



Engineering Management of CNN-LSTM-Based Mineral Exploration Decisions: A Multi-Objective Framework for Drilling Portfolio Prioritization

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Abstract

This study aimed to develop and evaluate an integrated engineering-management framework that combines CNN-LSTM-based mineral prospectivity prediction with multi-objective optimization for prioritizing drilling targets under geological, economic, operational, strategic, and risk-related constraints. This applied quantitative study was conducted with 218 mineral exploration and engineering professionals in Tehran, Iran, of whom 206 complete expert records were retained for analysis. Geological, geochemical, geophysical, remote-sensing, topographic, and historical drilling data were integrated and processed using a hybrid convolutional neural network–long short-term memory model. The CNN-LSTM output was incorporated into a multi-criteria drilling decision framework including expected mineralization value, drilling cost, geological confidence, accessibility, technical resources, implementation time, uncertainty, operational risk, environmental sensitivity, safety, and strategic compatibility. Multi-objective portfolio optimization was then performed under alternative budget and management scenarios, followed by sensitivity analysis. The CNN-LSTM model demonstrated strong predictive performance on the independent test set, with accuracy of 0.898, precision of 0.883, recall of 0.909, F1-score of 0.896, ROC-AUC of 0.944, specificity of 0.886, and binary cross-entropy loss of 0.249. The balanced baseline portfolio achieved the highest efficiency score of 0.901, selecting nine targets with mean prospectivity of 0.857, expected portfolio value of 7.56, mean risk of 0.26, and total cost of USD 13.97 million. The AI-only ranking showed higher mean prospectivity (0.906) but lower efficiency (0.806) and higher risk (0.41). Sensitivity analysis showed strong ranking stability, with Spearman correlations ranging from 0.81 to 0.94. Integrating CNN-LSTM prospectivity prediction with multi-objective portfolio optimization produced more balanced and resource-efficient drilling decisions than either AI-only or conventional weighted ranking, demonstrating the value of combining predictive intelligence with engineering-management constraints.

Keywords: CNN-LSTM; Mineral Exploration; Drilling Portfolio; Multi-Objective Optimization; Engineering Management; Mineral Prospectivity Mapping; Decision Support

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1. Introduction

Mineral exploration is fundamentally a decision-making process under conditions of incomplete information, high capital intensity, geological uncertainty, and substantial asymmetry between the cost of unsuccessful drilling and the value created by a successful discovery. Exploration organizations must decide not only where mineralization is most likely to occur but also which targets should receive scarce drilling capital, in what sequence they should be tested, and how geological opportunity should be balanced

against financial, operational, environmental, and strategic constraints. Historically, exploration targeting depended heavily on expert geological interpretation, overlay analysis, and heuristic integration of geological, geochemical, geophysical, and structural evidence. The development of geographic information systems transformed this process by permitting multiple geoscientific evidence layers to be standardized, spatially integrated, weighted, and analyzed within a common computational environment [1]. Nevertheless, contemporary mineral exploration



increasingly involves volumes and varieties of data that exceed the practical capacity of conventional map-overlay and manually weighted decision procedures. Modern projects routinely incorporate high-resolution geophysics, multispectral and hyperspectral remote sensing, geochemical sampling, structural interpretation, digital elevation models, historical drilling records, and other heterogeneous sources of evidence. The resulting management problem is therefore no longer confined to identifying anomalous locations; it requires a systematic framework capable of translating complex geoscientific information into economically and operationally defensible drilling decisions.

Mineral prospectivity mapping has developed as one of the principal approaches for integrating diverse exploration evidence and estimating the relative favorability of locations for undiscovered mineralization. Prospectivity models are intended to reduce a large search space into a smaller set of targets that deserve detailed investigation, thereby improving exploration efficiency and supporting the allocation of limited resources. However, practical application of prospectivity mapping involves challenges concerning data quality, scale, spatial dependence, model assumptions, uncertainty, and the relationship between statistical predictions and geological reasoning. Hronsky and Kreuzer emphasized that prospectivity mapping must ultimately serve practical exploration targeting rather than operate as an isolated computational exercise, particularly because technically sophisticated predictions provide limited organizational value if they cannot be translated into decisions concerning where exploration resources should actually be committed [2]. Similarly, contemporary reviews of prospectivity modeling have shown that data-driven methods have expanded rapidly, but model selection, interpretability, sampling design, representation of geological processes, validation, and transferability remain critical methodological issues [3]. These concerns are particularly relevant to drilling, where an apparently favorable target may still be unattractive when its expected value is considered together with depth, access, drilling expenditure, logistical requirements, uncertainty, safety, environmental sensitivity, and competition for organizational resources.

The growth of big-data analytics and machine learning has substantially expanded the analytical capabilities available for mineral exploration. Machine-learning methods can identify nonlinear relationships among multiple predictors without requiring all geological interactions to be

specified in advance, allowing the discovery of complex signatures that may be difficult to represent through conventional statistical or knowledge-driven procedures. Early applications of deep learning to mineral prospectivity demonstrated that multilayer architectures could extract informative patterns from large, multivariate geoscience datasets and produce useful representations of exploration favorability [4]. More recent developments have reinforced the importance of machine-learning-based mapping as a major methodological direction in quantitative mineral exploration because it enables sophisticated representation learning, classification, spatial prediction, and integration of heterogeneous data sources [5]. At the same time, the increasing computational sophistication of such approaches creates a management challenge: improved predictive accuracy does not automatically imply improved exploration investment decisions. A model may correctly rank geological favorability while disregarding the cost and risk structure associated with testing those predictions. Consequently, an engineering-management framework must connect predictive intelligence with project-selection logic so that artificial intelligence contributes directly to the prioritization of executable drilling portfolios.

Deep learning is especially relevant to this problem because mineral systems are expressed through multidimensional spatial patterns rather than isolated variables. Convolutional neural networks (CNNs) are capable of identifying local spatial features and hierarchical relationships in gridded data, making them suitable for processing geological maps, alteration information, geophysical surfaces, remote-sensing products, and other spatially organized exploration layers. Reviews of deep-learning applications in mining demonstrate that CNNs and related architectures have been increasingly employed for geological characterization, mineral prospectivity, image interpretation, geotechnical analysis, and other data-intensive mining problems, although challenges remain in data availability, model transparency, generalization, and integration with domain expertise [6]. More broadly, the rapid growth of multisource geoscience applications between 2018 and 2025 has demonstrated a transition from relatively simple neural architectures toward deeper, hybrid, and multimodal systems that can integrate complementary evidence from geology, geophysics, geochemistry, remote sensing, and related data streams [7]. This development is important for exploration management because the economic attractiveness of deep learning is ultimately dependent on whether richer data integration generates

sufficiently reliable improvements in target discrimination to justify its inclusion in high-cost drilling decisions.

Long short-term memory (LSTM) networks offer an additional capability by representing ordered and dependent patterns that conventional feedforward architectures may not preserve adequately. Although LSTM models were originally developed for sequential data, their capacity to learn dependencies across ordered feature representations has been adapted to geoscientific prospectivity problems. The integration of geoscientific evidence weighting with an LSTM architecture has demonstrated the potential of recurrent deep-learning methods for recognizing complex exploration relationships and producing meaningful prospectivity predictions [8]. A combined CNN-LSTM architecture is therefore conceptually attractive for mineral exploration because CNN layers can extract spatially localized representations from heterogeneous evidence, while LSTM layers can capture higher-order dependencies across the resulting feature sequences. Such hybridization potentially reduces the limitations associated with reliance on either spatial feature extraction or sequential dependency learning alone. For drilling management, however, the relevant output is not merely a classification result. The prospectivity probability produced by the hybrid network must be treated as one component of a larger decision system in which the attractiveness of each target is assessed relative to competing opportunities.

The reliability of data-driven prospectivity mapping also depends on the explicit recognition of uncertainty. Geological observations are incomplete, exploration datasets are spatially uneven, negative labels may reflect insufficient investigation rather than true absence of mineralization, and preprocessing choices can materially affect model outputs. Uncertainty may originate from input data, conceptual geological models, evidence weighting, spatial representation, sampling procedures, model structure, and validation strategies [9]. Recent research has further demonstrated that uncertainty can be introduced by the analytical workflow itself, meaning that choices concerning preprocessing, data transformations, variable selection, model configuration, and evaluation can alter the resulting prospectivity surface even when the underlying geological data remain unchanged [10]. These observations are crucial from an engineering-management perspective because decisions based on apparently precise prospectivity scores may generate excessive confidence unless uncertainty is reflected in target assessment. A drilling portfolio should therefore avoid equating the highest predicted probability

with the best managerial decision and should instead evaluate whether the expected geological benefit remains attractive after uncertainty, financial exposure, and operational risk are incorporated.

The distinction between geological ranking and commercial prioritization has become increasingly important as exploration organizations seek to improve capital discipline. Exploration targets differ not only in probability of mineralization but also in potential deposit value, confidence of interpretation, required drilling depth, access conditions, implementation time, equipment demands, permitting constraints, and strategic relevance. Partington et al. argued that ranking mineral exploration targets should be explicitly connected to commercial decision-making and incorporated within exploration information systems rather than being treated solely as a geoscientific classification activity [11]. This perspective moves target ranking from prediction toward engineering management. A target with slightly lower geological potential may rationally receive higher priority if it can be tested at substantially lower cost, carries lower operational uncertainty, or complements other projects within the exploration program. Conversely, a geologically exceptional target may be deferred when its cost, risk, implementation requirements, or strategic incompatibility make it inefficient relative to alternative opportunities. Consequently, the managerial unit of analysis should extend beyond individual target scores to the composition of the overall drilling portfolio.

Project portfolio management provides an appropriate theoretical and analytical foundation for this transition because exploration drilling shares the principal characteristics of capital-project selection: multiple competing alternatives, limited resources, interacting objectives, uncertain outcomes, and the need to maximize organizational value rather than individual project performance. Engineering portfolios require resource allocation mechanisms that consider opportunity cost and ensure that capital, technical personnel, equipment, and time are assigned to combinations of projects that best serve organizational objectives [12]. Within engineering environments, effective portfolio management also requires the simultaneous treatment of resource optimization and risk balancing, because focusing solely on expected returns can concentrate exposure in technically attractive but operationally fragile projects [13]. These considerations closely correspond to mineral exploration, where drilling capacity and investment budgets are finite and where each

additional borehole represents a commitment of resources that cannot simultaneously be used to evaluate another target. The problem is therefore inherently combinatorial: decision-makers must determine not simply which target is best, but which combination of targets constitutes the best portfolio under specific organizational constraints.

Multi-objective optimization is particularly well suited to this type of problem because exploration decisions rarely have a single objective. Organizations may seek to maximize predicted mineralization potential and expected value while simultaneously minimizing drilling cost, geological uncertainty, operational risk, environmental burden, and implementation time. These objectives are often conflicting, meaning that improvement in one dimension may require deterioration in another. The mathematical foundations of multi-objective optimization emphasize that such problems generally do not possess a single universally optimal solution; rather, they generate sets of Pareto-efficient solutions in which no objective can be improved without worsening at least one other objective [14]. For exploration managers, the Pareto perspective is more realistic than an unconstrained ranking because it makes trade-offs explicit. A high-value portfolio may cost more; a low-risk portfolio may sacrifice geological upside; and a low-cost portfolio may contain a larger proportion of second-tier targets. Management must therefore identify a preferred compromise from a set of efficient alternatives rather than assuming that one criterion can represent the entire decision.

The project portfolio literature provides several methodological precedents for solving such multi-objective selection problems. Doerner et al. demonstrated how Pareto-based optimization can be combined with advanced search procedures to identify efficient project portfolios under multiple criteria and constraints [15]. Comprehensive mathematical approaches have similarly shown that project portfolio selection can integrate multiple objectives rather than reducing decision quality to a single project-level score [16]. Interactive multi-objective programming further enables decision-makers to explore alternative portfolio configurations and incorporate organizational preferences into selection and scheduling processes [17]. Sustainability and resource limitations can also be embedded directly into portfolio-selection and scheduling models, allowing investment decisions to reflect constrained resources and multiple dimensions of performance simultaneously [18]. These developments suggest that a drilling portfolio can be modeled more rigorously when predicted geological opportunity is optimized jointly with financial and

operational requirements rather than when targets are independently ranked and selected until the budget is exhausted.

Optimization research also highlights the importance of maintaining diversity among candidate solutions and avoiding premature concentration around locally attractive alternatives. Metaheuristic methods such as GRASP and path relinking have been applied to complex optimization problems in which solution quality depends on exploring diverse regions of the decision space rather than selecting alternatives according to a single greedy rule [19]. Although mineral drilling prioritization differs in application domain, the underlying implication is relevant: portfolio design benefits from systematic exploration of alternative combinations because several portfolios may have similar expected value while differing materially in cost, risk, and strategic exposure. The management problem thus extends beyond computing a weighted score for each target. A robust framework should construct competing portfolios, examine non-dominated solutions, and determine whether the preferred combination remains stable when assumptions concerning criterion importance, budget levels, or risk tolerance change.

This distinction is especially important when artificial intelligence is incorporated into engineering decision-making. If a CNN-LSTM model is used only to produce a prospectivity map, the result remains primarily a geoscientific output. If the highest-probability targets are automatically selected, the decision becomes vulnerable to the assumption that geological probability is equivalent to investment desirability. A more defensible approach is to use CNN-LSTM prospectivity as a technically derived decision criterion and integrate it with expected mineralization value, drilling cost, geological confidence, logistical feasibility, resource availability, operational risk, environmental sensitivity, safety considerations, implementation time, and strategic compatibility. Such an architecture preserves the predictive advantages of deep learning while preventing the algorithm from becoming the sole determinant of capital allocation. It also establishes a clearer boundary between prediction and prescription: the neural network predicts geological potential, whereas the portfolio model prescribes a feasible combination of drilling opportunities given organizational objectives and constraints.

Despite advances in both mineral prospectivity modeling and project portfolio optimization, these streams of research have largely developed as separate analytical domains. Deep-learning studies in mineral exploration primarily

evaluate predictive discrimination, spatial targeting ability, and methodological performance, whereas portfolio studies generally focus on project value, scheduling, resource constraints, sustainability, and risk without incorporating target-level geological predictions generated from multisource deep-learning architectures. This separation creates an important research gap. A high-performing prospectivity model does not by itself indicate how many targets should be drilled under a fixed budget, which high-potential targets should be postponed because of excessive risk, or how the optimal portfolio changes when management emphasizes cost containment rather than geological upside. Likewise, a generic portfolio model cannot effectively prioritize exploration opportunities if its assessment of geological potential does not exploit contemporary machine-learning capabilities. Integration is therefore necessary to move from mineral prediction toward intelligent exploration governance.

A further gap concerns evaluation criteria. Machine-learning performance is typically assessed using accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve, or related predictive metrics, whereas engineering-management systems must also be evaluated according to portfolio value, total cost, risk exposure, efficiency, resource utilization, and robustness to preference changes. An integrated approach should therefore demonstrate both that the CNN-LSTM model generalizes adequately to unseen data and that its inclusion improves the quality of portfolio decisions. Sensitivity analysis is particularly important because criterion weights and strategic priorities are not immutable. Management preferences can change with commodity prices, capital availability, organizational risk tolerance, drilling capacity, regulatory requirements, or new geological information. A credible decision framework should accordingly examine whether the highest-priority targets and the preferred portfolio remain reasonably stable under plausible changes in managerial assumptions.

The convergence of multisource geoscience analytics, hybrid deep learning, and multi-objective portfolio optimization consequently offers an opportunity to reconceptualize mineral exploration as an integrated engineering-management problem. Such a framework can transform geological information into prospectivity estimates, translate those estimates into comparable target-level decision criteria, and optimize combinations of drilling projects subject to budgetary, operational, and risk constraints. It can also provide managers with a Pareto

frontier rather than a single opaque recommendation, enabling explicit comparison of portfolios oriented toward geological value, cost minimization, risk reduction, or balanced performance. This approach is consistent with the broader evolution of mineral exploration toward data-intensive decision systems while recognizing that prediction quality, uncertainty management, capital allocation, and managerial judgment must operate together rather than independently. By linking artificial intelligence with portfolio-level optimization, drilling decisions can be evaluated not merely according to where mineralization is most likely to occur, but according to where limited exploration resources can generate the strongest overall balance of geological opportunity, expected value, cost efficiency, operational feasibility, and acceptable risk.

Accordingly, the aim of this study was to develop and evaluate an integrated engineering-management framework that combines CNN-LSTM-based mineral prospectivity prediction with multi-objective optimization to prioritize drilling targets and construct resource-efficient mineral exploration portfolios under competing geological, economic, operational, strategic, and risk-related objectives.

2. Methodology

This study employed an applied, quantitative, and predictive-optimization research design to develop and evaluate an engineering management framework for prioritizing mineral exploration drilling portfolios through the integration of a convolutional neural network–long short-term memory (CNN-LSTM) model and multi-objective decision analysis. The study was conducted in Tehran, Iran, where a substantial proportion of the country's mineral exploration consulting companies, mining engineering organizations, technical contractors, research institutions, and corporate mineral-development offices are headquartered. The research population consisted of mining engineers, exploration geologists, geophysicists, geospatial analysts, drilling engineers, mineral resource specialists, project managers, and senior technical decision-makers who were professionally involved in mineral exploration planning, drilling-project evaluation, geological modeling, or investment prioritization. A total of 218 eligible professionals were recruited through purposive and criterion-based sampling. Eligibility criteria included holding at least a bachelor's degree in mining engineering, geology, geophysics, geomatics, industrial engineering, or a related discipline; having a minimum of three years of

professional experience in mineral exploration, drilling, geological modeling, or mining-project management; and having practical familiarity with the evaluation or prioritization of mineral exploration targets. Participants who provided incomplete evaluations or had no direct experience with exploration decision-making were excluded. After data screening, 206 complete expert records were retained for the engineering-management component of the analysis. The participants were drawn from mining and exploration companies, consulting engineering firms, governmental or semi-governmental mineral organizations, and universities or research centers located in Tehran. The analytical design combined two complementary levels of evidence. At the technical level, geological, geochemical, geophysical, remote-sensing, topographic, and historical drilling information from mineral exploration targets was processed to generate prospectivity estimates using the CNN-LSTM architecture. At the managerial level, the model-generated geological potential was integrated with engineering, economic, operational, environmental, and risk-related criteria to determine the relative priority of candidate drilling projects. The unit of technical analysis was the mineral exploration target or prospective drilling block, whereas the unit of managerial analysis was the drilling opportunity evaluated as a potential member of an exploration portfolio. The framework was designed to reproduce the actual conditions of engineering management in mineral exploration, in which decisions cannot be based solely on predicted mineralization probability but must simultaneously consider expected geological value, drilling cost, uncertainty, logistical feasibility, environmental constraints, and portfolio-level resource limitations.

Data collection was performed through an integrated mineral exploration database and a structured engineering-management decision instrument. The technical database combined multiple sources of information commonly used in mineral prospectivity assessment. Geological variables included lithological units, structural features, alteration zones, distances from major faults and geological contacts, and spatial relationships with known mineral occurrences. Geochemical information consisted of standardized elemental concentration and anomaly indicators derived from available exploration samples, while geophysical variables included processed magnetic, radiometric, and other available anomaly layers relevant to the targeted mineralization system. Remote-sensing information was used to represent spectral alteration signatures and surface characteristics, and digital elevation data were incorporated

to account for topographic and terrain-related effects. Historical borehole and exploration records provided information concerning drilling location, depth, mineralized intercepts, grade indicators, and positive or negative exploration outcomes. All spatial variables were transformed into a common coordinate reference system, harmonized to a consistent spatial resolution, and converted into numerical raster or sequential representations suitable for computational modeling. Continuous variables were normalized before model estimation, whereas categorical geological information was numerically encoded. Missing or anomalous observations were evaluated during preprocessing, and records that could not be reliably reconstructed were excluded from model development. Spatial windows centered on candidate exploration locations were subsequently generated as inputs for the convolutional component of the hybrid architecture. The CNN layers were used to extract local spatial features and interactions among geological, geochemical, geophysical, and remotely sensed indicators, while the LSTM component was used to capture ordered dependencies in the resulting feature sequences and historical exploration information. The output of the CNN-LSTM model was expressed as a normalized prospectivity score indicating the predicted likelihood or relative potential of economically meaningful mineralization for each candidate target.

For the engineering-management component, a structured Drilling Portfolio Prioritization Instrument was developed specifically for the study to translate technical predictions into actionable exploration decisions. The instrument was constructed through a review of mineral exploration project-management principles and consultation with experienced professionals in exploration geology, drilling engineering, mining economics, and project management. The decision framework included geological prospectivity, expected mineralization value, confidence in the geological interpretation, expected drilling cost, required drilling depth, accessibility and logistical difficulty, availability of equipment and technical resources, implementation time, geological uncertainty, operational risk, environmental sensitivity, health and safety considerations, and strategic compatibility with organizational exploration objectives. The CNN-LSTM prospectivity score constituted the principal data-driven technical criterion and was incorporated alongside the managerial criteria rather than being treated as an independent final decision. Experts assessed the importance of the decision criteria and evaluated the candidate drilling

opportunities using standardized rating scales. Criterion importance was measured on a five-point scale ranging from 1, indicating very low importance, to 5, indicating very high importance, while the performance of each drilling target on qualitative criteria was assessed using a five-point scale ranging from very unfavorable to very favorable. Objective indicators, including estimated drilling expenditure, depth, predicted prospectivity, implementation duration, and measurable logistical parameters, were entered directly into the decision matrix rather than being converted into subjective expert ratings. To establish content validity, the initial instrument was reviewed by a panel of specialists in mining engineering, mineral exploration, drilling management, and quantitative decision analysis. Items considered ambiguous, redundant, or insufficiently relevant to portfolio-level exploration decisions were revised before final administration. Internal consistency of the multi-item managerial dimensions was evaluated using Cronbach's alpha and composite reliability, with coefficients of 0.70 or greater considered acceptable. The combined database consequently provided a standardized decision matrix in which each drilling alternative was characterized by both machine-learning-derived geological potential and engineering-management attributes required for portfolio optimization.

Data analysis was conducted in sequential stages encompassing data preprocessing, CNN-LSTM model development, predictive performance assessment, multi-criteria decision normalization, and multi-objective portfolio optimization. During preprocessing, continuous exploration variables were examined for missing values, extreme observations, scale inconsistencies, and distributional differences and were subsequently normalized to prevent variables with large numerical ranges from disproportionately influencing neural-network learning. Spatial and sequential input structures were then generated from the integrated exploration database. To reduce information leakage and obtain a realistic estimate of predictive generalizability, the data were divided into training, validation, and independent test subsets using a 70%, 15%, and 15% allocation, respectively, while maintaining an appropriate balance between mineralized and non-mineralized observations. The convolutional component of the model extracted multidimensional spatial patterns associated with favorable geological environments, geochemical anomalies, structural controls, and geophysical responses. The extracted representations were subsequently supplied to the LSTM component to model dependencies

among ordered geological and exploration features. Fully connected layers transformed the resulting latent representation into a final mineral prospectivity probability. Model parameters were estimated through back-propagation using the Adam optimization algorithm, and binary cross-entropy was used as the principal loss function for classification. Validation loss was monitored during training, and early stopping was employed to reduce overfitting. Dropout regularization was incorporated between selected layers, and model hyperparameters, including the number of convolutional filters, kernel dimensions, LSTM units, dropout rate, batch size, and learning rate, were selected according to validation performance. Predictive accuracy was evaluated using accuracy, precision, recall, F1-score, receiver operating characteristic area under the curve, and confusion-matrix indicators. Because the practical purpose of the system was exploration targeting rather than statistical classification alone, the spatial correspondence between high-prospectivity predictions and known mineralized locations was also examined.

Following predictive modeling, the CNN-LSTM prospectivity probabilities were incorporated into the drilling decision matrix together with the economic, engineering, operational, environmental, and risk criteria. Benefit criteria, for which higher values represented more desirable drilling opportunities, and cost criteria, for which lower values were preferred, were separately identified and normalized to comparable scales. Expert judgments concerning criterion importance were aggregated to derive criterion weights, and consistency across expert evaluations was examined before construction of the final weighted matrix. A multi-objective optimization model was then formulated to identify the drilling portfolio that simultaneously maximized expected mineral exploration value and cumulative CNN-LSTM prospectivity while minimizing total drilling cost, implementation risk, and relevant operational or environmental burdens. Binary decision variables indicated whether each candidate drilling target was selected for inclusion in the portfolio. The optimization process was subject to realistic engineering-management constraints, including the total exploration budget, maximum available drilling capacity, implementation time, equipment availability, and operational feasibility. Rather than reducing all management objectives to a single unrestricted score, Pareto-based optimization was used to identify non-dominated portfolios representing alternative trade-offs between geological

opportunity, expenditure, and risk. A compromise solution was subsequently selected from the efficient solution set according to the normalized distance from the ideal combination of maximum expected geological value and minimum resource consumption and risk.

The robustness of the proposed decision framework was additionally evaluated through sensitivity and scenario analyses. Criterion weights were systematically varied to determine whether changes in managerial priorities substantially affected the ranking or selection of drilling targets. Alternative budget levels were also examined to assess how capital constraints influenced the composition and expected value of the recommended exploration portfolio. Particular attention was given to the stability of target prioritization when greater importance was assigned separately to geological prospectivity, drilling cost, risk reduction, and strategic value. The performance of the integrated framework was compared with rankings based only on CNN-LSTM prospectivity and with conventional weighted managerial prioritization to determine whether the combination of artificial intelligence and multi-objective engineering management generated a more balanced allocation of exploration resources. Descriptive statistics were calculated for the main decision criteria, and correlations among continuous variables were examined to identify potential redundancy in the optimization matrix. Statistical analyses and data preprocessing were performed using Python and SPSS, while the CNN-LSTM architecture was implemented using Python-based deep-learning libraries. Multi-objective optimization and sensitivity analyses were conducted computationally using the standardized decision matrix. Statistical significance was evaluated at the 0.05 level where inferential testing was applicable, while machine-learning and optimization performance was primarily interpreted through predictive metrics, Pareto efficiency, portfolio value, cost, risk, and solution stability.

3. Findings and Results

The final expert sample consisted of 206 participants whose responses were complete and eligible for inclusion in the engineering-management analysis. Of these participants, 154 (74.8%) were men and 52 (25.2%) were women. The mean age of the participants was 41.63 years ($SD = 8.27$), with ages ranging from 29 to 61 years. In terms of academic qualification, 49 participants (23.8%) held a bachelor's degree, 112 (54.4%) held a master's degree, and 45 (21.8%) held a doctoral degree. The respondents represented a broad range of professional specialties related to mineral exploration and drilling decision-making. Specifically, 52 participants (25.2%) were mining or exploration engineers, 39 (18.9%) were geologists or economic geologists, 24 (11.7%) were geophysicists, 18 (8.7%) were geospatial or remote-sensing specialists, 29 (14.1%) were drilling or mine-planning engineers, and 44 (21.4%) were project managers, technical directors, mineral-resource specialists, or senior exploration decision-makers. The participants had an average of 13.84 years of professional experience ($SD = 6.91$), and 137 respondents (66.5%) reported more than 10 years of direct professional experience in mineral exploration, drilling, mining-project evaluation, or related technical management. Regarding organizational affiliation, 89 participants (43.2%) worked in private mining, exploration, or engineering consulting companies, 57 (27.7%) were employed by governmental or semi-governmental mineral organizations, 33 (16.0%) were affiliated with universities or research institutions, and 27 (13.1%) worked in other technical, investment, or project-management organizations. These characteristics indicated that the sample included both technically specialized professionals and managerial decision-makers with sufficient experience to evaluate the geological, economic, operational, environmental, and strategic dimensions of mineral exploration drilling portfolios.

Table 1. Descriptive Statistics of the Main Technical and Engineering-Management Decision Variables

Variable	Mean	SD	Minimum	Maximum
CNN-LSTM prospectivity score	0.64	0.18	0.21	0.94
Expected mineralization value score	0.67	0.15	0.28	0.93
Geological interpretation confidence	3.78	0.64	2.20	4.90
Estimated drilling cost (million USD)	1.84	0.71	0.62	3.74
Expected drilling depth (m)	486.27	173.42	185.00	910.00
Accessibility and logistical feasibility	3.54	0.73	1.90	4.80
Equipment and technical resource availability	3.68	0.66	2.10	4.90
Implementation time (months)	7.42	2.37	3.00	13.00
Geological uncertainty	2.73	0.79	1.20	4.50

Operational risk	2.61	0.71	1.30	4.30
Environmental sensitivity	2.44	0.76	1.10	4.40
Health and safety risk	2.37	0.68	1.10	4.20
Strategic compatibility	4.02	0.58	2.40	4.90
Overall managerial priority score	0.69	0.14	0.31	0.92

As shown in Table 1, the candidate drilling opportunities demonstrated considerable variation across both geological potential and managerial feasibility dimensions. The mean CNN-LSTM prospectivity score was 0.64 (SD = 0.18), indicating that the overall candidate pool contained a moderate-to-high concentration of technically promising exploration targets, although the range from 0.21 to 0.94 demonstrated substantial heterogeneity in predicted mineralization potential. The mean expected mineralization value score was similarly favorable at 0.67 (SD = 0.15), while the average confidence in geological interpretation was 3.78 (SD = 0.64), suggesting that most candidates were supported by reasonably consistent geological and geophysical evidence. The economic burden associated with drilling was more heterogeneous, with an average estimated drilling cost of USD 1.84 million (SD = 0.71) and expected drilling depths ranging from 185 to 910 m. The mean accessibility and logistical feasibility score was 3.54 (SD = 0.73), and equipment and technical resource availability

averaged 3.68 (SD = 0.66), indicating generally acceptable but nonuniform operational conditions across targets. The average implementation period was 7.42 months (SD = 2.37), reflecting meaningful differences in operational complexity. Risk-related indicators showed moderate average levels, with geological uncertainty of 2.73 (SD = 0.79), operational risk of 2.61 (SD = 0.71), environmental sensitivity of 2.44 (SD = 0.76), and health and safety risk of 2.37 (SD = 0.68). Strategic compatibility received the highest mean among the qualitative managerial criteria, with a mean of 4.02 (SD = 0.58), indicating that most candidate projects were broadly consistent with organizational exploration objectives. The overall managerial priority score averaged 0.69 (SD = 0.14), but the wide observed range from 0.31 to 0.92 confirmed that high geological prospectivity did not necessarily correspond to high portfolio attractiveness after cost, risk, resource, environmental, and strategic considerations were simultaneously incorporated.

Table 2. Predictive Performance of the CNN-LSTM Mineral Prospectivity Model

Performance Indicator	Training Set	Validation Set	Test Set
Accuracy	0.934	0.907	0.898
Precision	0.921	0.891	0.883
Recall	0.948	0.918	0.909
F1-score	0.934	0.904	0.896
ROC-AUC	0.972	0.951	0.944
Specificity	0.919	0.896	0.886
Sensitivity	0.948	0.918	0.909
Positive predictive value	0.921	0.891	0.883
Negative predictive value	0.944	0.923	0.914
Binary cross-entropy loss	0.181	0.236	0.249

The predictive performance results presented in Table 2 demonstrated that the CNN-LSTM architecture achieved a high and comparatively stable level of discrimination between favorable and unfavorable mineral exploration locations. Training-set accuracy reached 0.934, while validation and independent test accuracy values were 0.907 and 0.898, respectively. The relatively small decline from training to validation and test performance suggested that the regularization, validation monitoring, and early-stopping procedures were effective in limiting substantial overfitting. On the independent test set, precision was 0.883, indicating

that 88.3% of locations predicted as favorable mineralization targets were correctly identified, while recall reached 0.909, demonstrating that the model successfully identified more than 90% of the actual favorable cases. The resulting test-set F1-score of 0.896 indicated a strong balance between precision and sensitivity. The ROC-AUC value of 0.944 on the test data provided further evidence of strong discriminatory capacity and indicated that the hybrid architecture was highly effective in separating relatively prospective locations from less favorable exploration zones. The test-set specificity was 0.886, showing that the model

also performed well in identifying negative or lower-potential cases and therefore did not achieve high sensitivity solely through excessive positive classification. The positive predictive value and negative predictive value were 0.883 and 0.914, respectively, indicating that both favorable and unfavorable classifications had high practical reliability. Binary cross-entropy loss increased only moderately from 0.181 in the training set to 0.249 in the test set, which further supported satisfactory model generalization. Examination of spatial prediction outputs additionally showed that areas

receiving the highest CNN-LSTM prospectivity probabilities were concentrated around combinations of favorable lithological units, structural intersections, geochemical anomalies, geophysical signatures, and alteration patterns rather than being randomly distributed across the exploration area. Therefore, the machine-learning component provided a sufficiently accurate technical basis for subsequent integration with portfolio-level engineering-management criteria.

Table 3. Integrated Ranking of the Fifteen Highest-Priority Candidate Drilling Targets

Rank	Target	CNN-LSTM Prospectivity	Expected Value	Normalized Cost	Normalized Risk	Strategic Compatibility	Integrated Priority Score
1	T-07	0.94	0.91	0.42	0.24	4.80	0.918
2	T-12	0.91	0.88	0.39	0.28	4.70	0.895
3	T-03	0.89	0.86	0.35	0.31	4.60	0.874
4	T-18	0.87	0.84	0.47	0.26	4.70	0.857
5	T-05	0.85	0.82	0.32	0.29	4.50	0.842
6	T-21	0.88	0.83	0.55	0.36	4.60	0.824
7	T-09	0.82	0.80	0.30	0.25	4.40	0.816
8	T-14	0.84	0.78	0.44	0.32	4.50	0.804
9	T-02	0.79	0.77	0.27	0.23	4.30	0.793
10	T-25	0.86	0.81	0.68	0.45	4.40	0.775
11	T-16	0.78	0.75	0.36	0.34	4.20	0.761
12	T-11	0.81	0.74	0.53	0.40	4.30	0.748
13	T-06	0.75	0.72	0.31	0.28	4.10	0.739
14	T-20	0.83	0.76	0.71	0.48	4.20	0.721
15	T-04	0.73	0.70	0.29	0.30	4.00	0.713

Table 3 presents the integrated ranking of the fifteen highest-priority drilling targets after combining CNN-LSTM-generated prospectivity predictions with expected mineralization value, cost, risk, logistical feasibility, strategic alignment, and other engineering-management criteria. Target T-07 achieved the highest integrated priority score of 0.918 and simultaneously exhibited the highest CNN-LSTM prospectivity probability of 0.94, an expected-value score of 0.91, relatively moderate normalized cost of 0.42, low normalized risk of 0.24, and very high strategic compatibility of 4.80. This combination made T-07 the most attractive candidate under the integrated decision framework. T-12 ranked second with a priority score of 0.895, followed by T-03 at 0.874, T-18 at 0.857, and T-05 at 0.842. Although all of these alternatives showed high predicted mineral prospectivity, their relative ranking was influenced by differences in cost, operational exposure, and strategic suitability. Importantly, the results showed that geological prospectivity alone was insufficient to determine final portfolio priority. For example, T-21 had a CNN-LSTM prospectivity score of 0.88, which was higher than

the score of T-05 at 0.85, but T-21 ranked sixth because of its higher normalized cost and risk. Similarly, T-25 had a strong CNN-LSTM score of 0.86 and expected-value score of 0.81 but was ranked tenth due to substantially higher cost and risk burdens. Target T-20 showed the same pattern, receiving a prospectivity score of 0.83 but ranking only fourteenth because of its relatively high normalized cost of 0.71 and risk score of 0.48. Conversely, T-02 ranked ninth despite a lower prospectivity score of 0.79 because its comparatively low cost and risk improved its managerial attractiveness. These findings demonstrate that the proposed framework altered the ordering of candidate projects when compared with a purely geological ranking and systematically favored drilling opportunities that provided a stronger balance among technical potential, resource requirements, risk exposure, and strategic relevance. The results therefore support the fundamental premise of the study that machine-learning predictions should be embedded within a broader engineering-management decision framework rather than treated as a stand-alone exploration recommendation.

Table 4. Multi-Objective Portfolio Optimization Results under Alternative Budget and Management Scenarios

Scenario	Budget Limit (million USD)	Number of Selected Targets	Mean Prospectivity	Expected Portfolio Value	Mean Risk	Total Cost (million USD)	Portfolio Efficiency Score
Geological-value dominant	15.0	8	0.892	7.13	0.34	14.82	0.842
Cost-minimization dominant	15.0	10	0.801	7.38	0.27	12.46	0.861
Risk-minimization dominant	15.0	9	0.817	6.94	0.22	13.08	0.873
Balanced baseline	15.0	9	0.857	7.56	0.26	13.97	0.901
Restricted-budget balanced	10.0	6	0.871	5.18	0.24	9.72	0.887
Expanded-budget balanced	20.0	12	0.839	9.41	0.29	19.31	0.894
AI-only ranking	15.0	8	0.906	7.21	0.41	14.94	0.806
Conventional weighted ranking	15.0	9	0.814	7.02	0.31	14.31	0.834

The multi-objective optimization results in Table 4 demonstrate that the composition and performance of the drilling portfolio varied systematically according to the managerial objective structure and resource constraints. Under the geological-value-dominant scenario, eight projects were selected, generating a high average CNN-LSTM prospectivity score of 0.892 and expected portfolio value of 7.13; however, the scenario also resulted in a relatively high mean risk of 0.34 and used almost the entire USD 15 million budget, with a total cost of USD 14.82 million. In contrast, the cost-minimization scenario selected ten projects at a substantially lower total cost of USD 12.46 million. Although its mean prospectivity declined to 0.801, the larger number of lower-cost projects produced an expected portfolio value of 7.38 and a higher overall portfolio efficiency score of 0.861. The risk-minimization scenario produced the lowest mean risk, equal to 0.22, and selected nine targets with a total investment of USD 13.08 million. Nevertheless, its expected portfolio value of 6.94 was lower than that obtained under the balanced configuration, illustrating the opportunity cost associated with aggressive risk avoidance. The balanced baseline scenario generated the highest overall portfolio efficiency score of 0.901. It selected nine drilling targets, achieved an average prospectivity of 0.857, produced the highest expected portfolio value among the scenarios operating under the standard USD 15 million budget at 7.56, maintained a comparatively low mean risk of 0.26, and required USD 13.97 million in total expenditure. Under a restricted budget of USD 10 million, the optimization process selected six targets with a mean prospectivity of 0.871, indicating that the model concentrated scarce investment resources on technically strong projects while

excluding less efficient alternatives. Expanding the budget to USD 20 million increased the selected portfolio to 12 projects and expected total value to 9.41, although mean prospectivity fell moderately to 0.839 as additional second-tier targets entered the portfolio. The comparison models were particularly informative. The AI-only ranking generated the highest mean prospectivity of 0.906 but also produced the highest mean portfolio risk of 0.41 and almost completely exhausted the available budget, resulting in a relatively low efficiency score of 0.806. The conventional weighted-ranking method yielded an efficiency score of 0.834, lower than all three optimized managerial scenarios and substantially below the balanced multi-objective solution. Collectively, these results indicate that neither maximum geological prospectivity nor conventional weighted scoring alone produced the most efficient investment portfolio. The integrated framework generated superior trade-offs by preserving a high level of geological opportunity while simultaneously controlling expenditure and risk exposure.

Sensitivity analysis further demonstrated that the major results were robust to moderate changes in criterion weights. When the weight assigned to CNN-LSTM prospectivity was increased or decreased by 10%, seven of the nine projects selected in the balanced baseline portfolio remained unchanged. Similarly, when the weight assigned to drilling cost was increased by 15%, six of the original nine projects remained within the optimized portfolio, although lower-cost targets T-02 and T-09 moved upward in priority. Increasing the weight assigned to geological and operational risk by 15% produced a shift toward T-07, T-12, T-09, and T-02, all of which combined relatively high prospectivity with comparatively low risk. By contrast, high-cost and

higher-risk targets such as T-20 and T-25 were consistently excluded from the efficient portfolio across most scenarios despite their favorable CNN-LSTM prospectivity scores. Across all tested weight configurations, T-07 and T-12 remained within the first three positions, while T-03 appeared among the top five alternatives in 92% of the tested scenarios. The Spearman rank correlation between the

baseline integrated ranking and the rankings obtained under the sensitivity scenarios ranged from 0.81 to 0.94, indicating strong overall stability. These findings suggest that the portfolio recommendations were not dependent on a narrowly specified set of weights and that the integrated model retained its principal managerial conclusions under plausible changes in organizational preferences.

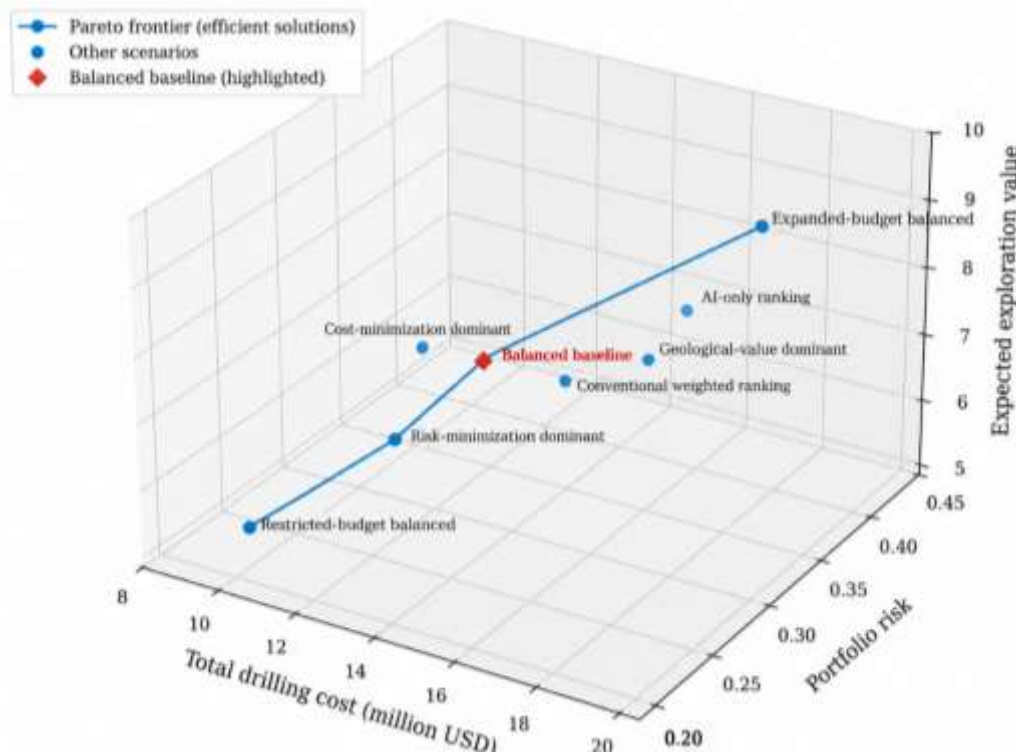


Figure 1. Pareto Frontier of Optimized Drilling Portfolios According to Expected Exploration Value, Total Drilling Cost, and Portfolio Risk

The Pareto-frontier analysis illustrated a clear nonlinear trade-off among expected exploration value, total drilling expenditure, and aggregate portfolio risk. Portfolios positioned toward the high-value end of the frontier achieved progressively greater expected mineral exploration returns but required disproportionately higher expenditure and generally accepted greater geological and operational risk. Conversely, low-cost and low-risk portfolios preserved financial and operational resources but omitted several technically attractive drilling targets and therefore generated lower cumulative expected value. The balanced baseline portfolio was located close to the knee region of the Pareto frontier, where further increases in expected value required substantially larger increases in cost or risk. This position supported its selection as the preferred compromise portfolio because it simultaneously preserved a high level of predicted geological opportunity, avoided excessive expenditure, and maintained a risk profile substantially below that of the AI-only solution. The graphical pattern therefore confirmed the

numerical optimization results and demonstrated that the proposed decision framework did not simply maximize one criterion at the expense of all others. Instead, it identified a set of non-dominated portfolio alternatives from which decision-makers could select according to organizational strategy, capital availability, and tolerance for exploration uncertainty. Overall, the findings demonstrate that integration of CNN-LSTM mineral prospectivity predictions with multi-objective engineering-management optimization generated a more balanced, stable, and resource-efficient basis for prioritizing mineral exploration drilling investments than either predictive modeling or conventional managerial scoring used independently.

4. Discussion and Conclusion

The present study developed and evaluated an integrated engineering-management framework in which CNN-LSTM-based mineral prospectivity prediction was combined with

multi-objective portfolio optimization to support drilling prioritization under geological, economic, operational, and risk-related constraints. The findings showed that the proposed architecture performed well at both the predictive and managerial levels. The CNN-LSTM model achieved strong classification performance, with a test accuracy of 0.898, precision of 0.883, recall of 0.909, F1-score of 0.896, and ROC-AUC of 0.944. At the portfolio level, the integrated model generated target rankings that differed meaningfully from rankings based solely on geological prospectivity. The highest-ranked target, T-07, combined very high prospectivity with favorable cost, low risk, and strong strategic compatibility, while some targets with high CNN-LSTM scores, such as T-25 and T-20, were assigned lower portfolio priorities because of their higher cost and risk burdens. The balanced baseline scenario produced the highest portfolio efficiency score of 0.901 under the standard USD 15 million budget, outperforming both the AI-only ranking and the conventional weighted-ranking approach. Sensitivity analysis further showed that the preferred target set was comparatively stable, with rank-order correlations ranging from 0.81 to 0.94 across alternative weighting structures. Taken together, these findings indicate that deep-learning predictions can provide a strong technical foundation for exploration targeting, but the greatest managerial value is obtained when those predictions are embedded within a portfolio-level optimization process rather than used as direct drilling decisions.

The high predictive performance of the CNN-LSTM model is consistent with the broader development of deep learning in mineral exploration. Previous research has demonstrated that deep architectures are capable of extracting complex nonlinear relationships from heterogeneous geoscientific datasets, particularly when geological, geochemical, geophysical, and remote-sensing information is integrated in a common analytical framework [4]. The strong ROC-AUC and recall values observed in the present study suggest that the hybrid model was effective in distinguishing favorable from unfavorable exploration locations and in identifying a high proportion of genuinely promising targets. This aligns with the increasing use of machine learning for mineral prospectivity mapping as a means of moving beyond conventional linear or manually weighted evidence-combination procedures [5]. It is also consistent with recent reviews showing that deep-learning methods are particularly useful when exploration data are multisource, spatially structured, and characterized by complex interactions that are difficult to specify explicitly in

traditional models [6, 7]. In this sense, the CNN component likely contributed to spatial feature extraction from geological and geophysical inputs, while the LSTM component provided an additional mechanism for representing ordered dependencies among extracted features and historical exploration information.

The present findings are also consistent with previous research specifically emphasizing LSTM-based prospectivity modeling. Wang and Zuo showed that LSTM-based approaches can improve the representation of complex dependencies in mineral prospectivity mapping when combined with appropriate evidence-weighting procedures [8]. The current results extend that logic by embedding LSTM within a hybrid CNN-LSTM architecture, thereby combining spatial representation learning with sequential or ordered dependency modeling. The relatively small reduction in predictive accuracy between the training, validation, and test sets further suggests that the model generalized reasonably well rather than simply memorizing training patterns. This is important because deep-learning applications in mineral exploration are often vulnerable to limited sample size, spatial autocorrelation, class imbalance, and overfitting. The observed stability across data partitions therefore provides practical support for the use of hybrid architectures when preprocessing, validation, regularization, and early stopping are appropriately managed.

However, the strong predictive metrics should not be interpreted as evidence that prospectivity alone is sufficient for drilling prioritization. One of the most important findings of this study was the discrepancy between geological favorability and final portfolio rank. For example, T-21 exhibited a higher CNN-LSTM prospectivity score than T-05 but ranked lower after cost and risk were included. Likewise, T-25 and T-20 remained geologically attractive but were downgraded because of comparatively unfavorable cost and risk profiles. This pattern directly supports the view that exploration targeting must be connected to commercial and managerial decision-making. Partington et al. argued that exploration target ranking should form part of a broader information system that supports commercial decisions rather than functioning as a purely geological exercise [11]. The present study provides empirical support for that proposition by showing that a target can be technically promising while remaining managerially inefficient. This distinction is critical in real exploration environments, where the objective is not merely to maximize geological probability but to allocate limited capital across competing opportunities.

The results also reinforce longstanding concerns about uncertainty in mineral prospectivity mapping. Although the CNN-LSTM model showed high classification performance, the portfolio model treated geological uncertainty and related managerial risk as separate decision dimensions rather than assuming that predictive probability fully captured uncertainty. This is consistent with the argument that uncertainty in prospectivity mapping arises from multiple sources, including input data quality, geological conceptualization, evidence representation, spatial processing, model structure, and validation design [9]. Zhang et al. further showed that uncertainty can emerge from the analytical workflow itself, including preprocessing choices and modeling decisions, meaning that seemingly precise outputs may still reflect methodological contingencies [10]. The current study addressed this problem by avoiding direct translation of high prospectivity into automatic project selection. Instead, prospectivity was combined with geological confidence, cost, operational risk, and strategic factors, thereby reducing the likelihood that a technically uncertain but numerically high-scoring target would dominate the portfolio solely because of model output.

The portfolio optimization results strongly support the use of a multi-objective rather than single-objective decision structure. The balanced baseline scenario achieved an efficiency score of 0.901, higher than the geological-value-dominant, cost-minimization, risk-minimization, AI-only, and conventional weighted-ranking scenarios. This result is theoretically consistent with multi-objective optimization, in which decision quality depends on achieving acceptable trade-offs among conflicting objectives rather than maximizing one objective in isolation [14]. In the present study, maximizing prospectivity alone generated a portfolio with the highest mean geological score but also the highest mean risk and almost complete budget utilization. Conversely, aggressive risk minimization reduced exposure but sacrificed expected portfolio value. The balanced solution occupied a compromise position that preserved strong prospectivity while controlling cost and risk. This outcome illustrates the practical meaning of Pareto efficiency in exploration management: the preferred solution is not necessarily the portfolio with the highest geological score, lowest risk, or lowest cost, but the one located near the most favorable trade-off region among these competing objectives.

The finding that the balanced solution outperformed the AI-only ranking is particularly important. The AI-only

scenario achieved the highest average prospectivity score of 0.906, but its efficiency score was only 0.806 because it also produced the highest mean risk and used nearly the entire available budget. This demonstrates that predictive superiority at the target level does not automatically generate superior capital allocation at the portfolio level. Similar principles have been recognized in project portfolio selection research, where the value of a project cannot be determined independently of resource constraints, interactions among alternatives, and organizational priorities [16]. The present study therefore extends portfolio-selection logic into mineral exploration by treating drilling opportunities as competing capital projects rather than independent predictions. This approach is also consistent with engineering resource-allocation research emphasizing that large-scale project decisions require optimization of limited resources across multiple candidate activities rather than isolated evaluation of each activity [12].

The results further align with prior work on resource-constrained and multi-objective portfolio selection. Hoseini et al. showed that project portfolio selection becomes more realistic when resource limitations, sustainability considerations, scheduling, and multiple objectives are incorporated simultaneously [18]. In the current study, budget, drilling capacity, time, risk, and strategic feasibility functioned as constraints that modified which technically attractive targets could be included in the final portfolio. The restricted-budget scenario is particularly illustrative: when the available budget was reduced to USD 10 million, the model selected only six targets but preserved a relatively high mean prospectivity score of 0.871. This indicates that optimization concentrated scarce resources on the most efficient opportunities rather than merely selecting the cheapest alternatives. Conversely, expanding the budget to USD 20 million increased total expected portfolio value but moderately reduced average prospectivity because additional second-tier targets entered the portfolio. This pattern is consistent with the logic of marginal allocation, whereby additional resources eventually finance alternatives of progressively lower relative quality.

The findings also correspond with the project portfolio management literature emphasizing risk balancing. Omid argued that engineering portfolios should be managed not only through resource optimization but also through explicit balancing of risk across selected projects [13]. The present results support this perspective because portfolios driven exclusively by geological potential accepted substantially higher risk than the balanced solution. By jointly minimizing

risk and cost while maximizing expected exploration value, the model produced portfolios that were more defensible from a managerial standpoint. This is particularly relevant in mineral exploration, where uncertainty is structurally unavoidable and where multiple high-risk targets can create excessive concentration even if each target is individually attractive. The integrated framework therefore supports diversification across drilling opportunities and avoids overcommitting resources to a small number of technically appealing but operationally fragile projects.

The Pareto-frontier results provide additional evidence for the appropriateness of the multi-objective approach. The balanced baseline portfolio was positioned near the knee region of the frontier, where additional improvements in expected exploration value required disproportionately greater increases in expenditure or risk. This type of compromise solution is consistent with the logic of Pareto-based project portfolio selection, in which decision-makers are presented with a set of non-dominated alternatives rather than one mechanically determined optimum [15]. Interactive multi-objective programming has similarly been proposed as a useful mechanism for project selection because managers may prefer different efficient portfolios depending on strategic priorities and changing resource conditions [17]. The present findings support that perspective by showing that geological-value-dominant, cost-dominant, risk-dominant, and balanced portfolios can all be efficient under different preference structures, while the balanced portfolio provides the strongest overall compromise under the baseline conditions.

The relatively high stability observed in the sensitivity analysis further strengthens confidence in the model. Seven of the nine projects selected in the balanced portfolio remained unchanged when the prospectivity weight was varied by $\pm 10\%$, and the rank correlations across alternative weighting schemes ranged from 0.81 to 0.94. This indicates that the preferred portfolio was not an artifact of one narrowly defined weighting configuration. Such robustness is important because multi-criteria and multi-objective models can be sensitive to managerial preferences. The ability of T-07 and T-12 to remain among the highest-ranked alternatives across multiple scenarios suggests that these targets possessed structurally strong combinations of geological potential, cost efficiency, and risk characteristics rather than benefiting from a particular weighting scheme. At the same time, the upward movement of T-02 and T-09 when cost received greater emphasis illustrates that the

framework remained responsive to genuine shifts in managerial priorities.

The findings also have implications for the role of optimization algorithms in exploration management. Portfolio-selection problems can contain many feasible combinations, particularly when the number of candidate targets increases. Research on combinatorial optimization has shown that efficient search procedures are necessary to avoid dependence on simple greedy selection strategies and to explore diverse regions of the solution space [19]. In the context of drilling, this means that selecting targets one by one according to descending prospectivity may overlook portfolios with superior combined value. The integrated framework addressed this issue by evaluating combinations of projects rather than treating each target independently. This distinction is important because a portfolio containing several moderately strong, low-cost, low-risk targets may outperform a set composed of the highest-probability but expensive and risky targets.

From a geoscientific perspective, the findings remain consistent with the broader evolution from conventional GIS-based targeting toward data-intensive and machine-learning-supported prospectivity analysis. GIS-based integration remains foundational because exploration evidence must still be spatially harmonized and represented within a common analytical environment [1]. However, the present results suggest that the role of GIS increasingly extends toward supplying structured inputs for advanced predictive models and decision systems rather than serving only as a weighted-overlay platform. This transition also responds to the practical issues highlighted by Hronsky and Kreuzer, who emphasized that prospectivity mapping should be designed around its ultimate exploration-targeting function [2]. The current study advances this principle by extending the output of spatial prediction into explicit investment prioritization.

Overall, the study demonstrates that the principal contribution of CNN-LSTM modeling in mineral exploration may not lie solely in improving classification accuracy, but in strengthening the evidence base available for engineering management. The integrated framework connects prediction, uncertainty, project evaluation, and portfolio optimization in one decision chain. This integration addresses a gap between geoscientific modeling and managerial execution that has remained evident in much of the prospectivity literature. Previous work has documented the increasing sophistication of data-analysis methods for exploration targeting [3], the expansion of deep-learning

applications in mining [6], and the growing capacity of multisource deep-learning systems [7]. The present findings suggest that the next stage of development should focus not merely on producing better maps, but on embedding those maps within transparent and resource-constrained decision systems capable of supporting actual drilling programs.

The study has several limitations that should be considered when interpreting the findings. First, although the expert sample included 206 professionals with varied technical and managerial backgrounds, the participants were drawn from organizations located in Tehran, and the resulting managerial weights and preference structures may not fully represent exploration organizations operating in other regions or institutional contexts. Second, the technical performance of the CNN-LSTM model depended on the quality, spatial resolution, completeness, and preprocessing of the available geological, geochemical, geophysical, remote-sensing, and drilling data. As with any data-driven exploration model, errors or inconsistencies in the underlying datasets could influence predicted prospectivity. Third, the portfolio model used normalized estimates of cost, risk, and expected value and therefore represents a structured decision-support environment rather than a complete reproduction of all contractual, regulatory, market, and field-level uncertainties encountered in real drilling campaigns. Fourth, the optimization model treated the principal decision criteria as measurable and comparable, whereas some strategic or environmental considerations may be more qualitative and context-dependent. Finally, the study evaluated portfolio performance through modeled efficiency and scenario analysis rather than through long-term prospective observation of actual drilling outcomes, so the practical economic benefits of the proposed framework would require further confirmation through field implementation.

Future studies should test the proposed framework across different mineral commodities, geological terrains, and exploration maturity levels to determine the extent to which the results generalize beyond the present application. Research could compare CNN-LSTM performance with transformer-based, graph neural network, ensemble-learning, and multimodal deep-learning architectures and examine whether these approaches improve both prospectivity accuracy and portfolio-level decision quality. It would also be valuable to incorporate probabilistic cost distributions, commodity-price uncertainty, conditional drilling outcomes, and dynamic learning from newly acquired borehole data so that portfolio priorities can be

updated sequentially during exploration campaigns. Future models could explicitly represent dependencies among targets, including shared infrastructure, spatial clustering, geological correlation, and learning spillovers from one drill hole to adjacent targets. More advanced optimization approaches could also incorporate real options, stochastic programming, robust optimization, or evolutionary multi-objective algorithms. Longitudinal field studies are particularly recommended to compare predicted portfolio performance with actual discovery rates, drilling expenditures, delays, and economic outcomes over several exploration cycles.

Exploration companies should avoid using machine-learning prospectivity scores as stand-alone instructions for drilling and should instead incorporate them into formal portfolio-management procedures that also consider expected value, cost, uncertainty, logistics, safety, environmental exposure, and organizational strategy. Decision-makers should establish standardized data-governance procedures before model development so that geological, geophysical, geochemical, remote-sensing, and historical drilling datasets are consistently validated, harmonized, and documented. Portfolio reviews should be repeated whenever major new drilling results, budget changes, commodity-price shifts, or operational constraints alter the decision environment. Managers should also use scenario and sensitivity analysis routinely rather than relying on one fixed set of criterion weights, because different strategic conditions may justify different efficient portfolios. For high-value drilling programs, the Pareto frontier should be presented directly to technical and executive decision-makers so that trade-offs among expected geological value, cost, and risk are visible and transparent. Finally, organizations should maintain human expert oversight throughout the process, using the CNN-LSTM and optimization outputs as structured decision-support tools rather than substitutes for geological interpretation, engineering judgment, and accountable investment governance.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

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All procedures performed in this study were under the ethical standards.

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