Generative Prior Transformation model for mineral resources evaluation and prediction (MineralGPT): A case study of prospective target area selection for the Xiaoshan-Xiongershan area gold polymetallic deposit

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Abstract: Mineral resources are an important material foundation for economic and social development. The mineral resources evaluation and prediction will provide scientific basis for the development, utilization, and protection of mineral resources. The existing traditional mineral resource comprehensive evaluation methods are costly, time-consuming, and have limited data processing and analysis capabilities. However, computer-based comprehensive evaluation methods often have fixed patterns and cannot incorporate as much expert knowledge as possible into the algorithms. Additionally, the utilization rate of some multi-source heterogeneous data, especially text data, is low. Given these challenges, this study transforms expert knowledge and artificial analysis methods into priori rules and proposes a novel approach for mineral resource evaluation and prediction - the Generative Prior Transformation Model, abbreviated as MineralGPT. The MineralGPT framework is driven by the description, storage and analysis of prior knowledge to support various model algorithms such as data processing and analysis, metallogenic information extraction and prospecting prediction, content generation and optimization. Taking the optimization of the gold polymetallic mine prospecting target area in the Xiaoshan-Xiongershan area as an example, experiments on the optimization model of the prospecting target area based on term weighting in MineralGPT show that MineralGPT supported by a small amount of data are almost consistent with the expert evaluation. Compared with the large-scale language model (such as ChatGPT) that requires massive data and computing power, it has the advantages of low cost, fewer limitations and high customization. MineralGPT, which introduced the rule-based description, storage and analysis of prior knowledge, provides a new method for mineral resources evaluation and prediction, and also provides a new idea for the development of a new generation of artificial intelligence technology combining rules and learning.

Keywords: Mineral resources evaluation and prediction; Generative prior transformation model; Calculation of term weighting; Term association analysis; Prospecting target area optimization

- Highlight 1 We proposed a new method that recognizes the information of mineral features in mined geologic texts as well as the relationships between named entities. This method is not only effective with a small amount of data, but also does not require huge arithmetic power to accomplish these tasks.
- Highlight 2 We transformed rules into a description language that can store and dynamically parse rules on a computer platform. This approach allows rules to be dynamically extended, making them more flexible and easier to maintain.
- Highlight 3 The mineralGPT framework has model management capabilities that enable process-oriented operations, similar to a workflow approach. It supports parallel and serial processing and provides a mechanism to manage the entire process efficiently.

1 Introduction

Mineral resources play a pivotal role in human survival and development. As the human demand for mineral resources continues to grow with the constant improvement of productivity, it has promoted the extended development of mineral resource evaluation methods. In the early stages of mineral resource evaluation methods research, the assessment of mineral resources relied predominantly on geological experience for qualitative evaluation. However, with the advancement of computer technology, it has gradually shifted towards quantitative analysis and assessment in recent times.

The International Union of Geological Sciences (IUGS) established six standardized methods for estimating mineral resources in 1976, encompassing the regional value estimation method, volume estimation method, abundance estimation method, ore deposit modeling method, Delphi method, and comprehensive evaluation method. This laid the foundation for quantitative assessment methods in mineral resource prediction. Subsequently, various scholars proposed different methods, driving the development of quantitative assessment approaches, such as: American scholars introduced the “three-part quantitative assessments” method to find mineral resources(Singer, 1993). Zhao (2002)proposed the “Three-Component” quantitative resource prediction and assessment method. Cheng (2006)proposed the nonlinear theory to ore prognosis. Wang (2010) proposed a method of synthetic information mineral resources prognosis. With the development of Geographic Information System (GIS) technology, many scholars (Cheng, 2007; Chen *et al.*, 2008; Zhang *et al.*, 2010) applied to mineral forecasting, among which MRAS mineral resource evaluation system is widely used. Additionally, some scholars(Martin *et al.*, 2007; Chamrar *et al.*, 2019; Wang *et al.*, 2021) adopt three-dimensional metallogenic prediction methods. Currently, with the continuous development of computer technology, big data and machine learning methods have become the development trend of mineralization prediction(Zhou *et al.*, 2017; Yao and Jiangnan, 2021).

Several scholars use machine learning methods for mineralization prediction. Research in this area such as K-value clustering(Paasche and Eberle, 2009), neural network(Oh and Lee, 2010), support vector machine(Zuo and Carranza, 2011), Self-organizing clustering(Abedi *et al.*, 2013), random forest(Carranza and Laborte, 2016; Gao *et al.*, 2016). In addition, some scholars have adopted the association rule method to evaluate the mining area. The association rule method(He *et al.*, 2011; Chang *et al.*, 2018; Liu and Zhou, 2019; Chen *et al.*, 2020) is based on applying the association rule algorithm to mine the correlation of tectonic geological big data related to mineralization. The Exploration Information Systems (EIS) is currently being implemented to automatically generate mineral prospectivity maps by integrating an interrogatable library of mineral systems with GIS (Yousefi *et al.*, 2019). As an emerging field, the knowledge map is gradually being used in mineral resource prediction (Enkhsaikhan *et al.*, 2021; Yang *et al.*, 2021; Yuan *et al.*, 2021; Zhou *et al.*, 2021) and is currently in its early stages. It is to carry out mineral resource prediction by constructing the knowledge map of related deposits to achieve knowledge-driven mineral resource prediction. However, the above methods usually require manual labeling and extraction of knowledge, which will have a certain bias and affect the result to some extent. The current analytical methods rely mainly on fieldwork, geological exploration, and map data. In contrast, the utilization rate of text data is low(Filchev *et al.*, 2021), and often through manual methods to extract knowledge information from the text and input it into the model. This approach results in heavy human intervention and limits the comprehensiveness of the extracted data. With the emergence of language models, they present a potential way to reduce human intervention by being able to extract text knowledge(Yuan *et al.*, 2023) and perform reasoning automatically. However, although large-scale language models can be used in a wide range of domains to generate text content intelligently(Wang, 2023), they still have some shortcomings in problem-solving in specialized domains. First, they lack a deep understanding of specialized knowledge and can only be data-driven for text generation, limiting their practicality in evaluation and prediction. Secondly, they mainly rely on data learning and lack strict scientific principles or rules to restrict text generation. Finally, more computational power and data are required to deal with specialized problems, which may limit the model's performance and be more computationally intensive.

Therefore, this study aims to address the limitations of the current language model in mineral prediction and general method prospecting. We propose a generation prior transformation model (MineralGPT) for mineral resources evaluation and prediction, which introduces prior knowledge and combines with the computer, utilizes the language model to process mineral data, and supports intelligent mineral prediction and evaluation in order to respond to the needs of specialized domains without relying on huge computational resources.

The subsequent segments of the paper are organized as follows. Section 2 introduces the MineralGPT framework. Section 3 details the experiments of MineralGPT based on the optimization of the gold polymetallic mine prospecting target area in the Xiaoshan-Xiongershan area. Section 4 presents the experimental results and analysis. Lastly, Section 5 culminates the paper and recommends future research and enhancements.

2 MineralGPT

2.1 Overall framework

MineralGPT is designed to address mineral evaluation challenges by emulating human thought processes and integrating extensive a priori knowledge. This approach facilitates the swift extraction of reliable and practical information on mineral resources, even within constraints of limited data and computational resources, culminating in scientific mineral resources evaluation. It is driven by knowledge description, storage and analysis, and runs various data processing and analysis, metallogenic information extraction and prospecting prediction, content generation and optimization models and algorithms to support mineral resources evaluation and prediction. The MineralGPT framework includes rule description and driving engine, core model and model scheduling management, content model and model interaction, and domain model. These core parts work together to support mineral resources evaluation and prediction. The framework structure is shown in Fig. 1.

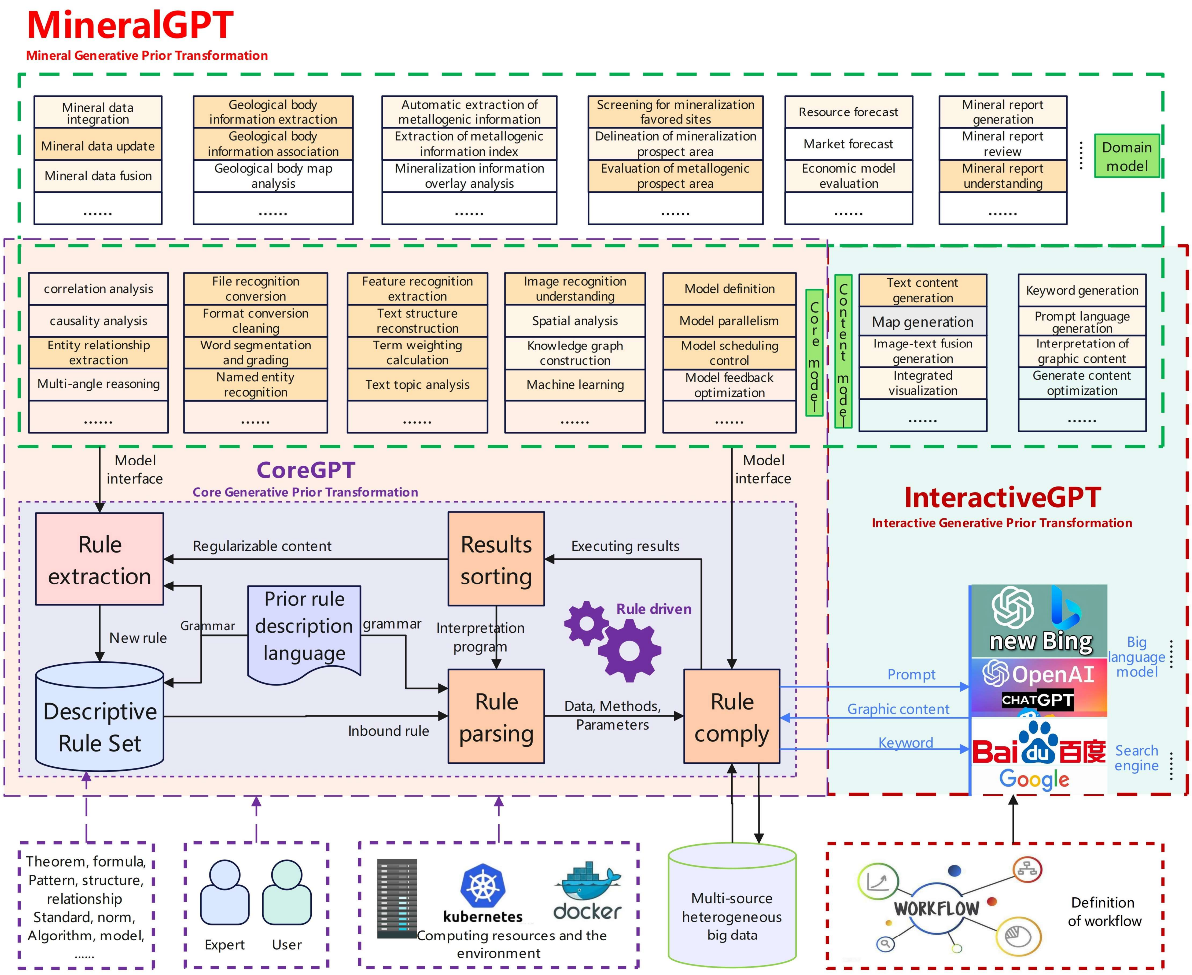

Fig. 1 The MineralGPT framework structure

The framework is summarized from the bottom up into three layers: 1) rule description, driving engine, core model, and model scheduling management constitute the core layer (CoreGPT), which realizes the most fundamental and essential processing and analysis of geological and mineral data. 2) CoreGPT, the content model, and model interaction together form the interaction layer (InteractiveGPT), enabling the output of model results and the input of external capabilities. 3) InteractiveGPT and domain model constitute the application layer (MineralGPT), which realizes the mineral resources evaluation and prediction based on prior knowledge and language model.

2.2 Rule description and driving engine

The rule description language, the rule description, and the rule-drive engine within CoreGPT constitute the core components of MineralGPT. “G” stands for generative, content-oriented generation, “P” represents prior knowledge and its parsing and processing, and “T” signifies the transformation through model invocation based on rules that represent prior knowledge. Together, G, P, and T enable understanding based on prior knowledge to drive the invocation of different models to process input data and transform it into another form of required data. Specifically: 1) The rule description language employs keywords and grammar for general or particular category tasks. Its purpose is to formalize the expression of the content and requirements of tasks to be processed. 2) Based on the rule description language, the rule description transforms task content and requirements into a computer-understandable formal rule set. Experts and users construct this rule set according to the previously accumulated knowledge and experience or automatically extracted and generated by the computer through the rules defined by experts and users. The rule description can cover a variety of information or processing methods, including theorems, formulas, laws, and algorithms. 3) The rule-drive engine: The computer matches applicable subsets of rules from the rule set based on the current task content and requirements during the actual problem-solving process. The parsing and extraction of detailed information on the data, techniques, and methods for each rule generated from prior knowledge are accomplished by the rule parsing engine of CoreGPT. Subsequently, it matches corresponding computer processing modules and instructions (corresponding to the specific function of the core model, content model, and domain model in Fig. 1) and executes them to achieve the expected results. Through the cooperation of rule description language, rule description, rule-drive engine and various models, human experience can be transformed into computer executable instructions so that the computer can reason, make decisions and perform operations according to the rules defined in advance when solving practical problems.

Taking the extraction of Chinese geological named entities as an illustration, it becomes evident that the designated entities in geological data typically exhibit precise terminological suffixes. For instance, within the stratigraphic nomenclature entities, one encounters elements like boundary, system, unity, order, group, assembly, and section. Similarly, plates, synclines, anticlines, faults, discrepancies, and configurations characterize geological structures. Additionally, named entities such as rock masses, deposits, and ore bodies manifest analogous patterns. These specific tail words can be combined with prefix word items to signify distinct geological entities or occurrences. Exempli gratia: “Fengshan gold deposit” and “almond body structure”. Henceforth, it is discernible that the suffixes of such designated entities are predominantly fixed. Consequently, we adopt a method based on multiple regular rules(Deng *et al.*, 2021). By delineating the rule description language, constructing a comprehensive set of rules for recognizing generic Chinese geological named entities, developing a corresponding model for named entity recognition, and invoking a rule-driven engine, it is feasible to achieve compositional recognition of Chinese geological named entities.

2.3 Core model and model scheduling management

The foundational model of CoreGPT is constructed based on the rule description and driving engine of MineralGPT, which covers a variety of essential models to support the operation of the domain model for different aspects of geologic data processing. For instance, 1) File recognition conversion: identifies and converts various file formats to the required formats. 2) Format conversion Cleaning: cleans and converts data formats to ensure compliance with specified standards or norms. 3) Word Segmentation and grading: segments and grades text, categorizing terms by their importance or other characteristics. 4) Named entity recognition: identifies entities of specific significance in geological texts. 5) Feature recognition extraction: this process involves extracting key features from data, for example, identifying structural characteristics of geological documents and traces of mining on the earth's surface from geological remote sensing data(Deng *et al.*, 2023). 6) Text structure reconstruction (Deng *et al.*, 2022): converts geological data into Markdown format to standardize text structure. 7) Term weight calculation(Deng *et al.*, 2019): computes the weight of terms within texts to reflect their significance or relevance. 8) Text topic analysis: identifies themes or contents in texts by analyzing words, phrases, or topics, aiding in understanding the text's meaning and potential connections. 9) Image recognition understanding: this involves techniques such as image pre-processing, principal component analysis, and grading of anomaly information, for example, extracting vector information from geological maps or mineralization alteration information from remote sensing images (Deng *et al.*, 2011). 10) Spatial analysis: uses spatial analysis tools to study the spatial distribution and relationships of geological phenomena. 11) Knowledge graph construction: builds knowledge graphs in the field of geology, recording relationships and attributes among geological knowledge. 12) Machine learning: applies machine learning algorithms and techniques to learn features from geological data. 13) Model definition: defines and describes specific models or algorithms for geological data processing or analysis tasks. 14) Model parallelism: decomposes geological data processing or analysis tasks into multiple, concurrently running subtasks. 15) Model scheduling control: manages and controls the scheduling and execution of geological data processing or analysis tasks. 16) Model feedback optimization: optimizes and adjusts geological data processing or analysis models based on feedback from task execution. 17) Correlation analysis: analyzes the correlation between different attributes or variables in geological data, revealing their relationships and influencing factors. 18) Causal analysis: identifies causal relationships between different attributes or variables in geological data to understand their causal connections and mechanisms. 19) Entity relationship extraction: extracts relationships between entities from geological data. 20) Multi-angle reasoning: integrates multiple perspectives or viewpoints to reason and analyze geological data, achieving a more comprehensive and accurate understanding and conclusion. Such models may be developed using different programming languages and adhere to specific interface specifications.

The invocation of the core model by upper-level domain models presents diverse and intricate scenarios. For example, a domain model may invoke certain core models in parallel or sequentially. Concurrently, multiple domain models may invoke the same core model simultaneously, and a core model may need to dynamically adjust the number of parallel instances to support multiple invocation requests. As an illustration, when analyzing and processing geological texts, parallel models are employed to concurrently segment the text, recognize named entities, and grade terms. Model scheduling management becomes critical to ensure coherent operation between different models within MineralGPT. This management process encompasses complex tasks such as resource allocation, task assignment, and performance monitoring. Specifically, we have containerized the models using Docker. The models' inputs, outputs, parameters, as well as the execution sequence and mode between models, are rule-described and uniformly stored in a database. Data and parameters are transmitted, and models are initiated, monitored, and terminated via a WebAPI interface. The management of the model lifecycle within a microservices architecture is supported by Kubernetes and Istio. It aims to ensure that each model receives the appropriate computational resources and maintains a coordinated and unified operational state while handling various tasks. Therefore, we employ an efficient cloud-native microservices framework for managing and scheduling all models, ensuring the model systems can work together and achieve the best performance(Liu *et al.*, 2023) (CPU: Intel Xeon Gold 6238R @ 2.2GHz and Intel Xeon Silver 4210R @ 2.4GHz; GPU: NVIDIA RTX A500). This method provides a new potential support mechanism and technical system for identifying, extracting, and analyzing mineral resource information. This showcases the potential for automation and intelligence in mineral resource management and predictive evaluation.

The execution criteria and model scheduling strategies of the core model adhere to corresponding a priori rules based on a rule description language, and the rule-drive engine propels the execution and scheduling management of various core models. In our model, rules can include both univariate and multivariate variables, where variables can take various forms such as a single data name/data item or a list thereof, a model name, or a list of models to be executed in sequence. They could also be a code snippet capable of embedding algorithms, interface names, etc. The rule expressions are akin to logical expressions, containing variables, logical operators, execution priority symbols, mathematical operators, and regular expressions, among others. For example, when dealing with the "conversion of geological document formats into textual data" facing multi-conditional rules, we adopted the following strategy(Deng *et al.*, 2022) : To handle multi-conditional rules, i.e., rules containing multi-condition descriptive languages such as "and &&" or "or ||". Based on the characteristics of these multi-condition descriptive languages, we decompose the rule into multiple sub-rules and iterate through these sub-rules in sequence, evaluating each rule until all sub-rules have been processed. The specific algorithm implementation is as follows: 1) Acquire the multi-conditional rule R. 2) Process the multi-conditional rule R to determine whether it contains the control characters "and &&" or "or ||". 3) Use the control characters "and &&" or "or ||" as keywords to split the multi-conditional rule R into a list of sub-rules Rlist. 4) Iterate through the sub-rules list Rlist in sequence, reading and processing each sub-rule r until completion.

2.4 Content model and model interaction

The content model at the Interactive layer (InteractiveGPT) is established based on the foundation of the Core layer (CoreGPT), with their interactions occurring through mutual calls within the Interactive layer (InteractiveGPT). The content model generates various output-oriented contents such as maps, tables, reports, keywords, and prompts. Its implementation relies on the requirements of the input (results returned by the core model, domain model, and interactive model) and the desired content and format, all of which are governed by rule description. The content generation process is flexible, which can define the rule description according to the requirements and objectives of the application field, and then drive the content generation by the rule-drive engine. For example, when generating engineering geological survey reports, the content model can generate coherent and richly standardized reports based on input report templates and engineering geological survey information(Lei *et al.*, 2020). Similarly, when updating geological and mineralogical data, it can generate efficient maps and reports based on file associations, map styles, and topological relationships (Deng *et al.*, 2020). However, there are also these shortcomings in the modeling: 1) In practical applications, it is virtually impossible to exhaustively define rules because, even with computer or natural language processing technologies, we can only extract some specific and general rules, which may not be universally applicable; 2) For rules that are difficult to articulate, we currently embed them directly into specific models for encapsulation, which are then invoked by certain rules; 3) The complexity of managing many rules and models not only increases the system's structural complexity but also presents challenges in system operation and maintenance. The model interaction refers to the interaction with large language models (such as ChatGPT) and search engines (such as Baidu). It sends prompts to large language models and keywords to search engines to obtain results that meet the application requirements (text, pictures, pages), in which the content model generates prompts and keywords according to application requirements. With the help of a large language model based on large-scale data and computing power support and search engine interaction based on large-scale Internet public data support, we can obtain new knowledge beyond our limited data and various model capabilities. This process provides additional data supplementation for refining or optimizing model outputs related to multiple applications. Simultaneously, the results returned by the large language model and search engine must be read, extracted, and optimized before they can be used as inputs for a subsequent model. Also, the invocation of large language models and search engines, along with their invocation requisites and formats, result assessment patterns and criteria, and methods for outcome handling and optimization, are all implemented based on rule description language, rule description, and rule-drive engine.

2.5 Domain model of mineral resources evaluation and prediction

The domain model of the application layer (MineralGPT) is a complex and multifunctional system. It achieves a series of critical functionalities through the coordinated operation of several key components, including the rule-driven engine, core model, model scheduling management, content model, and model interactions. These functions include: 1) Mineral data updating: automatically acquiring and integrating the latest mineral data, including new exploration results, geological survey data, and developments in mineral resources. 2) Geological body information extraction: identifying and extracting specific geological body information from vast amounts of geological text data, such as rock types, stratigraphic structures, and mineralization zones. 3) Evaluation of metallogenic prospective area: analyzing geological, geochemical, and geophysical data to identify potential mineralization prospects and narrowing down these areas. 4) Mineral report understanding: parsing and understanding mineral-related reports, including geological survey reports and exploration reports. 5) Geological body information association: associating geological information from different sources, such as combining geological exploration data with geophysical data. This comprehensive integration of functionalities provides robust support for the assessment and prediction of mineral resources.

In the exemplification of evaluation of metallogenic prospect area, each stratum model is invoked to achieve the following progressively: 1) Core layer: Multi-source heterogeneous geological data for text format transformation (including format conversion, picture text recognition), format cleaning and structure reconstruction, word segmentation and geological named entity recognition, and term weighting calculation considering term classification and structural location characteristics. 2) Interaction layer: Based on the word segmentation and named entity optimization of large language model and search engine, standardized text and its corresponding word segmentation, named entity, structural location association table (or association graph) generation. 3) Application layer: Selection of geographical names and delineation in metallogenic prospective areas based on word association features, and evaluation of prospective area based on comprehensive indicator calculation(Liu, 2022). Specifically, the idea of the comprehensive index calculation and evaluation model of the prospective area is as follows.

1) Determine the number of practical terms: Through analyzing the actual term counts of each prospective area and the geological significance reflected by each term, it is observed that the weight values of terms ranked beyond the 200th position are significantly lower than those of the top-ranked terms (the ratio being less than 1%). Additionally, for terms exceeding 200, even adding one more term has a very minimal impact on the overall effect (less than 0.1%), essentially not significantly affecting the final outcome. Therefore, the first k terms (where k defaults to 200) are selected to participate in the calculation. If the actual number of terms is less than 200, the actual word count is used for the calculation.

2) Determine the correction coefficient for mineral deposits: The comparative relationships among the term weighting frequency of key deposit terms are computed within the range of effective term counts for each prospective area. The correction coefficient is calculated by an order of magnitude, and the correction coefficient is used to correct the cumulative term frequency through a divisional adjustment. The method for determining the correction coefficient is as follows: When the term weighting frequency of key deposits in the prominently ranked prospective areas differ by more than one order of magnitude, the correction factor is set to 1. When the difference is within one order of magnitude and close, the correction coefficient is set to 1+m (where m is the number of mineral deposits close in term weighting frequency and within one order of magnitude of the top-ranked deposit), indicating that m deposits collectively share all term weighting frequency. When the proximity is within one order of magnitude, the correction coefficient is set to 1+0.5n (where n is the number of mineral deposits close in term weighting frequency and within

one order of magnitude of the top-ranked deposit). When mineral deposit terms outside the prospective area are prominently ranked, the correction factor is increased by 2p (where p is the number of external mineral deposits) on the original basis.

3) Calculate the cumulative term weighting frequency: Within the effective term frequency range of each prospective area, the term weighting frequency of all terms is accumulated and calculated, and then the value is divided by the correction coefficient to obtain the cumulative term weighting frequency of the prospective area.

4) Obtain the maximum value of term weighting frequency: The maximum value of the term weighting frequency of each prospective area (ranking the first term weighting frequency) is used as a parameter for subsequent normalization.

5) Calculate the mean value of term weighting frequency: The cumulative term weighting frequency is used to divide the number of valid terms to obtain the mean value. This mean value expresses the amount of weight information carried by each term. Because the calculation range of each prospective area is different, the mean value has an apparent order of magnitude difference.

6) Calculate the information index: The primary weight coefficients for each term within the geological data document are consistent across prospective areas. However, the number of terms associated with different core keywords differs, resulting in a significant difference in the mean value of term weighting frequency. To mitigate differences across orders of magnitude, obtain the logarithm of the mean value based on ten (log10), yielding the information index for each prospective area.

7) Normalize the information index: Due to the difference in the calculation range, the cumulative term weighting frequency also appears to be cross-order of magnitude differences. Here, by dividing the maximum value of each prospect area, the term weighting frequency is roughly in the same range, and the normalized weight index is obtained.

8) Calculate the comprehensive index: The final evaluation index of the "comprehensive index" is obtained by multiplying the information index of each prospect area with the normalized weight index, which reflects the comprehensive characterization characteristics of the normalized associated terms of the prospective area.

9) Classification of prospective areas: The comprehensive index of prospective areas is divided into different grades according to a certain number of classifications based on the natural breakpoint method. The higher the comprehensive index, the higher the grade of the prospective areas, and conversely, the lower the comprehensive index, the lower the grade. The prospective areas with a close comprehensive index are classified into one grade,

thereby achieving the final rating of mineral exploration prospects based on the language model. The diverse computational procedures, methods, and parameters in the above process are all implemented through the rule description and realized using the rule-drive engine.

3 Optimization of prospecting targets for the Xiaoshan-Xiongershan area gold polymetallic deposit based on MineralGPT

3.1 Geological and mineral characteristics of the study area

The Xiaoshan-Xiongershan area is situated on the southern margin of the North China Craton, within a secondary tectonic unit characterized as a geological platform. Its crystalline basement consists of middle to deep metamorphic rock strata from the Taishan Formation. The overlying layers consist mainly of volcanic rocks from the Middle Proterozoic Xionger Group and sedimentary rocks from the Middle Proterozoic Guandaokou Group. The substratum of the Taihua Group exhibits multi-stage characteristics, profound metamorphism, and intense deformation. Conversely, the overlying strata are predominantly characterized by shallow-level ductile-brittle deformation. The Xiaoshan-Xiongershan ore cluster encompasses a series of small, medium, and large-scale polymetallic deposits.

The linear structures interpreted by remote sensing in the Xiaoshan-Xiongershan area gold polymetallic deposit are divided into three groups according to the strike. 1) NE-NNE trending fault structures: These constitute the principal ore-hosting and ore-controlling structures for gold and silver polymetallic deposits, serving as the predominant exploration indicators in the area. 2) Nearly SN trending linear structures: These structures, of smaller scale, are predominantly distributed in the western part of the Xiongershan area, specifically in the vicinity of Shagou. 3) NW-NWW trending linear structures: From south to north, it is intermittently distributed in a single or double row.

3.2 Processing of geological and mineral data oriented towards term association

The geological and mineral data of the Xiaoshan-Xiongershan area encompass a variety of document types, including geological maps, geological reports, rock and mineral identification reports, and scholarly literature. These are distributed across 542 directories, totaling 6018 files, with an aggregate size of approximately 6.68 GB. From the perspective of document quantities, the proportions of geological maps, geological reports, rock and mineral identification reports, and scholarly literature are 89.4%, 5.4%, 0.7%, and 4.5%, respectively. However, the proportions of text data from these sources, in terms of word count, are 2.7%, 87.5%, 0.4%, and 9.4%, respectively.

This indicates that our terms mainly originate from geological reports and scholarly literature. Among them, different types of geological data files exist in various formats, for example, most of the geological maps are stored in the MPJ format of MapGIS or the JPG format of the MPJ printout, and the reports are mostly stored in the DOC/DOCX format of Word, or the PDF format of the Word printout, or the PDF format of the scanning generation.

Many potential relationships exist between geological and mineral data, which are reflected in multiple levels such as files, terms, semantics and knowledge. 1) Files level: There are multi-dimensional associations between different geological files. For example, the MPJ (geological map engineering file) of MapGIS contains the layer files corresponding to WT, WL, and WP, establishing the inclusion relationship. In the directory where the MPJ file is located, there may be JPG files sharing the same filename as the MPJ file. Typically, these files represent images resulting from the print output of the MPJ geological map (the output relationship). 2) Terms level: There are correlations between the same nouns and language descriptions in different data. For example, the “Taihua Group” in different geological reports refers to the same stratigraphic combination (the homonymous relationship). Still, the stratigraphic lithology description of the “Taihua Group” in different reports may have different local details (the local difference relationship). 3) Semantics level: Different geological and mineral data have the same, similar, opposite, and other practical semantic features in expressing the same geological entity or geological phenomenon. For example, the stratigraphic thickness drawn on the geological map according to the scale is generally consistent with the stratigraphic thickness described in the geological report (the consistent relationship). However, subtle discrepancies cannot be ruled out (the semantic error relationship). Additionally, stratigraphic historical names in different reports, even if they differ, might share semantic consistency with current nomenclature (the synonymous semantic relationship). 4) Knowledge level: Geological knowledge from different sources strongly correlates with some aspects. For example, various geological reports consistently summarize the metallogenic geological conditions of the same deposit, which can be called the convergent relationship. Still, the knowledge in some reports is inevitably different from that of other sources, which can be called the divergent relationship.

Although the above four types of relationships exist in geological data, such connections are not directly manifested in the data. They necessitate human interpretation or algorithms designed by humans to be partially discerned. To extract fundamental features constituting various relationships within geological and mineral data in the study area (including but not limited to terms, named entities, parts of speech/types, term weighting frequency, and structures), we employ diverse models within the MineralGPT framework. These encompass file conversion models, text structure reconstruction models, named entity recognition models, hierarchical word segmentation models, and term weighting models, among others, to achieve this objective.

The steps are as follows: 1) The geological and mineral data is stored in the Hadoop big data platform environment, the Hadoop Distributed File System supported by the "Docker + Kubernetes" while maintaining its original directory structure. 2) Scanning and identifying geological and mineral data's file type and association relationship. 3) The diverse and heterogeneous geological data from various sources undergoes conversion into a text file format. For example, PDF/Word/Excel structures are transformed into Markdown format, while the vector map is converted into MIF/MID format using FME/MyFME. Employing Tesseract-OCR facilitates the identification of text within JPG/TIF files. 4) The Markdown files obtained by different conversion methods are standardized, and the document structure is reconstructed. 5) Word segmentation(Tang *et al.*, 2023; Guo *et al.*, 2024) and recognizing geologically named entities are performed on transformed and standardized textual data. 6) The word segmentation results are graded and the structural location characteristics are recorded to form a word file segmentation table, which records the information of different word segmentation (keywords and features) in other paragraphs of each file, encompassing details such as nomenclature, classification, grammatical attributes, and positional coordinates. Notably, each paragraph may feature multiple database entries chronicling diverse or analogous terms, with each term potentially occupying various positions across paragraphs. Each word in each paragraph may have multiple locations, and the number and location of each word in different paragraphs are different. The word segmentation summary table of other documents and research areas can be summarized through the statistics of the file segmentation table. 7) According to the term grading and structural position, the term grading weights, graded structural position weights, document paragraph association weights, document paragraph co-occurrence weights, and term composite weights are calculated, and finally, the term weighting frequency is obtained(Liu, 2022).

3.3 Association analysis of metallogenic favourability degree based on term weighting

In analyzing geological and mineral data within the research area, we reflect the differences in textual thematic representations of various elements by examining the term weighting frequency of specific terms in the word file segmentation table. The high rank of the term can reflect these differences, the structural position of the increased weights, and the close contextual connection. In essence, the more influential the feature, the more it is in a critical location, such as a headline section, and the closer the contextual connection, the higher the importance of the term in the text representation is indicated.

The association between various features in the geological and mineralogical data of the study area can be obtained through the relationship between feature word frequency and ranking, paragraph and term. The detailed steps are as follows: 1) The WordID of the current feature is obtained. 2) All paragraphs associated with the current WordID are obtained. 3) The term frequency of different features across all pertinent paragraphs are tallied and subsequently ranked. 4) A certain number of terms with the higher term frequency are used as associated features. Through these methods, we analyze the association characteristics of the study area from various aspects, such as stratigraphy, tectonics, rock mass, age, and material source. This endeavor aims to unearth information pertinent to mineralization.

Illustrating with an example of term weighting frequency association analysis focusing on the "diagenesis" and "mineralization" in the study area, we input the core keywords "diagenesis" and "mineralization" for term weighting frequency association query. The respective term associations are detailed in Table 1 and Table 2.

Table 1. Keyword term weighting frequency correlation characteristics of "diagenesis"

First-level terms and second-level terms sorted together					First-level terms sorted				
Order	WordID	Text	Levels	Weights	Order	WordID	Text	Levels	Weights
1	1123	Rock granite	2	3659.89	1	12659	Taihua group	1	2397.92
2	1094	Gold mine	2	3111.54	2	6089	Xionger group	1	2254.74
3	2736	Magma	2	3102.28	3	15562	Small porphyry body	1	331.21
4	1195	Porphyry	2	3014.00	4	15871	Wuzhangshan rock mass	1	286.70
5	12659	Taihua group	1	2397.92	5	16658	Blasting breccia body	1	272.42
6	6089	Xionger group	1	2254.74	6	16053	Granite body	1	231.42
7	2700	Breccia	2	1964.29	7	24602	Laoliwan rock mass	1	196.87
8	4112	Igneous rock	2	1830.09	8	1087	Brittle fracture	1	191.76
9	1219	Invasion	2	1215.78	9	16390	Ore-bearing structure	1	190.61
10	1240	Development	2	1175.79	10	14813	Huashan rock mass	1	190.41
11	2706	Quartz	2	939.13	11	18029	Mineralized Porphyritic Intrusion	1	186.66
12	156	Mineralization	2	760.45	12	18246	Tuoheyu rock mass	1	186.46
13	11830	Platinum	2	703.52	13	16408	Breccia body	1	185.52
14	1298	Gneiss	2	701.80	14	1205	Proterozoic	1	184.51
15	2864	Volcanic rock	2	697.57	15	19158	Qiyugou Mining Field	1	180.89
16	93	Igneous magmatic rock	2	605.23	16	12976	Structural fractures	1	143.25
17	10577	Andesite	2	564.48	17	16102	Jinshanmiao rock mass	1	139.85
18	1891	Faults	2	564.19	18	15849	Machaoying fault	1	137.27
19	92	Strata	2	524.52	19	15589	Qiyugou mining area	1	136.44
20	5590	Deep-seated rock	2	502.94	20	17114	Explosive breccia type gold deposit	1	131.56
21	2716	Pyrite	2	477.97	21	45002	Constitute metamorphic core complex structure	1	130.72
22	8376	Gold deposit	2	472.52	22	15860	Ore-conducting structure	1	102.92
23	1261	Uplift	2	460.29	23	42880	Waifangshan-Xushan Formation	1	102.77
24	4144	Mineralized rock mass	2	415.56	24	16022	Machaoying deep fault	1	102.37
25	15590	Qiyugou Mine	2	382.25	25	16842	Leimengou porphyry body	1	100.95

26	94	Metamorphic rock	2	381.20	26	16421	Shallow-ultrashallow acidic small rock mass	1	100.83
27	837	Basin	2	367.30	27	12486	Complex rock mass	1	100.72
28	3596	Hornblende	2	336.97	28	1203	Archean	1	100.62
29	15562	Small porphyry body	1	331.21	29	17353	Mineralized Porphyritic Body	1	99.28
30	927	Deposition	2	330.42	30	15872	Shallow phase granite porphyry-cryptoexplosive breccia small rock mass	1	99.09

Table 2. Keyword term weighting frequency correlation characteristics of "mineralization"

First-level terms and second-level terms sorted together					First-level terms sorted				
Order	WordID	Text	Levels	Weights	Order	WordID	Text	Levels	Weights
1	1094	Gold mine	2	742921.08	1	6089	Xionger group	1	118084.96
2	2736	Magma	2	210583.51	2	12659	Taihua group	1	115865.46
3	2716	Pyrite	2	162353.67	3	16355	Metallogenic structure	1	25724.96
4	2706	Quartz	2	152283.57	4	1205	Proterozoic	1	17218.70
5	2700	Breccia	2	132599.50	5	1203	Archean	1	13275.42
6	1123	Rock granite	2	126935.74	6	935	North China platform	1	13033.90
7	104	Minerals	2	124467.19	7	15849	Machaoying fault	1	11312.10
8	6089	Xionger group	1	118084.96	8	15679	Geological structure of the southern margin of the North China Block	1	9849.57
9	12659	Taihua group	1	115865.46	9	16408	Breccia body	1	7873.00
10	156	Mineralization	2	110198.93	10	1545	Middle Proterozoic	1	7869.19
11	1195	Porphyry	2	99629.31	11	22067	Xiaoshan mineralization cluster area	1	7868.61
12	8376	Gold deposit	2	87333.22	12	14103	Shanggong gold deposit	1	7868.41
13	1259	Surrounding rock	2	68884.29	13	14813	Huashan rock mass	1	7629.38
14	13947	Shanggong gold mine	2	67400.18	14	16658	Blasting breccia body	1	7623.82
15	11830	Molybdenum mine	2	66181.67	15	17804	North China plate	1	7385.27
16	3365	Galena	2	63460.32	16	14256	Guandaokou group	1	7377.05
17	4528	Veins	2	61502.16	17	15670	South China ancient plate	1	7374.47
18	106	Anomaly	2	51904.73	18	8406	Taiguyu	1	7139.12
19	3366	Thorsphalerite	2	41816.71	19	16053	Granite body	1	6892.07
20	15617	Qiyugou gold mine	2	36904.63	20	15501	Xiongershan mineralization cluster area	1	6637.11
21	1891	Faults	2	36162.62	21	14255	Luanchuan group	1	6399.75
22	3285	Bronze mine	2	33948.05	22	22345	Shanggong structure in western Henan	1	6157.21
23	2864	Volcanic rock	2	31986.36	23	16886	Mineral-controlled fracture	1	6153.91
24	1219	Invasion	2	30741.98	24	17114	Explosive breccia type gold deposit	1	6147.13
25	3361	Lead-zinc mine	2	30258.02	25	16502	Qiyugou gold deposit	1	6146.85
26	2441	Calcite	2	28790.34	26	22429	Western Henan mineralization cluster area	1	6141.46
27	1422	Confession	2	27311.94	27	1087	Brittle fracture	1	5899.15
28	93	Magma Rock	2	26327.76	28	15562	Small porphyry body	1	5653.14
29	837	Basin	2	26076.25	29	16813	Deep and large fracture	1	5650.26
30	16355	Metallogenic structure	1	25724.96	30	16044	Silver lead deposit	1	5408.27

Table 1and Table 2 are the term weighting frequency ranking results of the first 30 terms closely related to the "diagenesis" and "mineralization" (Weights is listed as the term weighting frequency of the terms). Table 1 is the ranking result of the first-level and second-level terms, and the right sequence of Table 1 is the ranking result of the first-level terms. From Table 1 and Table 2, it can be seen that the strata in the area are mainly the Taihua group and Xionger group. The rock mass in the area is developed, such as Huashan rock mass, Wuzhangshan rock mass, small porphyry body, and the diagenesis and mineralization are closely related to the structure.

3.4 Classification of prospecting areas based on term weighting

(1) Division of prospective areas

Based on the geological characteristics of the Xiaoshan-Xiongershan area gold polymetallic deposit, as well as various mineralization information features, and in accordance with the principles of target area delineation and the direction of finding minerals, the term weight values ranking of prospective areas was obtained through big data retrieval. This was combined with the manual preliminary judgment was carried out to determine whether the mineralization controlling factors and target area circling principles were satisfied. Finally, these prospective areas were classified into eight potential mineralization prospective areas. 1) Xiaoshan mineralization cluster area: Dafangshan gold-silver metallogenic prospective area, Shenjiayao gold-silver metallogenic prospective area, and Zhaojiagudong gold-silver metallogenic prospective area. 2) Xiongershan mineralization cluster area: Shagou-TieliuPing silver-lead prospective area, Shanggong-Qinggangping gold metallogenic prospective area, Dashimengou-Qiyugou gold metallogenic prospective area. 3) Periphery of Xiongershan mineralization cluster area: Beiling-Huaishuping gold metallogenic prospective area, Kangshan-Shizimiao gold metallogenic prospective area. The boundaries of the polygons in the Fig. 2 are predefined based on existing geological data and historical maps.

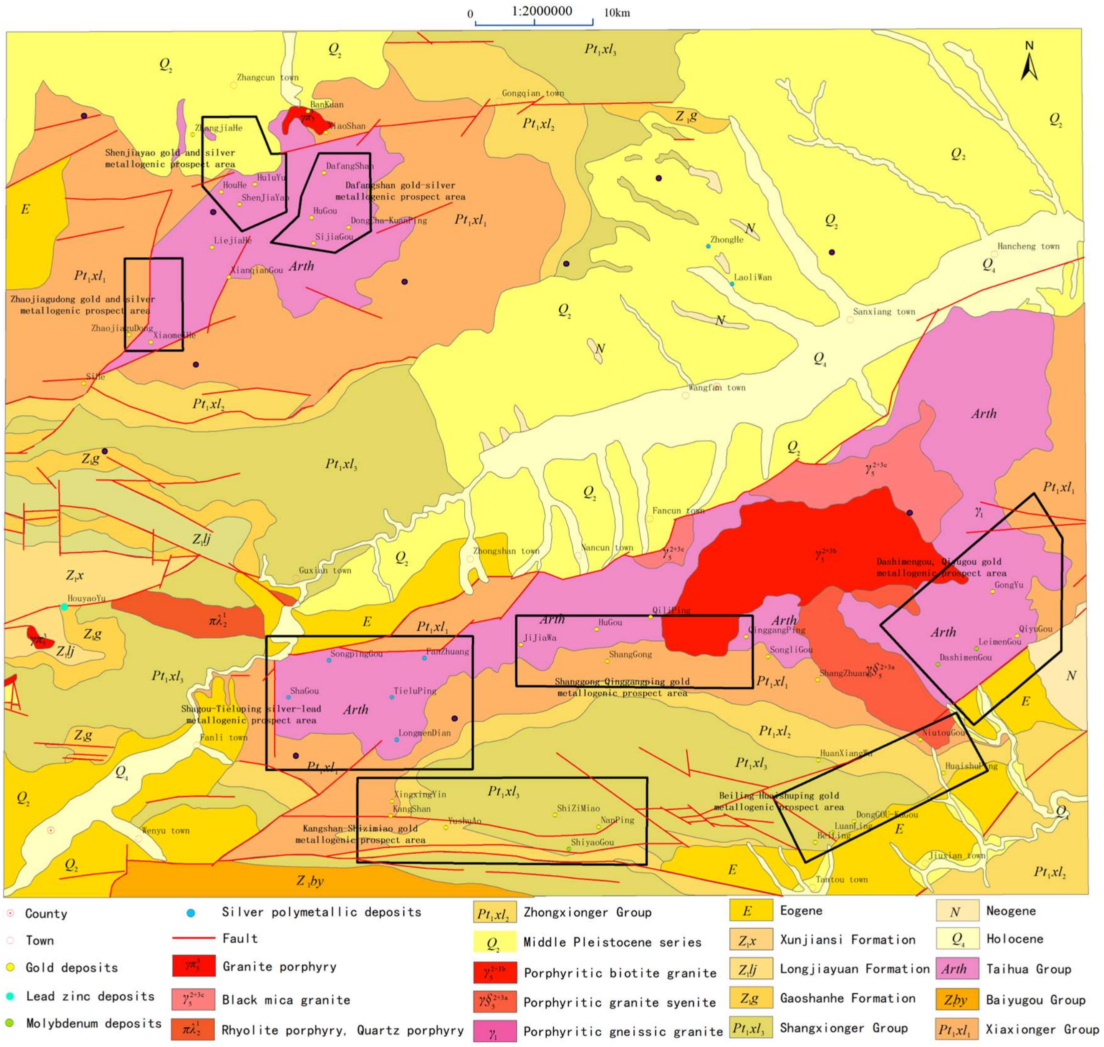

Fig. 2 Division of prospective areas

(2) Analysis of the characteristics of high-weight terms in prospective areas

The associated features of term weighting frequency can be obtained by inputting core features of the prospective area. Taking Dafangshan gold-silver metallogenic prospective area and Shenjiayao gold-silver metallogenic prospective area as examples, the term frequency ranking of the top 30 core terms is obtained by inputting "Dafangshan" and "Shenjiayao" as shown in Table 3 below.

Table 3. Keyword term weighting frequency correlation characteristics of "Dafangshan" and "Shenjiayao"

Dafangshan					Shenjiayao				
Order	WordID	Text	Levels	Weights	Order	WordID	Text	Levels	Weights
1	95	Structure	4	1166.70	1	12780	Shenjiayao gold mine	2	3745.26
2	16556	Dafangshan gold mine	2	831.01	2	95	Structure	4	2552.30
3	4528	Veins	2	746.06	3	836	Fracture	4	1277.17

4	836	Fracture	4	524.47	4	12659	Taihua group	1	1272.37
5	12659	Taihua group	1	344.53	5	4528	Veins	2	1079.92
6	2706	Quartz	2	212.04	6	3361	Lead-zinc mine	2	824.61
7	6089	Xionger group	1	170.93	7	156	Mineralization	2	788.34
8	13835	Silver-lead mine	2	166.61	8	797	Rock mass	4	694.01
9	2700	Breccia	2	124.89	9	2706	Quartz	2	635.24
10	839	Fracture structure	2	120.40	10	6089	Xionger group	1	580.55
11	243	Mineral control	4	120.14	11	2716	Pyrite	2	498.91
12	1195	Porphyry	2	112.13	12	1195	Porphyry	2	486.44
13	16554	Dafangshan structure	1	107.38	13	3365	Galena	2	401.51
14	17889	Quartz vein type gold deposit	2	94.91	14	3366	Thorsphalerite	2	302.10
15	1123	Rock granite	2	92.49	15	3285	Bronze mine	2	299.79
16	3361	Lead-zinc mine	2	92.38	16	1123	Rock granite	2	297.53
17	2736	Magma	2	77.86	17	1259	Surrounding rock	2	286.09
18	1259	Surrounding rock	2	64.26	18	2864	Volcanic rock	2	253.40
19	3365	Galena	2	63.47	19	1087	Brittle fracture	1	252.98
20	12442	Gold vein	2	62.39	20	1101	Contact	4	247.16
21	1201	Paleozoic	1	61.77	21	1205	Proterozoic	1	238.87
22	93	Igneous magmatic rock	2	60.95	22	1326	Overlapping	4	235.24
23	17024	Gold and silver deposit	1	59.79	23	11830	Molybdenum mine	2	201.29
24	3285	Bronze mine	2	59.22	24	2736	Magma	2	198.87
25	1087	Brittle fracture	1	59.02	25	839	Fracture structure	2	198.75
26	773	Skarn	2	57.93	26	26881	Shenjiayao group	1	195.16
27	2428	Turquoise	2	57.63	27	8406	TaiguYu	1	190.07
28	14813	HuaShan rock mass	1	56.60	28	2700	Breccia	2	189.41
29	935	North China platform	1	55.88	29	2428	Turquoise	2	156.90
30	16044	Silver-lead deposit	1	55.50	30	10509	Taihua rock group	1	154.92

Synthesizing the associated features of the eight metallogenic prospective areas reveals the following: 1) Each prospective area conforms to most delineation conditions, including stratigraphy, structure, igneous rock, and more. 2) The values of term weighting frequency in each prospective area vary significantly, closely related to the correlation between terms.

(3) Calculation of comprehensive index of prospective area based on comprehensive term weighting

Based on the comprehensive index calculation and evaluation model for prospective areas (section 2.5), the final evaluation indicators are obtained as shown in Table 4 (comprehensive index). The comprehensive index reflects the normalized comprehensive characteristics of the associated terms in the prospective areas. According to the comprehensive index calculation results for prospective areas and the principles of target area delineation, areas with high comprehensive indices and the potential for discovering new large ore deposits are classified as the A mineralization prospective areas. Areas with a moderate comprehensive index and the potential for finding medium or medium-large ore deposits are classified as the B mineralization prospective areas. The comprehensive index is low, and due to the limitation of surrounding rock, magmatic activity, and tectonic conditions, it is only possible to continue to find small and medium-sized deposits, which are classified as the C metallogenic prospect area.

Table 4. Comprehensive index calculation for the Xiaoshan-Xiongershan area gold polymetallic deposit

Target name	Xiaoshan			Xiongershan			Peripheral of Xiongershan	
	Dafangshan	Shenjiayao	Zhaojiagudong	Shagou-Tieluping	Shanggong-Qinggangping	Dashimengou-Qiyugou	Beiling-Huaishuping	Kangshan-Shizimiao
Count the number of valid terms used	108	200	30	200	200	200	124	200
The correction coefficient	1	1	1	2	1	1	1.5	3.5
Term weighting frequency cumulation	15165.24	27563.53	402.41	236727.9	881064.8	777093.6	3002.55	21930.76
Term weighting frequency maximum value	2444.15	3745.26	104.18	43043.31	210277.3	144902.4	495.92	7417.24
Term weighting frequency mean value	140.42	137.82	13.41	1183.64	4405.32	3885.47	24.21	109.65
Term information index	2.15	2.14	1.13	3.07	3.64	3.59	1.38	2.04
Normalization weight index	6.2	7.36	3.86	5.5	4.19	5.36	6.05	2.96
Comprehensive index	13.32	15.74	4.36	16.9	15.27	19.25	8.38	6.03
Target area classification	A	A	C	A	A	A	B	C

3.5 Evaluation of metallogenic favourability degree based on ChatGPT

(1) Experimental design and results of prompts for metallogenic favorable degree in the prospective area

ChatGPT is a language model based on the Generative Pre-train Transformer model, which the OpenAI company developed. It is one of the largest open language models in terms of users. Using the template "Henan province * * * * prospective area * * * * prospective area...... mineralization favorability difference", by sequentially inputting different query prompts into the ChatGPT dialogue, we can obtain information on the differences in metallogenic favorability for other areas. Taking "Dafangshan", "Shenjiayao", and "Zhaojiagudong" prospective areas as examples, the most helpful feedback results obtained through multiple queries are as follows: "(1) Dafangshan gold-silver metallogenic prospect area: It is located in the southwest of Nanyang City, Henan Province, and belongs to the southern section of the Taihang Mountains. The geological structure of the area is complex and the rock types are diverse, mainly metamorphic rocks and volcanic rocks. The mineralization is magmatic-hydrothermal and metamorphism, and gold and silver minerals are primarily distributed in quartz veins and quartz vein alteration zones. The area has a highly metallogenic favourability degree and a high development potential. (2) Shenjiayao gold-silver metallogenic prospect area: It is located in the southwest of Nanyang City, Henan Province, adjacent to the Dafangshan gold-silver metallogenic prospect area. The geological structure of this area is simple, and the rock type is mainly metamorphic. The mineralization is primarily magmatic-hydrothermal and metamorphism. Gold and silver minerals are mainly distributed in quartz veins and alteration zones. The metallogenic favorable degree of this area is relatively large, but the development potential is relatively small compared with the Dafangshan gold-silver metallogenic prospect area. (3) Zhaojiagudong gold-silver metallogenic prospect area: It is located in the southwest of Nanyang City, Henan Province, and belongs to the southern section of the Taihang Mountains. The geological structure of this area is simple, and the rock type is mainly metamorphic. The mineralization is primarily magmatic-hydrothermal and metamorphism. Gold and silver minerals are mainly distributed in quartz veins and alteration zones. The metallogenic advantage of this area is small, and the development potential is relatively small."

According to the above method, through multiple queries, a comparative text similar to the difference in metallogenic prospect between other prospective areas can be obtained.

(2) Results interpretation and grading evaluation

In the feedback text, the contrasting terms in the descriptions of "metallogenic favourability degree" and "development potential" can serve as criteria for discriminating differences in the prospective metallogenic favourability degree of the exploration areas. For example, in the statement "1) Dafangshan gold-silver metallogenic prospect area: ……The area has a higher metallogenic favourability degree and a high development potential." the terms "higher" and "high" reflected the metallogenic favorability and development potential. The results of multiple queries are summarized as Table 5.

Table 5. The summary of prospecting prediction query results based on the ChatGPT

Query serial	Prospective area	Metallogenic favourability degree	Development potential	Result
1	Dafangshan	Higher	High	Dafangshan > Shenjiayao > Zhaojiagudong
	Shenjiayao	Larger	Smaller	
	Zhaojiagudong	Smaller	Smaller	
2	Shagou-Tieluping	Higher	Better	Shagou-Tieluping≈Shanggong-Qinggangping > Dashimengou-Qiyugou
	Shanggong-Qinggangping	Higher	Better	
	Dashimengou-Qiyugou	Lower	Certainly	
3	Beiling-Huaishuping	Better	Higher	Beiling-Huaishuping > Kangshan-Shizimiao
	Kangshan-Shizimiao	General	General	
4	Shenjiayao	Higher	Better	Shenjiayao≈Dashimengou-Qiyugou > Beiling-Huaishuping
	Dashimengou-Qiyugou	Higher	Better	
	Beiling-Huaishuping	Lower	Certainly	
5	Zhaojiagudong	Higher	Larger	Zhaojiagudong≈Kangshan-

	Beiling-Huaishuping	Lower	Smaller	Shizimiao > Beiling-Huaishuping
	Kangshan-Shizimiao	Higher	Larger	

From Table 5 of the “Metallogenic favourability degree” and “Development potential” two columns, can be deduced that each query results in different prospective area in the comparison of the relationship between the “result” column, and then comprehensive the “results” of 5 inquiries are summarized as follows: Dafangshan≈Shagou-Tieluping ≈Shanggong-Qinggangping>ShenjiaoYao≈Dashimengou-Qiyugou>Zhaojiagudong≈Kangshan-Shizimiao≈ Beiling-Huaishuping. Based on this inference, the ChatGPT feedback text and manual summarization results are classified into three categories (ABC), denoted as ChatGPT*, and compared with the comprehensive index of Table 4 as follows Table 6.

Table 6. Comparison of evaluation results

Order	Mineralization cluster area	Prospective area	ChatGPT*	Comprehensive index	Target classification	Expert evaluation results
1	Xiaoshan	Dafangshan	A	13.32	A	A
2		Shenjiayao	B	15.74	A	A
3		Zhaojiagudong	C	4.36	C	C
4	Xiongershan	Shagou-Tieluping	A	16.90	A	A
5		Shanggong-Qinggangping	A	15.27	A	A
6		Dashimengou-Qiyugou	B	19.25	A	A
7	Peripheral of Xiongershan	Beiling-Huaishuping	C	8.38	B	B
8		Kangshan-Shizimiao	C	6.03	C	C

4 Analysis and discussion

4.1 Analysis of optimization results of prospecting target area

From the perspective of prior knowledge conversion, this paper uses the metallogenic prospect evaluation model of MineralGPT based on term weighting frequency calculation to classify and grade the prospect areas and analyze and evaluate the critical prospecting target area in detail. The research findings indicate that rule description and driving engine demonstrate commendable performance in computer utilization, capable of discerning metallogenic relationships and evaluating mining areas. This substantiates the efficacy of knowledge-driven patterns. By integrating prospective area based on term weighting frequency sorting and expert judgment from existing data, we ascertain that the selected prospecting target area aligns closely with the expert assessment method. This elucidates that the prospecting method of the metallogenic prediction model based on MineralGPT is feasible.

4.2 Validity evaluation of prior transformation model

The above experimental results show that the MineralGPT model can effectively use prior knowledge to extract and integrate metallogenic data information related to mineral resources from multi-source geological data. This process is not only the extraction of information but also the intelligent integration of geologic knowledge, and better results in mineral resources evaluation and prediction have been achieved. As shown in Table 6, the classification results based on the term weighting comprehensive index target area are consistent with the results found on expert experience prospecting. The expert experience prospecting method is based on previous work conducted in the area, relying on historical literature. This indicates that using the metallogenic prospect evaluation model in the MineralGPT is effective. Simultaneously, this approach can extract information from existing geological documents, significantly streamlining the time required for information extraction and enhancing the efficiency of mining geological data information.

Table 6 shows that the results from ChatGPT* are partly the same based on the term weighting comprehensive index for target area classification. Further method comparison and evaluation are detailed in Table 7 below:

Table 7. Method evaluation comparison

Evaluation perspective		Term weighting comprehensive index	ChatGPT*
Result	Effectiveness	Closer to expert judgment	Roughly comparable to general knowledge
	Availability	The numerical results can be directly used	Text results need to be manually summarized
Condition	Data	Mineralization cluster area	Large-scale data
	Calculation power	Stand-alone/small clusters	Large-scale computing power
Cost	Premise	None	Appropriate prompt word
	Resource	General	Ultra-high
Other	Manpower	Very little	General
	Expansion	Freedom	None

4.3 Necessity of introducing language model

The language model has been an essential innovation in artificial intelligence in recent years. It has achieved great success in the field of natural language processing and information processing. Mineral resource exploration projects usually involve massive amounts of geological, geophysical, geochemical, and remote sensing data. The scale of these data is vast, including a large amount of geological literature, measurement data, drilling information, etc. Traditional data processing and analysis methods may be unable to process such large-scale data effectively. Still, language models can process large-scale text data, which can help better manage and utilize these data.

Furthermore, transformation models based on prior knowledge typically rely on text sources such as scientific literature and geological reports. By harnessing the capabilities of large-scale language models, intelligent extraction and analysis of textual information can be achieved, enabling a more profound exploration of knowledge and the identification of potential correlations among diverse datasets. This provides robust support for comprehensive analysis, enhancing efficiency and accuracy in mineral resource exploration projects. Through language models, we will be able to comprehend and leverage textual information more comprehensively, thereby propelling the development and advancement of the field of mineral resource exploration. Hence, it is necessary to integrate language models in mineral resource evaluation and prediction.

4.4 Potential application prospects and limitations

The generative prior transformation model for mineral resource evaluation and prediction has good potential application scenarios, which can help the exploration team locate the possible mineralized bodies more accurately. By analyzing geological literature and expertise and combining large-scale data processing and natural language processing techniques, this method can provide a high-quality candidate list of target areas, saving time and resources. If the generative prior transformation model for mineral resource evaluation and prediction is combined with ChatGPT in the future, that is, the method is embedded into the ChatGPT large language model, the accuracy of mining area prediction can be improved. At the same time, besides mineral resources exploration, this method also has potential multi-domain applications, providing support for decision-making in different industries.

However, it should also be noted that the effectiveness of the model method is highly dependent on the quality and availability of data. Inaccurate or incomplete geological data, literature information limitations, and data acquisition difficulties may affect the accuracy of the preferred results. At the same time, there is also a need for how to finely and quantitatively delineate the target area. While it is possible to obtain quantitative assessments for specific areas, the question of effectively synthesizing and categorizing these scores warrants consideration.

In the future, we will consider embedding MineralGPT or its core functionalities and methods into various mineral resource platforms under the premise of permissible conditions, such as the Exploration Information Systems (EIS), the China Geological Cloud, or other similar systems, to enhance the capabilities of such systems.

5 Conclusion

In this study, we proposed a MineralGPT framework in mineral resources evaluation and prediction, which covers the core driving layer of the a priori transformation model and other vital components. Through this framework, we have successfully realized the intelligent analysis and information extraction of large-scale geological text data, providing a new data processing and prediction method for mineral resource exploration. For the optimal selection of the mineral prospecting target area, we designed the optimization model of the prospecting target area in the mineralization cluster area based on term weighting. This model integrates prior information transformation and natural language processing techniques, enabling the extraction of valuable information from geological texts. The results show that the performance of the optimization model of prospecting target area based on term weighting not only exceeds the traditional natural language processing model, such as ChatGPT, but also is highly consistent with the qualitative evaluation of experts in the field, which verifies its effect in the optimization of the prospecting target area. This study has brought innovative ideas and methods to the field of mineral resources exploration. We provided a new, data-driven approach by combining prior knowledge with large-scale text data. Through applying the MineralGPT framework, prior knowledge and natural language processing technology are effectively integrated, which provides strong support for metallogenic prediction. In the future, the performance and stability of the optimization model of prospecting target area in mineralization cluster area based on term weighting will be further improved, and its application scope will be expanded.

Acknowledgments

We thank the anonymous reviewers for their constructive suggestions to help us improve the manuscript of this paper. This research was funded by the National Natural Science Foundation of China (Nos. 42172330), the 2018 Henan Land and Resources Research Project (Grant Number: [2018]98-17),2021Henan Natural Resources Research Project (Grant Number: [2021]157-12) and High Resolution Satellite Project of the State Administration of Science, Technology and Industry for National Defense of PRC(No.80-Y50G19-9001-22/23).

Authorship contribution statement

Zhiyong Guo: methodology, software development, formal analysis, and writing - original draft. Jiqiu Deng: conceptualization, methodology, funding acquisition, writing, and supervision. Wenyi Liu: software, formal analysis, and writing.

Availability of data and material

The datasets generated during the current study are not publicly available due to a confidentiality agreement.

Declarations

Conflict of Interest The authors have no competing interests to declare that are relevant to the content of this article.

Reference

Abedi, M., Norouzi, G.H., Torabi, S.A., (2013). Clustering of mineral prospectivity area as an unsupervised classification approach to explore copper deposit. *Arabian Journal of Geosciences* 6, 3601-3613.https://doi.org/10.1007/s12517-012-0615-5

Carranza, E.J.M., Laborte, A.G., (2016). Data-driven predictive modeling of mineral prospectivity using random forests: A case study in Catanduanes Island (Philippines). *Natural Resources Research* 25, 35-50.https://doi.org/10.1007/s11053-015-9268-x

Chamrar, A., Oujidi, M., El Mandour, A., Jilali, A., (2019). 3D geological modeling of Gareb-Bouareg basin in northeast Morocco. *Journal of African Earth Sciences* 154, 172-180.https://doi.org/10.1016/j.jafrearsci.2019.03.023

Chang, L., Zhu, Y., Zhang, G., Zhang, X., Hu, B., (2018). Spatial correlation analysis of mineral resources information. *Acta Petrologica Sinica* 34, 314-318.https://www.sciengine.com/APS/doi/10.0000/2c8991fd97914774bd48db523a69dd97

Chen, J., Chen, Y., Wang, Q., (2008). Study on synthetic informational mineral resource prediction using GIS—a case stuay iIn Chifeng region,Inner Mongolia,China. *Earth Science Frontiers*, 18-26.https://doi.org/10.1016/S1872-5791(08)60035-4

Chen, M., Luo, X., Zhu, Y., Li, Y., Zhao, W., Wu, J., (2020). An apriori-based learning scheme towards intelligent mining of association rules for geological big data.https://doi.org/10.32604/iasc.2020.010129

Cheng, Q., (2006). Singularity-generalized self-similarity-fractal spectrum (3S) models. *Earth Science–Journal of China University of Geoscience* 31, 337-348.http://www.earth-science.net/en/article/id/1555

Cheng, Q., (2007). Mapping singularities with stream sediment geochemical data for prediction of undiscovered mineral deposits in Gejiu, Yunnan Province, China. *Ore Geology Reviews* 32, 314-324.https://doi.org/10.1016/j.oregeorev.2006.10.002

Deng, J., Dong, W., Guo, Y., Chen, X., Zhou, R., Liu, W., (2023). A Novel Remote Sensing Image Enhancement Method, the Pseudo-Tasseled Cap Transformation: Taking Buildings and Roads in GF-2 as an Example. *Applied Sciences* 13, 6585.https://doi.org/10.3390/app13116585

Deng, J., Li, C., Fang, Q., Lu, F., (2020). Key technology of intelligent matching and updating reserve data of mineral map. *Journal of Central South University (Science and Technology)* 51(07), 1902-1912.https://doi.org/10.11817/j.issn.1672-7207.2020.07.016

Deng, J., Lu, F., Liu, W., Li, C., He, M., (2019). Method and device for obtaining field document lexical item hierarchical weight, https://patents.google.com/patent/CN111079426A/en

Deng, J., Lu, F., Liu, W., Li, C., He, M., (2021). A method and apparatus for extracting geological named entities, China patent. URL https://www.zhangqiaokeyan.com/patent-detail/061204672779.html.https://patents.google.com/patent/WO2013086998A1/en

Deng, J., Xie, Y., Zhang, B., Mao, X., (2011). The Extraction of the Manganese Mineralization Alteration Information from the ETM+ Image and Ore Prognosis. *Remote Sensing for Land & Resources*, 102-105.http://en.cgsjournals.com/article/id/gtzyyg_gtzyyg201101020?viewType=HTML

Deng, J., Zou, Y., Xia, C., (2022). Standardization method of textual geological data in Markdown format. *Journal of Geology* 46, 120-135.https://qikan.cqvip.com/Qikan/Article/Detail?id=7107812297 (10.3969 /j.issn.1674-3636.2022.02.002)

Enkhsaikhan, M., Holden, E.-J., Duuring, P., Liu, W., (2021). Understanding ore-forming conditions using machine reading of text. *Ore Geology Reviews* 135, 104200.https://doi.org/10.1016/j.oregeorev.2021.104200

Filchev, L., Pashova, L., Kolev, V., Frye, S., (2021). Challenges and Solutions for Utilizing Earth Observations in the" Big Data" era. *arXiv preprint arXiv:2108.08886*

Gao, Y., Zhang, Z., Xiong, Y., Zuo, R., (2016). Mapping mineral prospectivity for Cu polymetallic mineralization in southwest Fujian Province, China. *Ore Geology Reviews* 75, 16-28.https://doi.org/10.1016/j.oregeorev.2015.12.005

Guo, Z., Deng, J., Zou, Y., Tang, Y., (2024). A hybrid method of combination probability and machine learning for Chinese geological text segmentation. *Computers & geosciences* 183, 105512.https://doi.org/10.1016/j.cageo.2023.105512

He, B., Cui, Y., Chen, C., Chen, J., (2011). Geology Spatial Data Mining Method for Regional Metallogenic Prediction. *Advances in Earth Science* 26, 615-623.http://www.adearth.ac.cn/EN/10.11867/j.issn.1001-8166.2011.06.0615

Lei, Y., Deng, J., Lin, J., Dick, J.M., Lessani, M.N., Liu, C., (2020). Research of Automatic Generation for Engineering Geological Survey Reports Based on a Four-Dimensional Dynamic Template. *ISPRS International Journal of Geo-Information* 9, 496.https://doi.org/10.3390/ijgi9090496

Liu, L., Deng, J., Tang, Y., (2023). A Dynamic Management and Integration Framework for Models in Landslide Early Warning System. *ISPRS International Journal of Geo-Information* 12, 198.https://doi.org/10.3390/ijgi12050198

Liu, W., 2022. Optimization of Exploration Targets and Big Data Analysis for Gold Polymetallic Deposits in Xiaoshan-Xiongershan Area. Central South University.(in Chinese with English abstract)

Liu, X., Zhou, Y., (2019). Application of association rule algorithm in studying abnormal elemental associations in the Pangxidong area in western Guangdong Province. *Earth Science Frontiers* 26, 125-130.https://doi.org/10.13745/j.esf.sf.2019.5.19

Martin, L., Perron, G., Masson, M., Milkereit, B., 2007. Discovery from 3D visualization and quantitative modelling, Proceedings of exploration, pp. 543-550

Oh, H.-J., Lee, S., (2010). Application of artificial neural network for gold–silver deposits potential mapping: A case study of Korea. *Natural Resources Research* 19, 103-124.https://doi.org/10.1007/s11053-010-9112-2

Paasche, H., Eberle, D.G., (2009). Rapid integration of large airborne geophysical data suites using a fuzzy partitioning cluster algorithm: a tool for geological mapping and mineral exploration targeting. *Exploration Geophysics* 40, 277-287.https://doi.org/10.1071/EG08028

Singer, D.A., (1993). Basic concepts in three-part quantitative assessments of undiscovered mineral resources. *Nonrenewable Resources* 2, 69-81.https://doi.org/10.1007/BF02272804

Tang, Y., Deng, J., Guo, Z., (2023). Candidate Term Boundary Conflict Reduction Method for Chinese Geological Text Segmentation. *Applied Sciences* 13, 4516. https://doi.org/10.3390/app13074516

Wang, S., (2010). The new development of theory and method of synthetic information mineral resources prognosis. *Geological Bulletin of China* 29, 1399-1403.https://www.researchgate.net/publication/298469139

Wang, S., Qu, T., He, R., Ding, Y., Liu, J., Chen, X., Li, B., Lu, X., (2021). 3D geological modeling and stratified skarn target prediction in the Jiama deposit, Tibet. *Geologcal Bulletin of China* 40, 2110-2122.http://dzhtb.cgs.cn/en/article/id/20211214

Wang, X., (2023). Intelligent text generation: recent advances and challenges. *Big Data Research*, 1.https://doi.org/10.11959/j.issn.2096-0271.2023014

Yang, M., Xue, L., Ran, X., Sang, X., Yan, Q., Dai, J., (2021). Intelligent mineral geological survey method: Daqiao-Yawan area in Gansu Province as an example. *Acta Petrologica Sinica* 37, 3880-3892.https://doi.org/10.18654/1000-0569/2021.12.16

Yao, M., Jiangnan, Z., (2021). Advances in the application of machine learning methods in mineral prospectivity mapping. *Bulletin of Geological Science and Technology* 40, 132-141.https://doi.org/10.19509/j.cnki.dzkq.2021.0108

Yousefi, M., Kreuzer, O.P., Nykänen, V., Hronsky, J.M., (2019). Exploration information systems–A proposal for the future use of GIS in mineral exploration targeting. *Ore Geology Reviews* 111, 103005.https://doi.org/10.1016/j.oregeorev.2019.103005

Yuan, L., Xinyu, M., Guoli, Y., Huiqun, Z., Wei, S., (2023). Survey of Causal Inference for Knowledge Graphs and Large Language Models. *Journal of Frontiers of Computer Science & Technology* 17.https://doi.org/10.3778/j.issn.1673-9418.2307065

Yuan, M., Li, S., Liu, X., (2021). Research on Standardized Model of Geological Knowledge Graph. *Journal of Jilin University (Information Science Edition)* 39, 215-222.https://doi.org/10.19292/j.cnki.jdxxp.2021.02.013

Zhang, W., Chen, L., Zhang, G., Doui, L., (2010). Ore-search beneficial degree and prospect prediction of gold deposit in east Junggar region. *Journal of Geology* 34, 5.https://doi.org/10.3969/j.issn.1674-3636.2010.02.144

Zhao, P., (2002). Three Component” quantitative resource prediction and assessments: theory and practice of digital

mineral prospecting. *Earth Science-Journal of china university of Geosciences* 27, 482-489.https://doi.org/10.3321/j.issn:1000-2383.2002.05.002
Zhou, Y., Li, P., Wang, S., Xiao, F., Li, J., Gao, L., (2017). Research progress on big data and intelligent modelling of mineral deposits. *Bulletin of Mineralogy, Petrology and Geochemistry* 36, 327-331.https://doi.org/10.3969/j.issn.1007-2802.2017.02.016
Zhou, Y., Zhang, Q., Huang, Y., Yang, W., Xiao, F., Ji, J., Han, F., Tang, L., Ou, Y., Shen, W., (2021). Constructing knowledge graph for the porphyry copper deposit in the Qingzhou-Hangzhou Bay area:Insight into knowledge graph based mineral resource prediction and evaluation. *Earth Science Frontiers* 28, 67-75.https://doi.org/10.13745/j.esf.sf.2021.1.2
Zuo, R., Carranza, E.J.M., (2011). Support vector machine: A tool for mapping mineral prospectivity. *Computers & geosciences* 37, 1967-1975.https://doi.org/10.1016/j.cageo.2010.09.014