between data points into conditional probabilities in high-dimensional space, reflecting their similarities; and (2) it subsequently aligns these conditional probabilities with the corresponding probabilities of other points (map points) in low-dimensional space (Liu et al., 2021). The *t*-SNE algorithm has been applied in various contexts within the fields of construction and mining engineering, as it offers improved visualization capabilities. The detailed mathematical formulation of *t*-SNE can be found in the authors' previous publication (Ullah et al., 2022).

3.2. *K*-means clustering

Clustering analysis is an effective method to prevent artificial divisions and reliance on supervision. In this approach, a dataset is grouped based on similarity, ensuring that each group maintains a high degree of internal coherence. The partitioning of the dataset is determined by the distances between data points, with similarity and dissimilarity criteria playing crucial roles in the division process. *K*-means clustering, an unsupervised machine learning technique, is widely used for partitioning observations into *K* distinct clusters. Each observation is associated with the cluster that has the nearest mean. The algorithm operates in two distinct phases: the first phase involves randomly selecting *K* initial cluster centers, while the second phase assigns each data point to the nearest center (Hartigan and Wong, 1979; Zhu et al., 2019). The most commonly used clustering criterion is the sum of squared Euclidean distances, which measures the distance between each data point and its corresponding cluster center (Likas et al., 2003). For a detailed mathematical formulation of *K*-means clustering, please refer to the authors' previous work (Kamran and Shahani, 2022).

3.3. Stochastic gradient boosting (SGB) algorithm

The Stochastic Gradient Boosting (SGB) algorithm was introduced by Friedman (2002), incorporating the concept of gradient descent into the boosting algorithm framework. As an ensemble learning technique, gradient boosting combines boosting with decision trees to iteratively build a model that aligns with the gradient direction of the loss function from the previously established model. The core of SGB lies in minimizing the loss function between the classification model and the actual function by iteratively refining the classification function.

During backpropagation, iterations update via the chain rule, which can sometimes lead to unstable gradients. Specifically, if the multiplier exceeds one, updates escalate rapidly with each iteration, leading to gradient explosion; if it is less than one, gradients decay with each iteration. To address gradient instability and mitigate gradient scaling effects from weight magnitude, Ioffe and Szegedy (2015) proposed batch normalization (BN), designed to support activation function formulation.

The computation cost of Stochastic Gradient Descent (SGD) does not scale with sample size, enabling sublinear convergence rates in convex problems (Johnson and Zhang, 2013). SGD enhances processing speed by reducing update time when handling multiple samples, eliminating redundant computations and accelerating calculations. In strongly convex problems, SGD achieves the highest convergence speed (Robbins and Monro, 1951; Nemirovski et al., 2009); even when problem conditions fall short of strong convexity, SGD maintains a high convergence rate. An asynchronous parallel strategy introduced by Liu et al. (2014) enables linear convergence under a required strongly convex condition. Furthermore, Sankararaman et al. (2019) demonstrates that, under the Polyak–Lojasiewicz (PL) condition, the iterative point

converges linearly to a stable point within its neighborhood. Additionally, [Khaled and Richterik \(2020\)](#) shows that if the PL condition is met, SGD can identify the global solution.

Several critical optimizations for SGD focus on enhancing speed and reducing fluctuation during convergence ([Ruder, 2016](#)). Selecting an appropriate learning rate improves convergence efficiency: a high learning rate can cause instability near the optimal solution, while a low rate may slow convergence, prolonging updates. Some acceleration methods involve taking a smaller step in a defined direction, further improving convergence speed.

4. Database acquisition and parameters

There is a significant likelihood that slope failure surfaces will be located near potential sliding surfaces. Excessive shear stress on these surfaces, caused by factors such as excavation at the slope's base or water seepage at its crest, can lead to local slope instability as illustrated in [Fig. 2](#). Several engineering case studies and theoretical analyses indicate that slope stability is primarily influenced by the physical and mechanical properties of the potential slide surface, key geometrical parameters, and external triggering factors. Due to their distinct behavior and the accessibility of their values, six attributes were considered for this study. These variables include unit weight (γ), cohesion (c), internal friction angle (φ), slope angle (β), slope height (H), and pore pressure ratio (r_u). In this study, a database comprising 404 slopes at risk of failure from different countries was compiled from [Liu et al. \(2023b\)](#) (see [Supplementary Data 1](#)). The statistical characteristics and data visualization will be presented in the discussion section of the slope stability database, incorporating the use of GenAI and prompt engineering through Python programming.

5. Results and discussion

5.1. Problem-solving procedure by employing GenAI for code generation

[Fig. 3](#) depicts the structured workflow employed to solve the problem. The process begins with a narrative prompt, intentionally free of mathematical formulations, allowing Google's Gemini to independently interpret and generate Python code. Once the code is generated and executed successfully, both the code and its results undergo thorough validation by users. Based on this validation, users provide iterative prompts to refine and correct the code until it is error-free. This process of refining and optimizing prompts continues until the outputs produced by Google's Gemini precisely meet the expected results.

5.2. Prompts by user, answers by Google's Gemini, and results

This section outlines the process of generating Python code for slope stability analysis. Initially, the dataset is loaded into the Google Colab directory, and Python code is subsequently generated through integration with Google Gemini. It is noteworthy that, although the prompt specifies the creation of code, it does not define the exact equations or underlying operational principles of the method. The structurally organized Python code generated by GenAI is presented in this section, with each segment corresponding to user-provided prompts clearly delineated in separate listings for clarity.

Prompt 1. I have uploaded a data file named 'Data.xlsx'. Please load it and display the first few rows.

Google's Gemini response: The code output shown in [Supplementary Data 2](#) was generated in response to Prompt 1. Google's Gemini initially invoked the pandas library to load an Excel file into a DataFrame. Following this, the `df.head()` function from pandas was used to display the first few rows of the DataFrame, defaulting to 5 rows. This feature is particularly useful for quickly inspecting the structure and contents of the DataFrame. [Supplementary Data 3](#) represent the first 5 rows of the slope stability database.

Prompt 2. Please provide the statistical summary of the dataset, including attributes like mean, median, standard deviation, minimum, and maximum values for each column.

Google's Gemini response: The code output depicted in [Supplementary Data 4](#) was generated in response to Prompt 2. In response to Prompt 2, the Python function `df.describe()` was called to display the statistical attributes of the slope stability database. This function, from the pandas library, provides a summary of key statistical measures for each numerical column in the DataFrame (`df`). [Supplementary Data 5](#) illustrates the statistical characteristics of the slope stability database.

Prompt 3. Please generate a heatmap of the dataset to visualize correlations between variables.

Google's Gemini response: The code output shown in [Supplementary Data 6](#) was generated in response to Prompt 3. The `seaborn` and `matplotlib.pyplot` libraries were imported to generate a heatmap of the input variables against the output data. [Fig. 4](#) presents the heatmap depicting the Pearson correlation coefficient (R) between each attribute. As shown in [Fig. 4](#), the correlation values among all variables were below 0.5, with the highest correlation being 0.41. This suggests that the relationships between the attributes were weak, implying that each attribute was sufficiently independent and relevant in predicting slope stability.

Prompt 4. Please generate histograms for each column in the dataset to visualize their distributions.

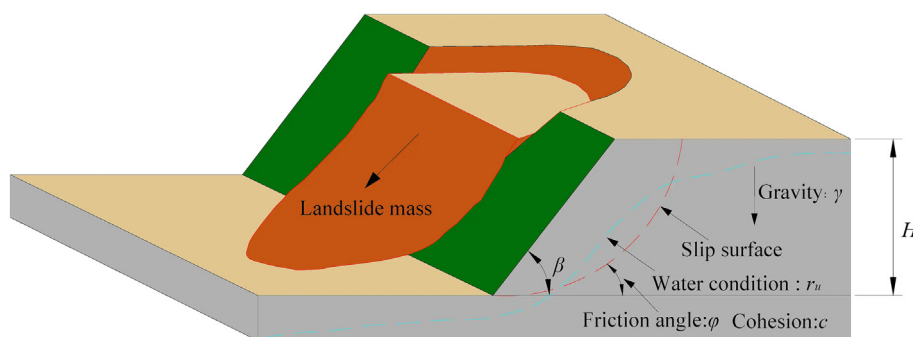


Fig. 2. The 3D representation of slope failure (after [Liu et al., 2023a](#)).

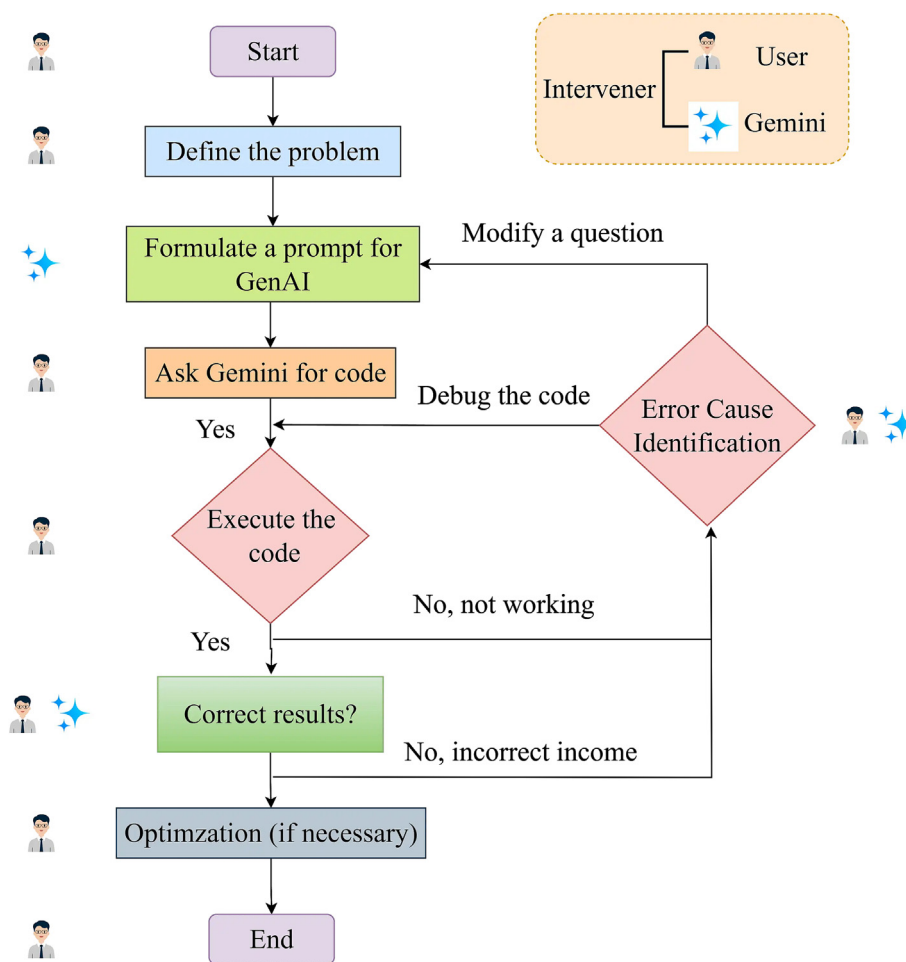


Fig. 3. The structured workflow of GenAI problem.

Google’s Gemini response: The code output presented in [Supplementary Data 7](#) was generated as a result of Prompt 4. The `sns.histplot(df[column], kde = True)` function was used to create a histogram with a Kernel Density Estimate (KDE). [Fig. 5](#) presents the histogram of the input attributes for the slope stability database.

Prompt 5. Please split the dataset into features (X) and target (y), with y being the last column in the data.

Google’s Gemini response: [Supplementary Data 8](#) displays the code generated in response to Prompt 5. The input data is selected from all columns except the last, which is designated as the output data.

Prompt 6. Please apply the t-SNE dimensionality reduction algorithm to the X data and visualize the results in 3D.

Google’s Gemini response: The code generated in response to Prompt 6 is shown in [Supplementary Data 9](#). t-SNE has been applied to the slope stability dataset to reduce the dimensionality from high resolution to low resolution. The resulting data is then visualized in a 3D plane as shown in [Fig. 6](#).

Prompt 7. Please apply the K-means clustering algorithm with 2 clusters to the t-SNE output data.

Google’s Gemini response: [Supplementary Data 10](#) shows the code that was generated based on Prompt 7. Based on the unstable and stable slope stability conditions, the t-SNE data is divided into two clusters using the K-means clustering algorithm. The resulting t-SNE data is then visualized in a 3D plane as illustrated in [Fig. 7](#).

Prompt 8. Please evaluate the results of the K-means clustering using the silhouette score.

Google’s Gemini response: [Supplementary Data 11](#) presents the code generated in response to Prompt 8. The researcher previously used the silhouette value to evaluate the results of the K-means clustering. In this case, the K-means clustering results for the slope stability dataset are assessed using the silhouette value. A silhouette score of 0.70 was obtained for the t-SNE acquired slope stability dataset.

Prompt 9. Please split the X_tsne and labels data into training and testing sets using a 75 : 25 ratio.

Google’s Gemini response: The code generated in response to Prompt 9 is provided in [Supplementary Data 12](#). The t-SNE data, along with the labels generated from the K-means clustering algorithm, are partitioned into training and testing datasets to facilitate the preparation of the data for supervised learning, with 75% allocated for training and 25% for testing.

Prompt 10. Please apply and fit the SGDClassifier algorithm on the X_tsne and labels training data and evaluate the results on the X_tsne testing and labels data using a classification report. Additionally, please replace the “Class 0” with “Unstable slope” and “Class 1” with “Stable slope” in the above classification report.

Google’s Gemini response: The code generated in response to Prompt 10 is shown in [Supplementary Data 13](#). The Stochastic Gradient Boosting Classifier is used to predict the unstable and stable levels in the slope stability dataset. To assess the performance of the classification algorithm, the researchers utilized performance evaluation metrics including the precision, recall, F₁-score, and accuracy ([Kamran et al., 2023](#)). This same evaluation

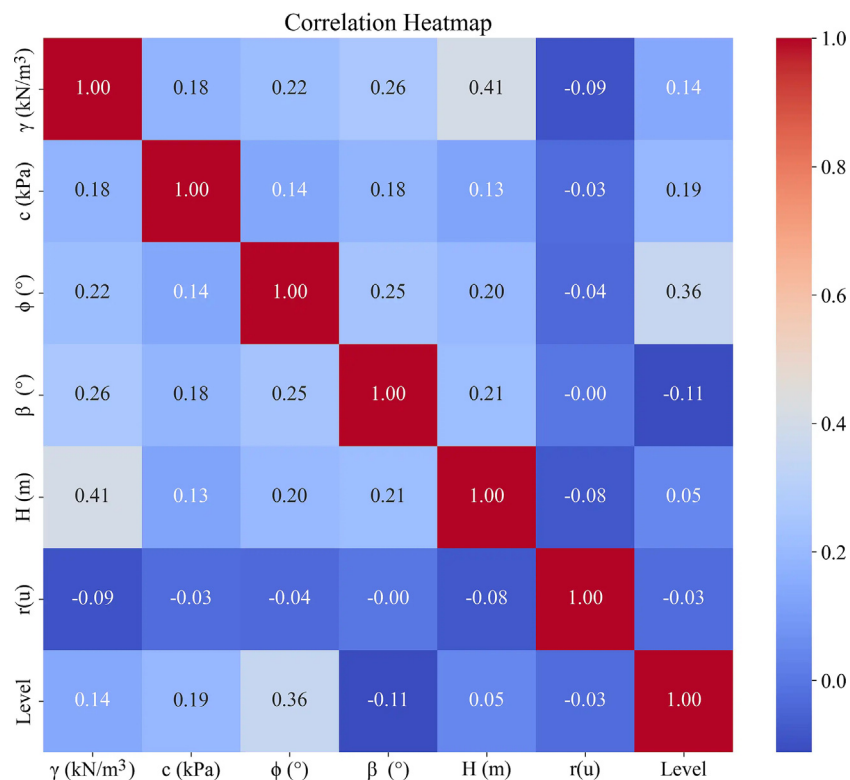


Fig. 4. Correlation matrix of slope stability database.

approach is applied in this study. [Supplementary Data 14](#) shows the classification report for both the unstable and stable classes.

Slope stability is a critical factor in ensuring safe, sustainable, and climate-smart mining operations. Stable slopes help prevent hazardous incidents such as landslides and rockfalls, safeguarding workers, equipment, and infrastructure. The risk of catastrophes and loss of life is reduced by ensuring that mining operations can proceed safely without interruptions by maintaining stability. Stable slopes facilitate more efficient resource extraction with minimal environmental disturbance, thereby reducing waste and safeguarding the adjacent ecosystems from a sustainability perspective. However, uncontrolled slope failures can result in severe environmental damage, such as the contamination of water sources and the devastation of habitats. Furthermore, slope stability is essential for the adaptation to climate change, as instability can be exacerbated by changing weather patterns, such as increased rainfall and extreme weather events, which promote water infiltration and erosion. By proactively managing slope stability, these risks are reduced, and the necessity for additional resources and energy to mitigate failures minimized, thereby contributing to more safe, sustainable and climate-resilient mining practices.

5.3. Strategic obstacles regarding the AI prompting procedure

To effectively utilize GenAI tools in the context of civil and mining engineering, users must engage with the technology in a precise and informed manner. GenAI systems are highly dependent on human input, with prompts serving as the primary configurations that guide the model's response generation. One of the main advantages of GenAI is its intuitive interface, which simplifies model prompting and facilitates human-like conversational outputs. Upon receiving a prompt, the GenAI system draws from its knowledge base to generate relevant content. To minimize bias,

prompts were carefully crafted using neutral language, balanced class representations, and domain-specific terminology to ensure clarity, reduce ambiguity, and guide the GenAI model toward generating objective and accurate outputs.

In the construction industry, professionals must consider several critical factors when selecting and applying GenAI tools and methodologies for specific tasks. First, it is essential to acknowledge that GenAI models, due to their reliance on training data, sometimes produce inaccurate information—a phenomenon known as “hallucination”. This occurs when the model generates content that appears plausible but lacks factual basis. Since GenAI is designed to generate novel outputs, there is a risk of it presenting erroneous information. To address this, robust validation mechanisms must be in place to verify the accuracy of AI-generated content. Cross-referencing these outputs with established facts, current data, historical trends, and expert evaluations is vital to minimize the risk of errors and improve overall reliability. To address the issue of hallucination in GenAI models, a robust validation framework that includes expert review, consistency checks across multiple runs, and iterative feedback for continuous improvement should be implemented.

Second, decision-makers in the area of construction industry must clearly define the specific requirements of their field when selecting a suitable GenAI model, ensuring that the chosen tool aligns with the organization's objectives and the specific tasks at hand. This process involves thoroughly understanding the model's functionality, evaluating the quality of the generated outputs, and, if feasible, assessing the data and training methods used in the model's development. Such insights provide a deeper understanding of the advantages and potential limitations of each model.

Finally, it is critical to assess the specific purpose for which the GenAI model was designed. The training approach used in model development significantly affects its behavior and performance. In fields like civil and mining engineering, understanding the oper-

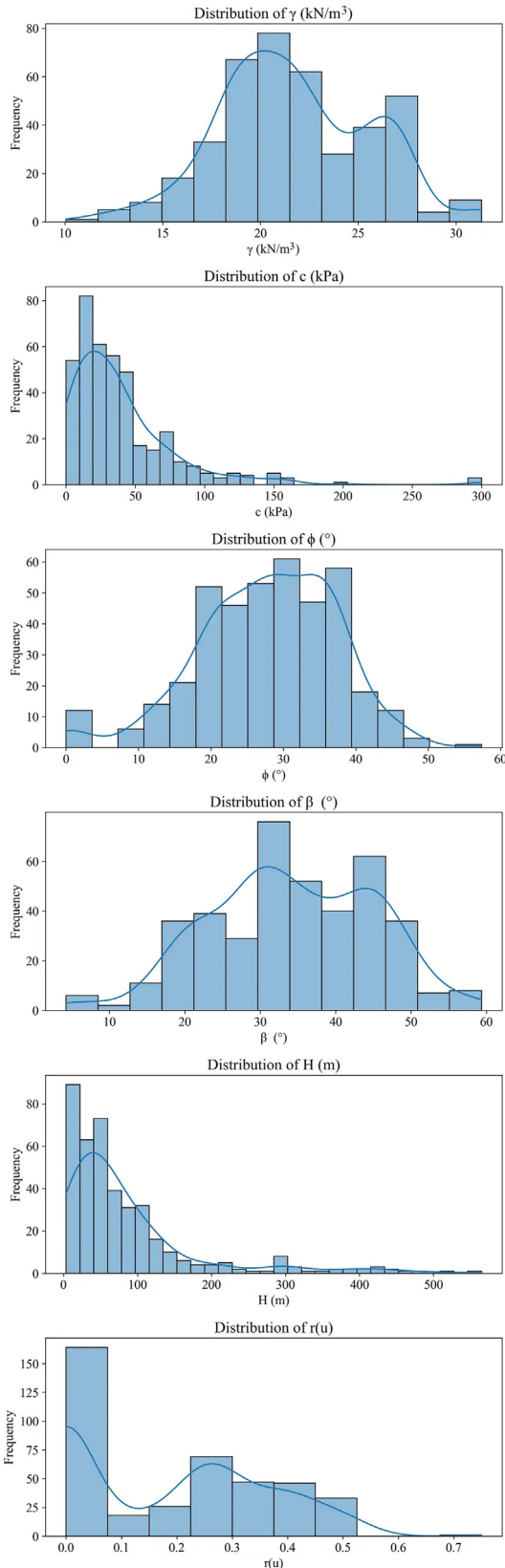


Fig. 5. Histogram of the input attributes for the slope stability database.

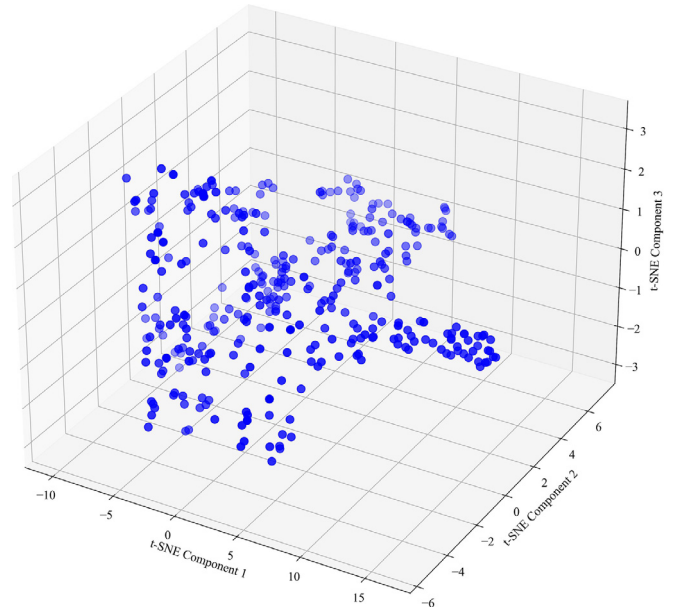


Fig. 6. t-SNE acquired slope stability dataset.

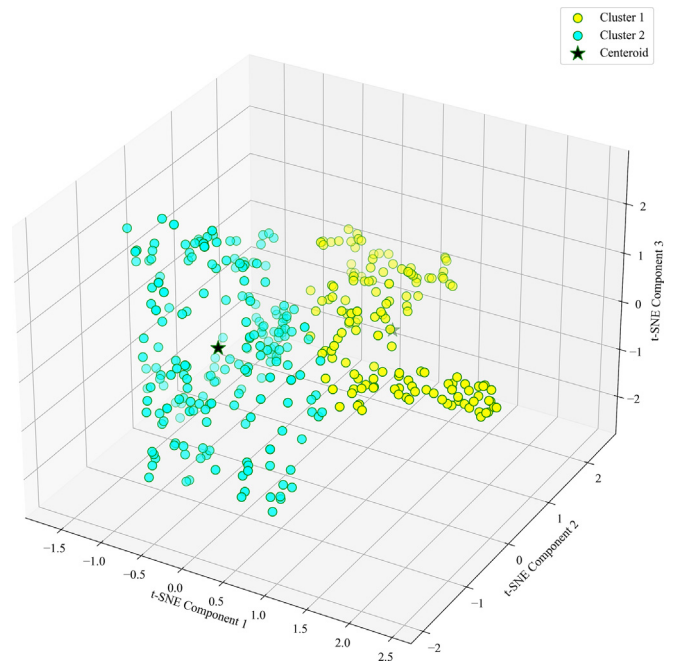


Fig. 7. t-SNE visualization with K-means clustering in slope stability database.

as the model’s capabilities, functionality, the complexity of the data, and the underlying training methodologies.

6. Conclusion

The proposed GenAI with prompt engineering mechanism has demonstrated its capability to evaluate slope stability in the field. Integrated with Python programming and powered by Google’s Gemini, this mechanism provides a powerful tool for analyzing and predicting slope stability factors. By leveraging advanced prompt engineering techniques, the system can optimize input data and refine the decision-making process, enhancing the accuracy and reliability of the evaluation. Initially, these prompts are

ational context is crucial for making informed decisions. Therefore, the selection of a GenAI model should be based on a careful analysis of the specific needs of the project, considering factors such

used for data analysis and visualization, followed by their application in both unsupervised and supervised machine learning models. Performance evaluation metrics reveal that these integrated approaches, which combine GenAI with prompt engineering predict the slope stability level with high accuracy. This integration of cutting-edge AI technology with Python enables a more efficient and scalable approach to solving complex slope stability challenges, making it a valuable asset for researchers and engineers in the field.

The integration of GenAI into civil and mining engineering is poised to revolutionize the sector, especially in promoting sustainable, environmentally friendly, and climate-conscious engineering practices. GenAI serves as a critical enabler of technological advancements that drive efficient, economically viable, and eco-friendly research in these fields. Its capabilities can accelerate the transition towards a more sustainable global ecosystem. However, as with any technological progress, skepticism remains, particularly regarding the potential risks associated with super-intelligent systems lacking proper safeguards. Issues such as the generation of inaccurate information due to biases in training data, latency in producing high-quality results, and the extensive computational resources required to train generative models pose significant challenges.

Furthermore, the lack of transparency in how GenAI models operate is a major barrier to widespread adoption. In fields like civil and mining engineering, where critical operational decisions rely on accuracy and reliability, the explainability and accountability of AI models are essential. To address this, integrating model-agnostic interpretability techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) can help engineers understand feature importance and model decision-making processes. Additionally, employing rule-based surrogate models can approximate complex GenAI outputs with simpler, more interpretable frameworks, facilitating easier validation and trust. Incorporating causal inference methods can also enable clearer identification of cause-effect relationships critical for safety and reliability in engineering applications. Finally, the development of visual analytics dashboards tailored to domain experts can provide interactive and intuitive insights into model behavior, enabling better oversight and accountability.

As GenAI continues to evolve, adopting these specific explainability techniques will be crucial to developing models that are more transparent, reliable, and accountable, ensuring their safe and effective application across all sectors, including civil and mining engineering.

CRediT authorship contribution statement

Muhammad Kamran: Conceptualization, Software, Investigation, Methodology, Writing – Review & Editing. **Muhammad Faizan:** Investigation, Methodology, Writing – review & editing. **Shuhong Wang:** Supervision, Project administration, Methodology, Investigation, Formal analysis. **Danial Jahed Armaghani:** Formal analysis, Funding acquisition, Investigation, Methodology, Resources. **Panagiotis G. Asteris:** Validation, Supervision, Project administration, Methodology, Formal analysis. **Biswajeet Pradhan:** Validation, Supervision, Software, Methodology, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The Corresponding

Author of this paper Biswajeet Pradhan is an Associate Editor of this Journal, and was not involved in the editorial review or the decision to publish this article.

Appendix A. Supplementary data

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