

Comprehensive Benefit Evaluation of Utilization and Disposal Technologies of Coal Chemical Waste Salts Based on the DANP-Cloud Model Framework

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Abstract

Coal chemical waste salt is a by-product of zero-liquid-discharge wastewater treatment in the coal chemical industry. Owing to its high salinity, complex impurity profile, and substantial compositional variability, its disposal and resource recovery remain highly challenging. This study investigated representative coal chemical waste salt samples from the Ningdong Energy and Chemical Industry Base and characterized their physicochemical properties and pollution profiles through compositional tracing, characteristic pollutant analysis, and laboratory testing. To identify suitable treatment pathways, a multidimensional integrated benefit evaluation system combining the DEMATEL (Decision-Making Trial and Evaluation Laboratory)-based ANP (Analytic Network Process) and a cloud model was developed to assess six waste-salt utilization and disposal technologies. The comprehensive benefit ranking was as follows: pyrolysis plus impurity removal and salt separation > ion-exchange membrane caustic soda production > impurity removal and salt separation > short-path sodium sulfate-to-ammonium production > MVR (Mechanical Vapor Recompression) plus rigid landfill > evaporation ponds plus flexible landfill. The results indicate that salt-separation technologies show superior overall applicability, whereas ion-exchange membrane caustic soda production provides the greatest environmental benefits. However, most resource recovery technologies remain constrained by limited product profitability and marketability. The proposed methodology provides decision support for high-value utilization of coal chemical waste salt in the Ningdong Industrial Base and may also serve as a reference for benefit evaluation in other engineering projects.

Keywords

Coal chemical waste salt; Pollution characterization; Utilization and disposal technologies; DANP; Cloud model

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1. Introduction

China has the world's third-largest coal reserves, accounting for 12.60% of the global total, and coal continues to play a dominant role in the country's energy supply and consumption^[1]. The coal chemical industry is an important component of clean coal utilization^[2]. Advanced coal chemical processes can partially substitute for petroleum and natural gas while converting coal into strategic energy reserves, giving the industry considerable national strategic importance^[3,4].

In China, coal resources and water resources are unevenly distributed and often spatially mismatched^[5]. The northern and northwestern regions, including Xinjiang, Inner Mongolia, Shanxi, and Shaanxi, contain more than 80% of the country's coal reserves but less than 10% of its water resources^[6]. Large coal chemical enterprises are therefore mainly located in coal-rich but water-scarce regions, where receiving water bodies are limited and wastewater discharge is strictly regulated^[7]. As a result, zero-liquid-discharge (ZLD) schemes have been widely adopted to alleviate the constraints imposed by limited water resources and strict environmental

requirements on sustainable industrial development^[8,9].

However, after the implementation of ZLD in modern coal chemical projects, waste salt becomes one of the major solid wastes generated^[9]. Its composition is strongly influenced by process routes and production stages, leading to substantial variations in both salt type and impurity content and a lack of standardized compositional data^[10]. Coal chemical waste salts often contain concentrated toxic and hazardous substances, including heavy metals, fluorides, and organic compounds^[11]. Because of their high solubility and mobility, these contaminants can readily migrate into soil and water bodies and pose environmental risks. Therefore, the standardized disposal and risk management of coal chemical waste salt have become increasingly urgent^[12].

In the early stage, coal chemical waste salt was mainly disposed of by landfill. However, with the rapid growth in waste salt generation and the tightening of pretreatment requirements under landfill-related policies, landfill costs have increased substantially, prompting enterprises to shift gradually toward resource recovery^[8,12]. For example, purified and detoxified waste salt may be used as a de-icing agent or in dyeing processes, while purified high-salinity brine may be



used in ion-exchange membrane caustic soda production to generate chlorine and hydrogen or in ammonium-alkali-related processes^[13]. Although waste salt resource recovery technologies have developed continuously in recent years, comparative studies on the comprehensive benefits of different utilization and disposal technologies remain limited. Previous studies on coal chemical wastewater and waste salts have mainly focused on ZLD process design, salt separation, organic pollutant removal, membrane fouling control, and individual resource recovery technologies. These studies have provided valuable information on treatment efficiency and process feasibility. However, three limitations remain. First, most studies focus on a single technology or a single pollutant-removal process, making it difficult to compare different utilization and disposal routes under a unified framework. Second, technology assessment is often based on technical or economic indicators alone, while environmental risks, product marketability, policy preference, and social acceptance are less systematically considered. Third, the relationship between waste-salt characteristics and technology suitability is often insufficiently discussed, even though salt type, organic contamination, moisture content, and inorganic impurities directly affect product quality, operating cost, and resource recovery potential. This makes it difficult for enterprises to identify the most suitable treatment pathway for their specific waste salt streams^[11]. Therefore, establishing a scientific and comparable comprehensive evaluation method is of great importance for waste salt management and technology selection.

Comprehensive benefit evaluation usually involves multi-level, multi-objective, and cross-dimensional indicator systems and is therefore inherently complex. In addition, many evaluation indicators are expressed using vague linguistic terms such as “good” or “excellent,” whereas conventional evaluation methods often focus mainly on randomness and are less effective in handling fuzziness. The cloud model, proposed by Li Deyi in 1995^[14], provides a mathematical framework that integrates randomness and fuzziness. It has been applied in areas such as comprehensive benefit evaluation of water resources and irrigation systems^[15] and energy-saving and benefit evaluation of power distribution systems^[16,17]. However, many existing studies treat indicator weights as fixed values and do not adequately consider interdependencies among indicators or the sensitivity of results to weight uncertainty. This may reduce the reliability and stability of the evaluation results. To address this issue, the present study combines the DEMATEL-based ANP (DANP) method with a cloud model to construct a comprehensive benefit evaluation framework for coal chemical waste salt utilization and disposal technologies that captures both indicator interdependence and mixed uncertainty.

The evaluation indicators for coal chemical waste salt utilization and disposal technologies usually exhibit coupling and feedback relationships. Traditional weighting methods, such as the analytic hierarchy process (AHP) and entropy weighting, generally assume independence among indicators and are therefore not well suited to representing the internal dependency structure of complex systems. The DANP method combines the causal analysis capability of DEMATEL with the network weighting mechanism of ANP, making it more suitable for multi-criteria decision-making problems involving mutual influence among indicators^[18]. It has been widely used in fields such as material selection^[19], resilience assessment^[20], and sustainability evaluation^[21]. Based on technical information collected from coal chemical waste salt disposal enterprises in the Ningdong

Energy and Chemical Industry Base, this study develops a comprehensive benefit evaluation model for waste salt utilization and disposal technologies. The aim is to provide decision support for high-value waste salt management in the Ningdong Base and to offer a methodological reference for benefit evaluation in other engineering projects.

2. Study Area and Methods

2.1 Study Area

The Ningdong Energy and Chemical Industry Base is one of China's four major modern coal chemical industrial zones. Located in central-eastern Ningxia, it is a key national hub for coal-to-liquids and coal-based olefin production, with a regional industrial output value exceeding CNY 180 billion (approximately USD 26.46 billion) in 2023. In the same year, the total amount of waste salt generated in the base reached 0.3260 million tonnes, including 0.2863 million tonnes of mixed salts and 0.0397 million tonnes of refined regenerated salts, comprising 0.0206 million tonnes of Na₂SO₄ and 0.0191 million tonnes of NaCl. Coal chemical waste salt was the dominant contributor, accounting for 93.35% of the total waste salt generated.

A total of 16 coal-chemical-related enterprises in the Ningdong Base were investigated in this study, including eight coal chemical enterprises, six petrochemical enterprises, which can be regarded as first-tier downstream producers in the coal chemical value chain, and two wastewater treatment enterprises equipped with desalination processes. Among these enterprises, seven were identified as waste-salt-generating sources and were therefore included in the subsequent analysis. Further details on these enterprises are provided in the [Supplementary Table S1](#).

2.2 Theoretical Origins of Waste Salt Characteristics

Characterizing coal chemical waste salt requires separate analysis of its major salt constituents and trace components, referred to here as characteristic pollutants. The major salt components can be quantified accurately through instrumental analysis. In contrast, characteristic pollutants are typically present at low concentrations and are highly diverse, while the waste salt matrix is complex. As a result, it is difficult to comprehensively identify them using conventional analytical methods alone. Therefore, theoretical analysis is required to predict likely pollutant types and guide targeted detection.

As shown in **Figure 1**, Characteristic pollutants in coal chemical waste salt mainly originate from three sources: regional natural conditions, production raw materials and auxiliaries, and water treatment chemicals. Raw coal and its derived products, such as naphtha and coal tar, may introduce complex organic compounds during downstream utilization, including petroleum solvents, benzene-series compounds, and polycyclic aromatic hydrocarbons. Although elements such as Pb, Cr, and As are generally present in coal only at ppm levels, the large scale of coal consumption in coal chemical production may still lead to the gradual accumulation of heavy metals in waste salt during long-term operation, potentially reaching hundreds of tonnes annually. In addition, water treatment chemicals are an important external source of salts and impurity ions. These chemicals may themselves contain trace heavy metal impurities, which can enter the waste salt system during brine concentration and crystallization. This further increases the complexity of waste salt composition and may hinder subsequent resource recovery.



Figure. 1 Analysis of the composition and sources of waste salt from coal chemical processing. Created by the authors using Microsoft PowerPoint 2024.

2.3 Characterization of Waste Salt Samples

A total of eight waste salt samples were collected from seven waste salt-generating enterprises in the Ningdong Base. The correspondence among sample ID, enterprise code, coal chemical production process, wastewater source, saline wastewater treatment process, and salt generation unit is provided in the [Supplementary Table S1](#). Among them, WS1 was collected from the evaporation pond of E1; WS2-1 and WS2-2 were collected from two distinct salt-containing wastewater treatment units of E2; WS3, WS4, and WS5 were collected from MVR-based salt crystallization units; and WS15 and WS16 were collected from centralized wastewater treatment and reuse enterprises. Because E2 operated two independent saline wastewater treatment processes and generated two distinct waste-salt streams, two samples were collected from this enterprise, whereas one sample was collected from each of the remaining enterprises. Moisture content was determined by drying, and ash content was determined by ignition^[22]. Organic functional groups in the waste salt samples were characterized by Fourier transform infrared spectroscopy (FTIR; Nicolet iS20, Thermo Fisher Scientific, Waltham, Massachusetts, USA) over a scanning range of 400 to 4,000 cm^{-1} . Organic components were analyzed by three-dimensional fluorescence spectroscopy using a fluorescence spectrophotometer (F-7000, Hitachi, Japan), and the fluorescence partitioning results are provided in the [Supplementary Table S2](#). Total organic carbon (TOC) was measured using a TOC analyzer (TOC-L CPH, Shimadzu, Japan).

Organic compounds in the waste salt were qualitatively analyzed by gas chromatography–mass spectrometry (GC–MS; 5977B, Agilent Technologies, Santa Clara, California, USA) after ultrasonic extraction with a mixed acetone/n-hexane solvent. The inorganic elemental composition was qualitatively characterized using an X-ray

fluorescence spectrometer (XRF; ZSX Primus II, Rigaku, Japan). The concentrations of metal elements, including Ca, Mg, Zn, Pb, Sr, Ni, Fe, Cu, Cr, Ba, Al, Li, and Mn, were determined by inductively coupled plasma optical emission spectroscopy (ICP-OES; Optima 5,300 DV, PerkinElmer, China). Before ICP-OES analysis, the samples were digested by microwave-assisted acid digestion using a mixture of nitric acid (HNO_3) and sulfuric acid (H_2SO_4).

The characterization results provided key input for the subsequent technology evaluation by linking waste-salt properties with technology suitability and evaluation indicators. Moisture and ash contents reflected pretreatment demand, disposal load, and potential operating cost. Organic pollutants, including TOC, phenols, and PAHs, were associated with residual pollution risk in recovered products and the need for thermal treatment or advanced oxidation. The dominant salt phases, including NaCl , Na_2SO_4 , and mixed salts, were used to judge the applicability of salt separation, chlor-alkali production, and sodium sulfate conversion routes. Inorganic impurities and heavy metals were related to product quality, membrane fouling or scaling risk, and secondary pollution potential. Therefore, the physicochemical and pollution characteristics of the waste salts were used to support the selection of evaluation indicators and the interpretation of the comprehensive benefit results.

3. Evaluation Model

3.1 DANP-Cloud Model Framework

The comprehensive benefit evaluation of coal chemical waste salt utilization and disposal technologies integrates the DANP weighting method with a cloud-model-based assessment framework, as shown in the **Figure. 2**.

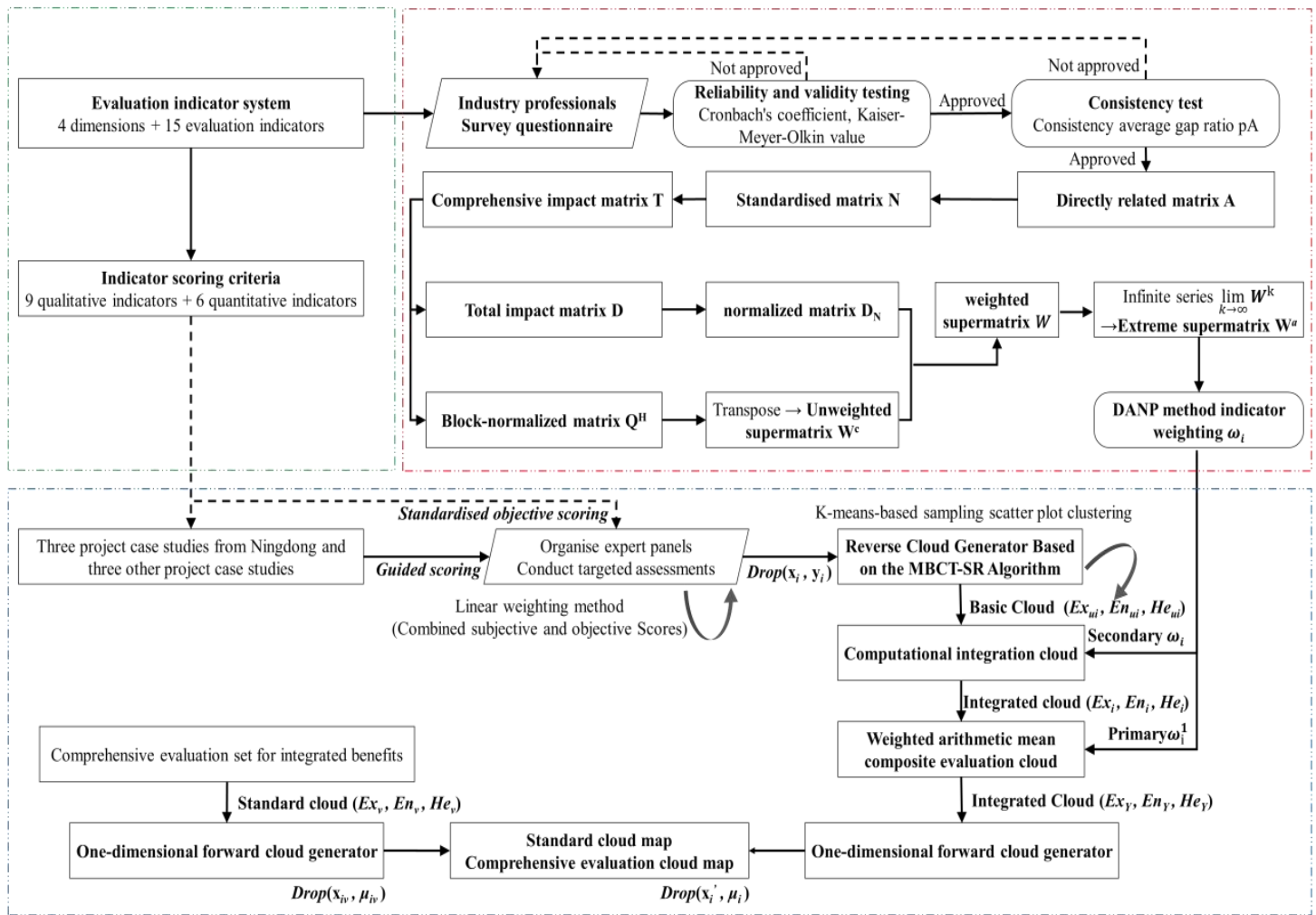


Figure. 2 A cloud model framework based on the DEMATEL-ANP (DANP) algorithm for evaluating the comprehensive benefits of coal chemical waste salt utilization and disposal technologies. Created by the authors using Microsoft PowerPoint 2024.

3.2 Data Collection

To ensure a scientific evaluation of the comprehensive benefits of coal chemical waste salt utilization and disposal technologies, this study established an analytical framework consisting of DANP-based weight determination and integrated cloud model evaluation. The data used in the evaluation comprised two components: data on inter-indicator influence relationships for DANP weight calculation, and expert scoring data for the evaluation of disposal technology schemes using the cloud model.

3.2.1 Indicator Influence Relationship Questionnaire (for DANP Weight Calculation)

Based on the typical characteristics of coal chemical waste salt and the current status of its utilization and disposal technologies, this study integrated field investigation results, literature review findings, and expert opinions to construct a comprehensive benefit evaluation indicator system for coal chemical waste salt utilization and disposal technologies. The indicator system is presented in **Table 1**. The system evaluates the comprehensive benefits of different technologies from four dimensions: technical, economic, environmental, and social.

For the economic benefit dimension, the definitions of B1 and B2 were further specified to account for equipment durability during long-term operation. Considering the corrosivity and scaling tendency of coal chemical waste salts, anti-corrosion design and scaling-control facilities were included in B1, while maintenance, depreciation, cleaning, shutdown, and equipment replacement costs caused by molten-salt corrosion during pyrolysis and scaling during evaporation-crystallization were included in B2. These factors were evaluated based on engineering case information and expert scoring. It can be used not only for the assessment of existing projects, but also to support investment decision-making for new projects. The degree of influence between indicators was assessed using a 0 to 4 scale, where 0 indicates no influence and 4 indicates the strongest influence.

To enhance the representativeness of the DANP weight setting process, questionnaire respondents were selected from stakeholders closely related to the management of coal chemical waste salt, including government management departments, universities or research institutions, testing institutions or social organizations, and production enterprises. A total of 32 questionnaires were distributed, and after excluding incomplete or logically inconsistent questionnaires,

30 valid answers were obtained. Among the valid respondents, 12 were from government management departments (40%); 10 were from production enterprises (33.3%); 5 were from universities or research institutions (16.7%); and 3 were from testing institutions or social

organizations (10%). This respondent structure covers policy supervision, engineering practice, and technical research, thereby enhancing the reliability and applicability of the indicator weight results.

Table 1. Evaluation indicator system for the benefits of utilization and disposal technologies for coal chemical waste salt

Criterion Level	Indicator Level	Indicator Description
A. Technical benefits	A1 Policy preference	Priority or guidance of relevant national policy documents issued by government agencies toward a specific technology (project).
	A2 Technological advancement	Domestic and international level of technological advancement, reflected by the number of main process steps and the scale of resource recovery products.
	A3 Energy consumption	Annual consumption of energy sources such as electricity, steam, and natural gas.
	A4 Technical applicability	Applicability of the technology to coal chemical waste salts and the local conditions, as well as the investor's capability and operational stability.
B. Economic Benefits	B1 Capital investment	Total capital investment required for construction of the engineering project, including equipment procurement, anti-corrosion design, scaling-control facilities, and salt-related treatment/disposal/utilization units.
	B2 Operating cost	Routine operating cost, including raw and auxiliary materials, water, electricity, chemicals, equipment maintenance, depreciation, and replacement costs associated with corrosion, scaling, and wear during long-term operation.
	B3 Product profitability	Profit generated from recovered products (e.g., regenerated salts, soda ash, chlorine, etc.) after commissioning.
	B4 Product marketability	Annual transaction volume (orders) and price fluctuation range of recovered products.
C. Environmental Benefits	C1 Residual pollution in products	Content of effective components (purity) in recovered products, reflecting residual contamination.
	C2 Annual waste-salt treatment capacity	Maximum annual scale of coal chemical waste-salt consumption (disposal or comprehensive utilization) under equivalent investment.
	C3 Additional pollutant generation	Number/types of secondary pollutants generated by the technology itself (waste gas, wastewater, solid waste), excluding subsequent treatment facilities.
D. Social Benefits	D1 Safety risk	Risk of sudden production accidents (e.g., explosion, poisoning) during operation.
	D2 Corporate investment willingness	Degree of enterprises' willingness to invest in waste-salt utilization/disposal projects under their needs and market conditions.
	D3 Local government satisfaction	Willingness and satisfaction level of local government authorities to promote and support the project during approval or stable operation.
	D4 Replicability and scalability	The degree of difficulty in replicating and scaling the engineering operational model across other regions within this province and other provinces.

3.2.2 Data Collection for Cloud Model Evaluation

After determining the indicator weights, this study conducted an expert scoring survey on six coal chemical waste salt utilization and disposal technology schemes. **Table 2** summarizes the calculation methods, scoring types, and data sources for each indicator. These six case studies primarily represent three major technical categories: landfill treatment, salt separation and recovery, and high-value chemical conversion. Case studies E1 and E5 are local disposal cases in Ningdong, representing evaporation ponds combined with flexible landfills and MVR combined with rigid landfills, respectively. Case E15 is a local resource recovery case in Ningdong, involving impurity removal and salt separation for the production of regenerated NaCl and Na₂SO₄. Cases A, B, and C are representative examples of off-site resource recovery, corresponding respectively to pyrolysis combined

with impurity removal and salt separation, the short-process conversion of sodium sulphate to ammonium hydroxide, and chlor-alkali production using ion-exchange membranes. For each case, data on raw materials, processing methods, recovered products, energy consumption, capital expenditure, operating costs, product profitability, product distribution, product quality, processing capacity, secondary pollutants, safety risks and replicability were collected through site surveys, company technical documentation, market information and expert consultation. Detailed scoring criteria and original case data are provided in the [Supplementary Table S3](#) and [Table S4](#). Of the six cases, three were typical local cases from the Ningdong Industrial Base, while the other three were drawn from external enterprises with representative core waste-salt disposal technologies. This design balances the practical needs of Ningdong with the representativeness and applicability of different technological pathways.

Table 2. Calculation methods and data sources of evaluation indicators for coal chemical waste–salt utilization and disposal technologies

Indicator	Indicator type	Calculation / scoring method	Data source
A1 Policy preference	Qualitative	Expert scoring based on national industrial policy guidance and technology promotion documents	Policy documents and expert judgement
A2 Technological advancement	Semi–quantitative	Sum of scores for the number of process steps, annual scale of recovered products, and the number of recovered product types	Engineering case data and expert judgement
A3 Energy consumption	Quantitative + expert correction	Objective data for electricity, steam, and natural gas consumption were normalized and integrated with expert scores	Engineering case data and expert scoring
A4 Technical applicability	Qualitative / semi–quantitative	Scored according to investor capability, suitability to waste–salt characteristics, environmental conditions, and operational stability	Field investigation and expert judgement
B1 Capital investment	Quantitative + expert correction	One–time project investment was normalized and integrated with expert scores	Engineering case data and expert scoring
B2 Operating cost	Quantitative + expert correction	Routine operating cost was normalized and integrated with expert scores	Engineering case data and expert scoring
B3 Product profitability	Quantitative + expert correction	Profit from recovered products was normalized and integrated with expert scores	Market data, engineering case data, and expert scoring
B4 Product marketability	Semi–quantitative	Sum of scores for trading frequency and price fluctuation range	Market data and expert judgement
C1 Residual pollution in products	Quantitative + expert correction	Product purity or effective component content was normalized and integrated with expert scores	Product quality data and expert scoring
C2 Annual waste–salt treatment capacity	Quantitative + expert correction	Annual waste–salt treatment capacity under equivalent investment was normalized and integrated with expert scores	Engineering case data and expert scoring
C3 Additional pollutant generation	Semi–quantitative	Scored according to the number and types of secondary pollutants	Process investigation and expert judgement
D1 Safety risk	Semi–quantitative	Scored according to the number of hazardous chemicals and potential accident sources	Process investigation and expert judgement
D2 Corporate investment willingness	Qualitative	Expert scoring based on enterprise willingness and market conditions	Field investigation and expert judgement
D3 Local government satisfaction	Qualitative	Expert scoring based on approval feasibility and local government acceptance	Field investigation and expert judgement
D4 Replicability and scalability	Qualitative	Expert scoring based on the difficulty of replicating the project in other regions	Engineering case analysis and expert judgement

The indicator system shown in **Table 1** was used as the scoring framework. To reduce subjectivity, scoring criteria and detailed rules were established for each indicator. The specific scoring rules are provided in the [Supplementary Table S4](#).

Among the indicators in the evaluation system, six indicators, namely A3, B1, B2, B3, C1, and C2, could be scored either quantitatively using objective engineering case data or qualitatively by experts. However, because these quantitative indicators differ in dimension, value range, and direction of preference, and because they include both benefit-oriented and cost-oriented variables, extreme-value standardization was used to transform the objective data into dimensionless values^[23]. The normalized results were then converted into a unified scoring scale for subsequent evaluation. To improve

scoring robustness and reduce the bias associated with purely subjective expert judgment, the objective scores were further integrated with expert assessments. The specific procedure was as follows:

Step 1. Dimensionalization of objective data

According to Eq. (1), data with different variation trends are normalised to obtain the standardised matrix X_{ij} :

$$X_{ij} = \begin{cases} \frac{x_{ij} - \min |x_{ij}|}{\max |x_{ij}| - \min |x_{ij}|}, & x_j \text{ is an efficiency – oriented indicator} \\ \frac{\max |x_{ij}| - x_{ij}}{\max |x_{ij}| - \min |x_{ij}|}, & x_j \text{ is a cost – based indicator} \end{cases} \quad (1)$$

where X_{ij} denotes the element of the score matrix corresponding to the i -th evaluation indicator and the j -th engineering case.

Step 2. Calculation of objective scores

According to Eq. (2), linear weighting is applied to recalculate the objective score of the i -th quantitative indicator for the j -th case:

$$W_{ij} = 100 \times Y_{ij} + 60 \quad (2)$$

where $Y_{ij} = X_{ij} / \sum_{j=1}^6 X_{ij}$ is the total number of evaluated cases, and 60 is the baseline value for objective scoring. If W_{ij} exceeds 100, it is capped at 100.

Step 3. Calculation of the integrated objective score

According to Eq. (3), the integrated score γ_{ij} of the six quantitative indicators for each engineering case is calculated as:

$$\gamma_{ij} = (1 - k) * \alpha_{ij} + k * W_{ij} \quad (3)$$

where α_{ij} represents the expert-assigned score of the i -th quantitative indicator for the j -th case, and k is the weighting coefficient, set to 0.618 (the golden ratio), which is commonly adopted as an empirical parameter in evaluation studies.

3.3 DANP Weighting Algorithm

In complex systems evaluation and multi-criteria decision-making (MCDM), interaction and feedback relationships often exist among evaluation indicators. Traditional hierarchical weighting methods cannot effectively capture the causal structure among criteria. DEMATEL can identify influence relationships and construct a total influence matrix, but its results mainly reflect influence intensity and cannot be directly converted into weights. ANP can derive stable weights through supermatrices within a network structure, but it usually requires extensive pairwise comparisons and does not clearly reveal causal relationships. Therefore, DANP combines the causal analysis capability of DEMATEL with the network weighting mechanism of ANP. It has been widely applied in fields such as corporate social responsibility evaluation^[24], green building assessment system optimization^[25], and sustainability evaluation of social rental housing^[26], enabling more reasonable characterization of criterion dependence and improving the effectiveness of weight calculation. In this study, DANP was used to determine the weights of the comprehensive benefit evaluation indicators for coal chemical waste salt utilization and disposal technologies, providing a basis for subsequent integrated evaluation and strategy optimization^[27].

The DANP weighting procedure comprises the following steps: (1) summing the individual sample matrices to obtain the direct-relation matrix A ; (2) normalising A ; (3) computing the total influence matrix T ; (4) constructing the dimensional total-influence matrix D ; (5) building the unweighted supermatrix W^c ; (6) normalising the dimensional total-influence matrix to obtain D_N ; (7) deriving the weighted supermatrix W ; (8) calculating the limit supermatrix W^a until convergence; and (9) extracting the final weights for each indicator. The detailed calculation results are provided in the [Supplementary Table S5](#).

Step 1. Construction of the direct-relation matrix

The questionnaire survey results provided by experts were aggregated by summing the corresponding matrices of all samples, yielding the direct-relation matrix A .

Step 2. Normalisation of the direct-relation matrix

The direct-relation matrix A was normalised using the row-sum maximum method to obtain the normalised matrix N :

$$N = \frac{A}{\max_{1 \leq i \leq n} \sum_{j=1}^p a_{ij}} \quad (4)$$

where a_{ij} denotes the element in matrix A , and the denominator represents the maximum row sum of matrix A (i.e., the infinity norm

$\|A\|_{\infty}$).

Step 3. Calculation of the total influence matrix

By introducing the identity matrix I , the total influence matrix T was calculated as:

$$T = \sum_{k=1}^{\infty} N^k = N(I - N)^{-1} = [t_{ij}]_{n \times n} \quad (5)$$

Step 4. Construction of the dimensional total-influence matrix

The total influence matrix T was partitioned according to different dimensions to construct the dimensional total-influence matrix D .

For a submatrix Q_{mk} extracted from T :

$$Q_{mk} = \begin{bmatrix} q_{11}^{mk} & \dots & q_{1i}^{mk} & \dots & q_{1k_j}^{mk} \\ \vdots & & \vdots & & \vdots \\ q_{i1}^{mk} & \dots & q_{ij}^{mk} & \dots & q_{ik_j}^{mk} \\ \vdots & & \vdots & & \vdots \\ q_{k_1 1}^{mk} & \dots & q_{k_j}^{mk} & \dots & q_{k_i k_j}^{mk} \end{bmatrix} \quad (6)$$

The dimensional influence matrix D is given by:

$$D = \begin{bmatrix} d_{11} & \dots & d_{1j} & \dots & d_{1m} \\ \vdots & & \vdots & & \vdots \\ d_{i1} & \dots & d_{ij} & \dots & d_{im} \\ \vdots & & \vdots & & \vdots \\ d_{m1} & \dots & d_{mj} & \dots & d_{mm} \end{bmatrix} \quad (7)$$

where each element d_{ij} is calculated as:

$$d_{ij} = \frac{\sum_{i=1}^{k_i} \sum_{j=1}^{k_j} q_{ij}^{mk}}{n} \quad (8)$$

Here, Q_{mk} denotes the submatrix extracted from the m -th row and k -th column of T ; k_i is the number of indicators in dimension i ; and q_{ij}^{mk} represents the element in the i -th row and j -th column of the submatrix.

Step 5. Construction of the unweighted supermatrix

Each submatrix Q_{mk} in T was normalised to obtain matrix Q^H . The transpose of Q^H was then assembled to form the unweighted supermatrix W^c .

Step 6. Normalisation of the dimensional influence matrix

Each element d_{ij} in matrix D was normalised by row summation to obtain the normalised dimensional influence matrix D_N :

$$d_{ij}^N = \frac{d_{ij}}{\sum_{j=1}^n d_{ij}} \quad (9)$$

Step 7. Construction of the weighted supermatrix

The weighted supermatrix W was obtained by multiplying the normalised dimensional influence matrix D_N with the unweighted supermatrix W^c :

$$W = D_N W^c = \begin{bmatrix} d_{11}^N W_{11}^c & \dots & d_{1j}^N W_{1j}^c & \dots & d_{1m}^N W_{1m}^c \\ \vdots & & \vdots & & \vdots \\ d_{i1}^N W_{i1}^c & \dots & d_{ij}^N W_{ij}^c & \dots & d_{im}^N W_{im}^c \\ \vdots & & \vdots & & \vdots \\ d_{m1}^N W_{m1}^c & \dots & d_{mj}^N W_{mj}^c & \dots & d_{mm}^N W_{mm}^c \end{bmatrix} \quad (10)$$

Step 8. Calculation of the limit supermatrix

The limit supermatrix W^a was obtained by repeatedly multiplying the weighted supermatrix until convergence:

$$W^a = \lim_{k \rightarrow \infty} W^k \quad (k = 1, 2, 3, \dots) \quad (11)$$

The computation was implemented in Python, with a convergence threshold of 10^{-4} and a maximum of 100 iterations. When the 4×4

submatrices in W^a converged, the DANP weights were obtained.

Step 9. Determination of indicator weights

The final weights of each indicator were extracted from the main diagonal of the limit supermatrix W^a [28,29].

3.4 Cloud Model Theory

In multi-criteria decision-making, evaluation information typically involves both randomness and fuzziness. For example, expert scoring systems and comprehensive evaluations often use qualitative terms such as “higher,” “fair,” and “lower,” which may be interpreted differently by different evaluators. In addition, the same concept may fluctuate randomly across samples. Traditional statistical models or single fuzzy methods are often insufficient to capture both types of uncertainty simultaneously, which may reduce the stability and interpretability of evaluation results. To address this issue, Li Deyi’s cloud model [14] provides a bidirectional mapping between qualitative concepts and quantitative data. It represents fuzziness and randomness through three numerical characteristics, namely expectation Ex , entropy En , and hyper-entropy He , which describe the center, discrete range, and uncertainty of the concept, respectively. Existing studies have shown that the cloud model is applicable to engineering evaluation and risk grading, including environmental water quality assessment [30] and land carrying capacity evaluation [31]. This approach improves the stability and interpretability of evaluation results.

3.4.1 Conventional Cloud Model Theory

Cloud models are mathematical frameworks integrating fuzziness and randomness to capture uncertainty in real-world systems, proposed by Professor Li Deyi in 1995 [14]. Given a qualitative concept C defined over a quantitative domain U , when $x \in U$ is regarded as a random realisation of C , its membership degree (or certainty) $\mu(x)$ is a random variable taking values in $[0,1]$ with a stable distribution trend. The distribution formed by all x and their $\mu(x)$ over U is termed a “cloud”, wherein each x constitutes a “cloud droplet”. Compared to traditional models assuming deterministic variables, cloud models are better suited to expressing the fuzziness and uncertainty inherent in complex systems. Given that the comprehensive benefit assessment of coal chemical waste salt utilization and disposal technologies involves multidimensional influencing factors, one-dimensional or two-dimensional cloud models struggle to fully characterise the system’s complexity. Therefore, this paper employs a multidimensional normal cloud model for modelling and evaluation.

3.4.2 Theory of Multidimensional Normal Cloud Models

The multidimensional normal cloud model is an extension of the one-dimensional normal cloud model and is suitable for representing multidimensional qualitative concepts. Let $U = \{x_1, x_2, \dots, x_m\}$ denote an m -dimensional quantitative universe, and let C be a qualitative concept defined on U . If the vector $X = (x_1, x_2, \dots, x_m)$ is a random realization in U and satisfies

$$X \sim N\left((Ex_1, Ex_2, \dots, Ex_m), (En')^2\right)$$

Where,

$$(En')^2 = ((En'_1)^2, (En'_2)^2, \dots, (En'_m)^2)$$

and

$$En' = (En'_1, En'_2, \dots, En'_m) \sim N(En, He^2)$$

with

$$En = (En_1, En_2, \dots, En_m), He = (He_1, He_2, \dots, He_m),$$

Then the certainty degree of X with respect to concept C , denoted as $\mu(x) \in [0, 1]$, satisfies Eq. (12). Under this condition, the

distribution of vector X over the multidimensional universe U constitutes an m -dimensional normal cloud model [32].

$$\mu(x) = \exp\left(-\sum_{j=1}^m \frac{(x_j - Ex_j)^2}{2(En'_j)^2}\right), j = 1, 2, \dots, m \quad (12)$$

3.4.3 Theory of Reverse Cloud Algorithms

For a given cloud model, the forward cloud generator is typically deterministic, whereas inverse cloud algorithms exhibit multiple implementations whose errors and stability vary with the specific method employed. Inverse cloud algorithms may be categorized as either deterministic or non-deterministic; owing to the practical difficulty of obtaining determinism in real-world scenarios, non-deterministic inverse cloud algorithms find more widespread application. Uncertain inverse cloud algorithms further comprise single-step and multi-step approaches: single-step algorithms (such as SBCT-1stM and SBCT-4thM) may encounter issues in practical applications where the He estimate becomes non-real due to hyper-entropy, thereby compromising evaluation reliability. In contrast, the multi-step inverse cloud transformation algorithm (MBCT-SR) avoids situations where $He^2 < 0$, exhibiting superior numerical stability. Nevertheless, MBCT-SR retains inherent randomness in parameter extraction. To enhance the robustness of cloud parameter estimation, this study employs a combination of exhaustive search strategies and K-means clustering for stability screening and optimisation of cloud parameters. K-means is a widely employed data mining clustering algorithm [33], which iteratively updates cluster centers while minimising the sum of squared distances between samples and cluster centers. This yields compact and well-separated clusters, thereby enhancing evaluation stability [34]. Consequently, this study employs MBCT-SR, integrating exhaustive search with K-means clustering to conduct a comprehensive benefit assessment of coal chemical waste salt utilization and disposal technologies. MBCT-SR procedures are outlined in Steps (1) – (3), while K-means procedures are detailed in Step (4).

Step 1. Estimation of the expectation

The mean value of the original dataset $X = \{x_1, x_2, \dots, x_i, \dots, x_n\}$ was calculated to obtain the expectation Ex_{ui} of the evaluation results for each indicator:

$$Ex_{ui} = \frac{1}{n} \sum_{i=1}^n x_i \quad (13)$$

where n is the number of samples (in this study, $n = 5$), and x_i denotes the comprehensive evaluation score given by the i -th expert.

Step 2. Random sampling and variance estimation

Random sampling was performed on the dataset X (five experts in total). In each sampling, r samples (i.e., the number of experts selected in one draw) were randomly extracted, and the procedure was repeated m times to form m new sample sets $S = \{S_{p1}, S_{p2}, \dots, S_{pm}\} (1 < p \leq m)$. For each sampled subset, the expectation $\bar{X}_i$ and variance Y_i^2 were calculated. Subsequently, the expectation $\bar{EY}^2$ and variance $\widehat{DY}^2$ of the m variance values Y_i^2 were obtained:

$$\bar{X}_i = \frac{1}{r} \sum_{j=1}^r s_{ji}, Y_i^2 = \frac{1}{r-1} \sum_{j=1}^r (s_{ji} - \bar{X}_i)^2 \quad (14)$$

$$\bar{EY}^2 = \frac{1}{m} \sum_{i=1}^m Y_i^2, \widehat{DY}^2 = \frac{1}{m-1} \sum_{i=1}^m (Y_i^2 - \bar{EY}^2)^2 \quad (15)$$

Step 3. Calculation of entropy and hyper-entropy

According to Eq. (16), the entropy $\widehat{En}_{ui}^2$ and hyper-entropy $\widehat{He}_{ui}^2$ under the given sampling conditions were calculated as:

$$\widehat{En}_{ui}^2 = \frac{1}{2} \sqrt{4(\widehat{EY}^2)^2 - 2\widehat{DY}^2}, \quad \widehat{He}_{ui}^2 = \widehat{EY}^2 - \widehat{En}_{ui}^2 \quad (16)$$

Step 4. Exhaustive sampling and clustering

In this study, the number of experts was five. The maximum possible numbers of samples drawn in a single sampling were C_5^2, C_5^3, C_5^4 (sampling one or five experts provides limited information). The repeated sampling numbers were set to 20, 40, 60, 80, and 100. Using an exhaustive strategy, 15 candidate results were obtained. According to Eq. (17), the centroid coordinates of entropy $\widehat{En}_{ui}$ and hyper-entropy $\widehat{He}_{ui}$ in the sampling scatter space were calculated and taken as the final output. The clustering relationships among sampling points are presented in the [Supplementary Figure. S1](#).

$$\min J(c) = \sum_{i=1}^n \|x_i - c\|, \quad c = \frac{1}{n} \sum_{i=1}^n x_i \quad (17)$$

3.4.4 Virtual Cloud Model Theory

To characterize cloud parameters across different dimensions and achieve multi-indicator information fusion, this study introduces a virtual cloud model. This involves weighting and integrating indicators based on their respective weights against the underlying base cloud, thereby forming a comprehensive conceptual cloud^[35]. The construction methods for virtual clouds primarily comprise the floating cloud method and the integrated cloud method: the floating cloud method is typically applicable to indicators exhibiting low correlation and near independence^[36]. Given the strong correlations among the 15 secondary indicators in this study, the integrated cloud method was employed to weight and synthesize secondary indicator cloud parameters. This yielded cloud parameters for the primary dimensions (technology, economy, environment, and society), characterizing the dimensional benefits of different technical cases. Following the derivation of primary indicator cloud parameters, a weighted arithmetic mean was further applied to synthesize the comprehensive evaluation cloud parameter. The formula for the integrated cloud method is as follows:

$$Ex_i = \frac{\sum_{i=1}^n (Ex_{ui} \times En_{ui} \times \omega_i)}{\sum_{i=1}^n (En_{ui} \times \omega_i)} \quad (18)$$

$$En_i = \sum_{i=1}^n (En_{ui} \times \omega_i) \quad (19)$$

$$He_i = \frac{\sum_{i=1}^n (He_{ui} \times En_{ui} \times \omega_i)}{\sum_{i=1}^n (En_{ui} \times \omega_i)} \quad (20)$$

where Ex_i , En_i , and He_i denote the cloud parameters of the first-level indicator (dimension); Ex_{ui} , En_{ui} , and He_{ui} represent the cloud parameters of the second-level indicator; and ω_i is the weight of the second-level indicator.

The calculation of the comprehensive evaluation cloud parameters is given as follows:

$$Ex_Y = \sum_{i=1}^n (Ex_i \times \omega_{i-}) \quad (21)$$

$$En_Y = \sqrt{\sum_{i=1}^n (En_i^2 \times \omega_{i-})} \quad (22)$$

$$He_Y = \sqrt{\sum_{i=1}^n (He_i^2 \times \omega_{i-})} \quad (23)$$

where Ex_Y, En_Y and He_Y denote the characteristic parameters of the comprehensive evaluation cloud for each technology case, and ω_{i-} represents the weight of the first-level indicator.

4. Results and Discussion

4.1 Moisture and Ash Content Analysis

As shown in the **Figure. 3 (a)**, the colour of WS3, WS4, WS5, and WS16 changed from yellow to greyish black after calcination, indicating that these samples may contain abundant long-chain hydrocarbons or non-volatile cyclic organic compounds that underwent anaerobic cracking or incomplete combustion at 600 °C. After calcination, WS1, WS2-1, and WS2-2 changed from loose powders to distinctly caked structures with increased whiteness, suggesting that the crystalline salts may be coated with organic matter mainly composed of short-chain hydrocarbons or volatile components. WS15 showed obvious yellowing after calcination, which may be related to the formation of yellow complexes among water treatment agents (PFS), ferric hydroxide compounds (γ -FeOOH), Ca^{2+} , Mg^{2+} , and macromolecular organic compounds^[37].

As shown in the **Figure. 3 (b)**, WS1 had the highest moisture content (57.29%), while WS5 had the lowest (2.39%). The moisture content of the remaining samples was approximately 10%. The moisture differences were closely related to the salt generation units. WS1 was collected from an evaporation pond, where passive evaporation and limited solid–liquid separation resulted in the highest moisture content. In contrast, WS3, WS4, WS5, and WS16 were generated from MVR-based crystallization processes, leading to much lower moisture contents. This indicates that the ZLD treatment process strongly affects the physical form and subsequent disposal cost of the waste salts. In addition, the volatile matter contents of WS2-1 and WS2-2 were 5.77% and 2.08%, respectively, consistent with their appearance after calcination. This further suggests higher contents of volatile or low-molecular-weight organic components that readily decompose under medium-temperature conditions.

4.2 Infrared Spectroscopy Analysis

Fourier transform infrared spectroscopy (FTIR) was used to characterize the functional groups in the waste salt samples. As shown in the **Figure. 3 (c)**, all eight samples exhibited characteristic absorption peaks at 3,440, 1,130, and 615 cm^{-1} . The weak and broad band at 3,440 cm^{-1} corresponds to O-H stretching vibrations, indicating the possible presence of alcohols, phenols, or ethers^[38], which is consistent with the results in Section 2.2. The lower intensities in WS1 and WS15 may be attributed to dilution effects from evaporation ponds and mine water, respectively, as well as the relatively better quality of the upstream wastewater. A pronounced peak near 615 cm^{-1} was observed in all samples, corresponding to the symmetric stretching vibration of SO_4^{2-} . In addition, the overall spectral profiles closely resembled that of pure Na_2SO_4 , indicating that Na_2SO_4 rather than $NaCl$ is the dominant component of the Ningdong waste salts^[39].

Moreover, no distinct absorption bands were observed in the 1,500 to 1,700 cm^{-1} region, suggesting that carbonyl-containing compounds such as esters and ketones are present at very low levels. This differs from the results in Section 2.2 and may be explained by the involvement of carbonyl groups in electron-transfer processes during ozone-catalytic oxidation, which limits their retention in the waste salts^[40,41]. Notably, WS2-1 and WS2-2 exhibited several additional weak peaks near 1,380 cm^{-1} and within the 615 to 1,130 cm^{-1} range, which may be attributed to aromatic C-H bending vibrations^[42] or aliphatic C-H vibrations^[41].

These features are consistent with the presence of benzene derivatives, polycyclic aromatic hydrocarbons, and phenolic compounds identified in Section 2.2.

4.3 Three-dimensional Fluorescence Spectroscopy Analysis

As shown in the [Supplementary Figure. S2](#), except for WS2-1 and WS2-2, the remaining waste salt samples exhibited similar three-dimensional fluorescence spectra, although their fluorescence intensities varied considerably. The fluorescence signals were mainly distributed in Region V, followed by Regions IV and III, with only minor contributions from Region II. This distribution indicates that organic matter in most waste salts mainly consists of refractory humic-like substances and intermediate products formed during biological treatment or ozone oxidation, together with small amounts of aromatic protein-like (tryptophan-like) and fulvic-acid-like components. The fluorescence spectra of WS2-1 and WS2-2 resembled those reported by Yuan *et al.* for coal gasification wastewater, in which the fluorescence peak in Region V may represent fingerprints of ester- and phenol-type organic compounds^[43].

As shown in the **Figure. 3 (d)**, WS6, WS2-1, and WS2-2 exhibited the highest fluorescence intensities ($> 6 \times 10^6$ A.U.), indicating more severe organic contamination and the presence of abundant macromolecular organic matter, possibly including degradation intermediates of phenolic compounds and polycyclic aromatic hydrocarbons. In contrast, the relatively low fluorescence intensity of WS1 may be attributed to its high moisture content and the use of efficient wastewater treatment processes, whereas the lower fluorescence intensity of WS15 may be related to the co-treatment of high-volume, low-organic-load mine water. In addition, **Figure. 3 (e)** shows that WS3, WS4, and WS5 exhibited identical proportions (83%) in Region V, suggesting that these samples share similar types of organic contamination.

4.4 Total Organic Carbon (TOC) Analysis

As shown in the **Figure. 3 (f)**, the TOC contents of WS2-1 and WS2-2 were markedly higher than those of the other samples, reaching 7,738.0 mg/kg and 2,954.4 mg/kg, respectively. The higher TOC contents of WS2-1 and WS2-2 were consistent with the production background of E2, which involves coal-based multi-industry chain deep processing and produces coke, methanol, benzene, xylene, and modified asphalt. These processes may introduce more refractory organic intermediates into saline wastewater, which are subsequently concentrated in waste salts during multi-effect evaporation and freeze crystallization. The distinct organic pollution characteristics of WS2-1 and WS2-2 are also consistent with the three-dimensional fluorescence results. WS16 exhibited a TOC content of 1,851.4 mg/kg, second only to WS2-1 and WS2-2, which is likely related to its role as a wastewater treatment enterprise receiving effluents from the pesticide, pharmaceutical, and new-material industries, leading to pollutant enrichment in the resulting waste salt. By contrast, WS15 originated from a centralized wastewater treatment and reuse system receiving mine water and coal chemical wastewater, which diluted the organic load and resulted in lower organic contamination. The remaining samples, namely WS1, WS15, WS3, WS4, and WS5, showed comparable TOC contents of approximately 1,000 mg/kg, indicating similar types of organic contamination. Overall, the TOC levels of these waste salts were substantially lower than those reported for waste salts from the pesticide, pharmaceutical, and dyeing industries (1.0×10^5 to 5.4×10^5 mg/kg)^[44], suggesting a more favourable potential for resource recovery.

4.5 Analysis of Organic Matter Content

Organic compound analysis focused on samples with relatively

high organic contamination, namely WS15, WS2-1, WS2-2, WS4, and WS16. Benzene-series compounds, which are typical refractory pollutants in coal chemical wastewater, were not detected in any of the five samples, indicating that the upstream ozone-catalytic oxidation process is highly effective and that benzene derivatives are unlikely to persist in waste salts in their original forms. As shown in the **Figure. 3 (g)**, nineteen phenolic compounds were detected to varying degrees across the samples, with WS2-1 and WS2-2 exhibiting the highest total phenol contents, at 32.61 mg/kg and 6.22 mg/kg, respectively. These results are consistent with the whitening observed after calcination and the relatively high volatile contents. Combined with the TOC results, the residual organics are more likely degradation intermediates, such as aliphatic hydrocarbons, carboxylic acids, and alcohols, rather than high-molecular-weight phenols or PAHs (> 10 kDa). Further enhancement of the ozone-catalytic oxidation unit in brine treatment could therefore reduce organic residues in waste salts^[45]. As shown in the **Figure. 3 (h)**, WS15 and WS2-1 exhibited the highest polycyclic aromatic hydrocarbon (PAH) contents, at 0.5515 mg/kg and 0.4032 mg/kg, respectively. PAHs with fewer than four rings were rarely detected, indicating that low-molecular-weight PAHs were effectively degraded during catalytic oxidation, whereas only trace amounts of four-ring and higher PAHs remained.

4.6 Analysis of Inorganic Matter Content

Eight waste salt samples were qualitatively characterized by X-ray fluorescence spectroscopy (XRF), and the results are provided in the [Supplementary Figure. S3](#). The major inorganic elements detected included Na, Mg, Al, K, Ca, Cl, Br, P, Mn, Zn, and Pb. Based on the dominant salt phases, WS1, WS3, WS4, and WS5 were mainly composed of Na_2SO_4 ; WS15 was dominated by NaCl; WS2-1 and WS2-2 were mixed salts consisting of Na_2SO_4 , K_2SO_4 , KCl, and NaCl; and WS16 was a mixture of NaCl and Na_2SO_4 . Different salt types imply different recovery routes: NaCl-type waste salts are suitable for chlorine-utilizing high-value processes, such as ion-exchange membrane chlor-alkali production, whereas Na_2SO_4 -type waste salts can be utilized in routes producing ammonium sulfate and soda ash. By contrast, mixed salts generally have low utilization value because of the high separation cost, making rigid landfill disposal more economically feasible.

Coal chemical waste salts are predominantly sodium-based. Based on the XRF results and the theoretical analysis in Section 2.2, the concentrations of 13 major metal ions were determined, and the results are shown in the **Figure. 3 (i)**. As shown in the **Figure. 3 (i)**, Ca^{2+} and Mg^{2+} were present at relatively high levels (10 to 10^3 mg/kg), which may be attributed to the background hydrochemical characteristics of the Ningdong region. Elevated Al^{3+} and Fe^{3+} concentrations (10 to 10^3 mg/kg) were mainly associated with iron- or aluminium-based water treatment agents. WS1, WS3, WS4, and WS5 exhibited comparatively high Cu concentrations (10^2 mg/kg), likely due to the use of catalysts in upstream coal chemical processes. For NaCl-type waste salts intended for resource recovery through ion-exchange membrane chlor-alkali, ions such as Ca^{2+} , Mg^{2+} , Al^{3+} , and Fe^{3+} can readily form hydroxide precipitates on the ion-exchange membrane and potentially destabilize operating conditions; therefore, their concentrations should be strictly controlled. Ba, Mn, and Sr mainly originated from environmental background sources (1 to 10^2 mg/kg), indicating that waste salts from different enterprises in Ningdong should be further classified according to key indicator differences prior to utilization. Overall, the contents of Zn, Ni, Cr, and Pb were low (< 50 mg/kg), suggesting a relatively low heavy-metal contamination level. Consequently, Na_2SO_4 -type waste salts in Ningdong may have advantages for the short-process route converting sodium sulfate to ammonium alkali, although residual Cu, Sr, and F in the products should still be carefully monitored.

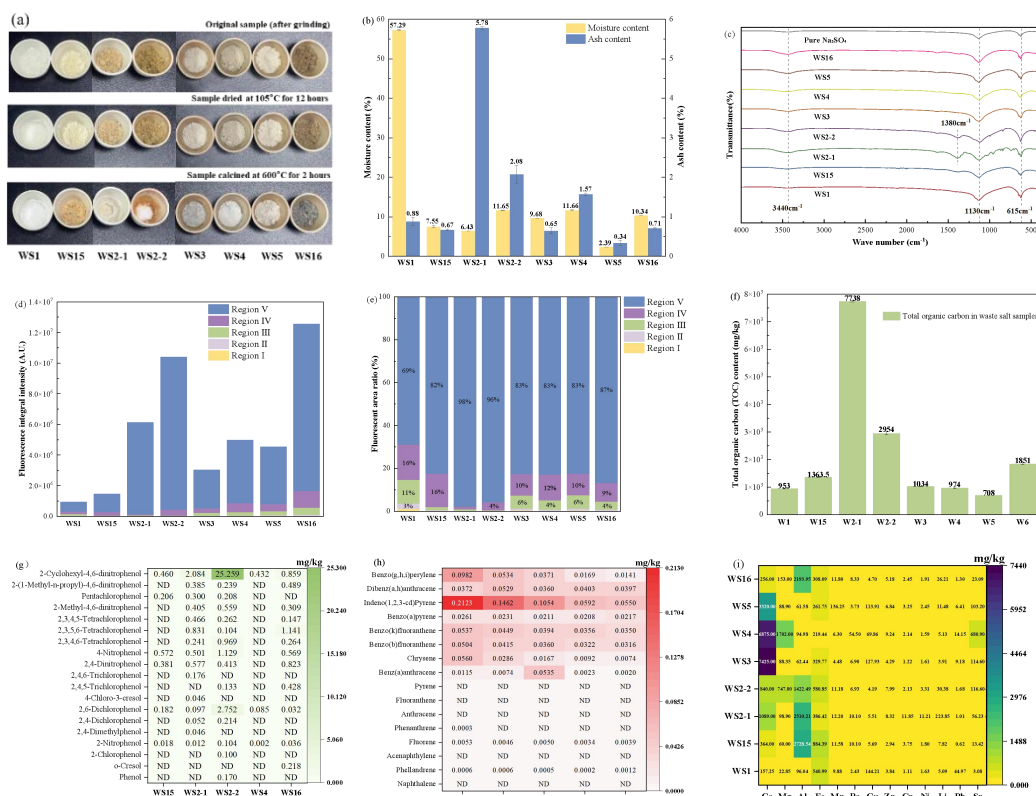


Figure 3 Morphology of the waste salt and characterization results of organic and inorganic pollutants. (a) Original sample; Sample dried at 105 °C; Sample after calcination at 600 °C; (b) Moisture content and ash content of waste salt; (c) Infrared spectral analysis results; (d) Three-dimensional fluorescence intensity; (e) Three-dimensional fluorescence area integration; (f) Total organic carbon (TOC) test results; (g) Test results for organic pollutant phenols; (h) Test results for polycyclic aromatic hydrocarbons (PAHs) as organic pollutants; (i) Heavy metal testing results. Created by the authors using Origin 2021 software.

4.7 Calculation Results of the DANP Weighting Algorithm

A total of 32 questionnaires were distributed, and 30 valid responses were collected. Indicator weights were calculated using the DANP procedure, and the results are presented in the [Supplementary Table S6](#). The results show only small differences among the four primary dimensions, indicating a relatively balanced multidimensional structure in the comprehensive benefit evaluation. The social dimension had a slightly higher weight, suggesting that factors such as corporate investment willingness, government support, and social acceptance exert a relatively greater influence on technology promotion. Among the secondary indicators, annual waste salt treatment capacity (C2), residual contamination in products (C1), and policy preference (A1) ranked highest. This indicates that environmental benefits and policy orientation dominate the evaluation framework, which is consistent with China's policy and management context for waste salt utilization and disposal. In contrast, safety risk (D1), energy consumption (A3), and product marketability (B4) ranked relatively low, suggesting that these factors may receive insufficient attention in decision-making.

4.8 Evaluation Results of Cloud Models

The technology evaluation was interpreted in combination with the characterization results of typical Ningdong waste salts. In particular, salt type, organic pollution level, moisture content, and inorganic impurity profile were used to explain differences in technical applicability, product quality, operating cost, and environmental benefit among the six technologies. The integrated scores for six quantitative indicators across six engineering cases are presented in the [Supplementary Table S7](#), and the integrated score

dataset for the 15 indicators is shown in the [Figure 4 \(a\)](#). [Figure 4 \(a\)](#) shows differences in expert preferences, which help reduce single-source bias and improve evaluation objectivity. Comprehensive benefits were classified into five grades, namely very poor, poor, fair, good, and very good, with an effective domain of $U = [0,100]$. The standard evaluation set and standard cloud are presented in the [Supplementary Table S8](#) and [Figure 4 \(b\)](#), respectively. The cloud parameters for each dimension and for the comprehensive evaluation cloud are listed in the [Supplementary Table S9](#). By inputting the four-dimensional cloud parameters and the comprehensive cloud parameters of each case from [Supplementary Table S9](#) into the forward cloud generator, the comprehensive evaluation cloud map and the dimensional evaluation cloud maps were obtained, as shown in the [Figure 4 \(c\)](#) and the [Figure 5](#).

As shown in the [Figure 4 \(c\)](#), the cloud droplets of the six cases are mainly distributed between 60 and 90, indicating that the evaluated schemes generally achieved a medium-to-high level of comprehensive benefit. Based on the expected value Ex , Case A (Pyrolysis + Impurity Removal and Salt Separation) showed the highest comprehensive benefit, followed by Case C (Ion-Exchange Membrane Caustic Soda Production), whereas Case E1 (Evaporation Pond + Flexible Landfill) showed the lowest. Both E1 and E5 are landfill-based schemes without resource recovery, which limits their applicability under Ningdong's constraints of increasing waste salt volume and limited storage capacity. Among them, E1 uses evaporation ponds, resulting in persistently high waste salt moisture content (57.4%), requiring larger landfill capacity and yielding slightly lower overall benefits than E5. Compared with E15, which also follows a salt separation route, Case A incorporates an additional

pyrolysis unit and therefore shows higher environmental and overall benefits. Case A had the lowest comprehensive entropy ($En = 0.803$), indicating greater expert consensus. Although Case C ranked second,

its score (1.28) indicates greater evaluation uncertainty. Case B ranked in the middle, likely influenced by factors such as technological maturity, product profitability, and marketability.

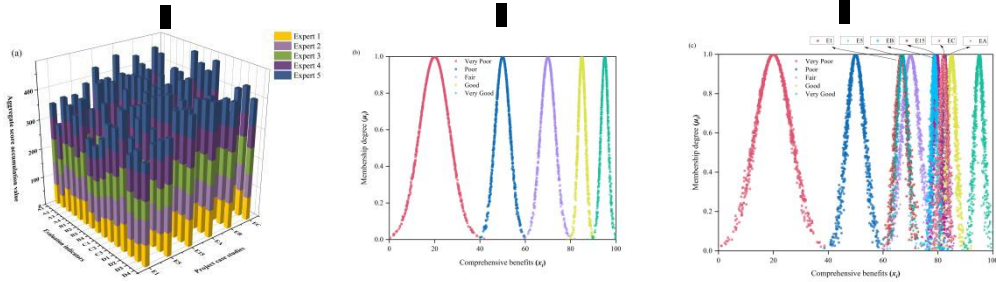


Figure.4 Comprehensive benefit evaluation process and cloud-model discrimination results of coal chemical waste salt utilization and disposal technologies. (a) Expert scoring results; (b) Standard cloud atlas; (c) Comprehensive benefits cloud map. Created by the authors using Origin 2021 software.

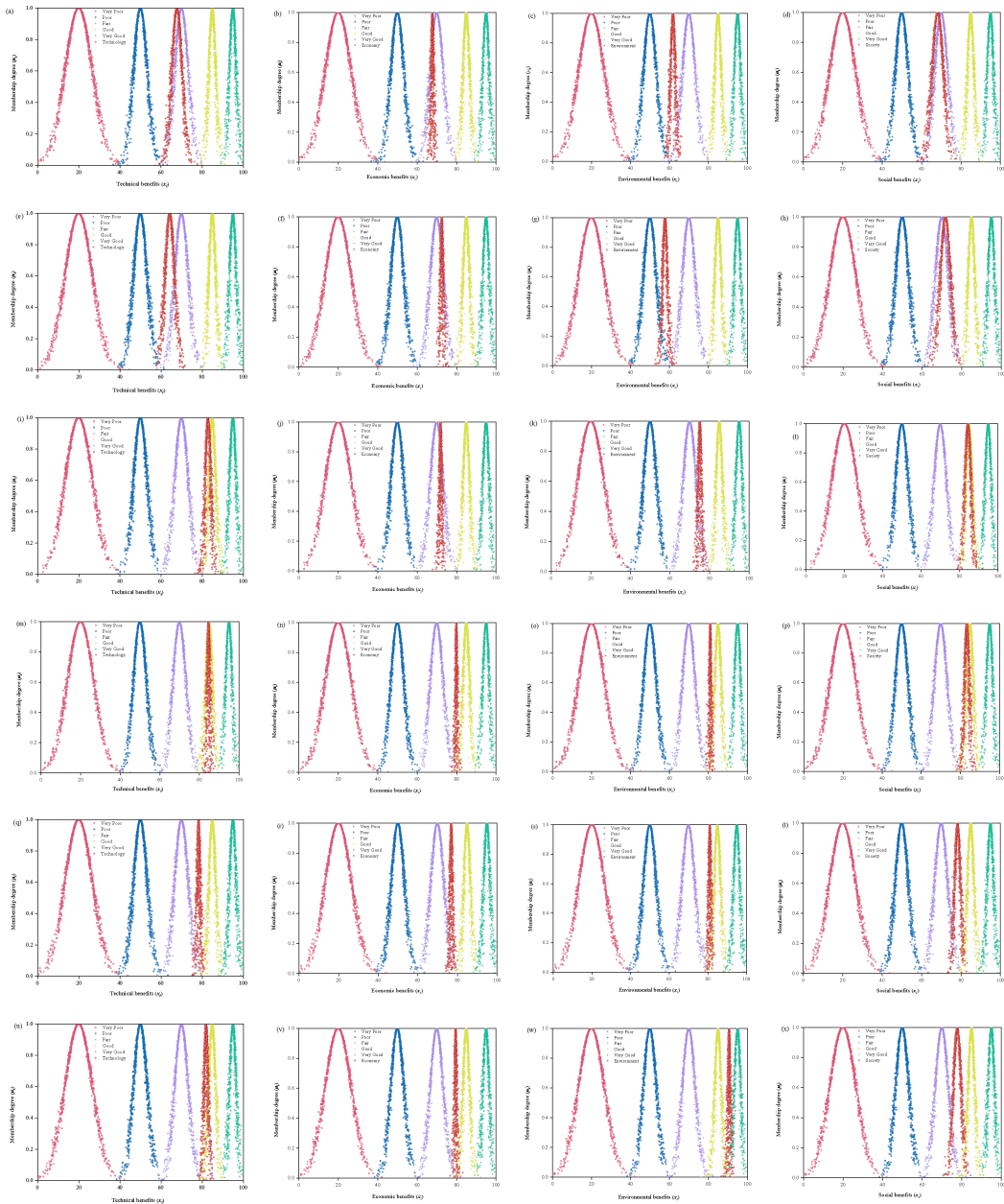


Figure. 5 Cloud diagrams for the technical, economic, environmental, and social dimensions. (a-d) Case E1; (e-h) Case E5; (i-l) Case E15; (m-p) Case A; (q-t) Case B; (u-x) Case C. Created by the authors using Origin 2021 software.

As shown in **Figure. 4** and **Figure. 5**, Case E1 (Evaporation Pond + Salt Evaporation + Flexible Landfill) scored below fair in the technical, economic, and social dimensions, and even lower in the environmental dimension. This indicates an outdated process route, limited resource recovery, and a relatively high environmental risk, which restricts its scalability. Case E5 (MVR + Rigid Landfill) scored above fair in the economic and social dimensions but below fair in the technical and environmental dimensions, indicating that it may serve as a transitional disposal option but offers limited technological advancement. Case E15 (Impurity Removal and Salt Separation) achieved good ratings in the technical and social dimensions, while the economic and environmental dimensions were above fair. This indicates strong applicability and acceptance of the salt separation route, although its performance is constrained by product profitability and product quality or pollution control requirements. Case A (Pyrolysis + Impurity Removal and Salt Separation) achieved good ratings in both the technical and social dimensions, and its economic and environmental dimensions approached good. Compared with E15, it showed clearer advantages in pollutant removal, cost-effectiveness, and treatment scale, indicating strong potential for wider application. The economic performance of the pyrolysis and evaporation-crystallization routes should be interpreted together with equipment durability. Pyrolysis may be affected by molten-salt corrosion, whereas evaporation-crystallization may suffer from scaling, heat-transfer deterioration, and more frequent cleaning or shutdown. Although these factors were included in B1 and B2, site-specific life-cycle cost assessment is still needed when long-term corrosion and scaling data become available. Case B (Short-path sodium sulfate-to-ammonium production) fell between fair and good across all four dimensions, indicating moderate overall performance. Although it can produce by-products such as baking soda and ammonium sulfate, its overall benefit was lower than that of salt separation technologies because of limitations in scale, operational stability, and profit margins. Case C (Impurity Removal + Ion-Exchange Membrane Caustic Soda) showed economic and social performance between fair and good. Its high energy consumption and market volatility weakened its economic advantage, but it performed well in terms of technological maturity, policy support, and low residual pollution risk. Its good technical rating and environmental performance approaching very good are consistent with engineering practice, further supporting the rationality of the indicator system and evaluation model.

5. Conclusions and Recommendations

This study systematically investigated the generation, utilization, and disposal of waste salt from coal chemical plants in the Ningdong Base. It analyzed the origins of waste salt composition and identified characteristic pollutants, thereby clarifying the physicochemical properties and pollution characteristics of typical waste salts. On this basis, a comprehensive benefit evaluation indicator system was established. The DANP method was used to determine indicator weights and reveal interrelationships among indicators. A cloud-model-based evaluation framework was then developed to compare three external resource recovery cases with three typical cases from Ningdong, so as to assess the applicability of external technologies to Ningdong waste salt. The main conclusions are as follows:

(1) The Ningdong Base contains 16 enterprises involving salt-containing coal chemical wastewater, of which 7 generate coal chemical waste salt after on-site treatment. Waste salt generation is

large and continues to increase, reaching 398,700 tonnes in 2024, a year-on-year increase of 22.30%, and accounting for 93.35% of the total industrial waste salt generated in the base. Meanwhile, the comprehensive utilization rate remained low at 13% in 2023, indicating an urgent need for resource recovery and high-value utilization. Pollutant identification showed that the characteristic pollutants mainly include petroleum solvents, heavy metals, phenols, esters, aromatic compounds, and polycyclic aromatic hydrocarbons.

(2) Based on pollutant identification, eight waste salt samples from seven enterprises were characterized. Waste salt from evaporation ponds showed the highest moisture content, at 57.40%, whereas the moisture contents of MVR and multi-effect evaporation waste salts were all below 12%; volatile matter ranged from 0.34% to 5.78%. Organic components mainly included alcohols, phenols, ethers, and aliphatic or aromatic compounds. Waste salts from coal-to-liquids processes mainly contained humic substances, aromatic protein-like substances, and fumaric-acid-like substances, whereas samples associated with coking and gasification were characterized by phenols and esters. Typical Ningdong waste salt had a TOC content of about 1,000 mg/kg, indicating relatively favourable conditions for resource recovery. In samples with relatively high organic contamination, benzene compounds were not detected and only trace amounts of phenols and PAHs remained, suggesting that the residual organics mainly consisted of degradation intermediates such as aliphatic hydrocarbons, carboxylic acids, alcohols, and esters. Na_2SO_4 was the dominant salt phase, accounting for about 90% of the samples, and the overall heavy-metal contamination level was low, with Zn, Ni, Cr, and Pb all below 50 mg/kg. These results indicate potential for high-value utilization in routes producing ammonium sulfate and soda ash.

(3) Based on the characteristics of Ningdong waste salt and its current disposal status, the DANP results showed clear interdependencies among evaluation indicators. Annual waste salt treatment capacity (C2), residual pollution in products (C1), and policy preference (A1) had the highest weights and were identified as the most influential indicators. In contrast, safety risk (D1), energy consumption (A3), and product marketability (B4) had relatively low weights, indicating that these factors may receive insufficient attention in current decision-making. Among all indicators, residual pollution in products (C1) and technological advancement (A2) played fundamental roles in shaping the overall evaluation results.

(4) Based on the indicator system and cloud model, the six technical schemes were ranked as follows in terms of comprehensive benefit: Case A (Pyrolysis + Impurity Removal and Salt Separation) > Case C (Ion-Exchange Membrane Caustic Soda Production) > Case E15 (Impurity Removal and Salt Separation) > Case B (Short-path sodium sulfate-to-ammonium production) > Case E5 (MVR + Rigid Landfill) > Case E1 (Evaporation Pond + Flexible Landfill). In terms of technical applicability, salt separation technologies outperformed ion-exchange membrane caustic soda production. In the social dimension, conventional salt separation performed better than salt separation routes coupled with additional thermal treatment. In the environmental dimension, the ranking was as follows: ion-exchange membrane caustic soda production > short-path sodium sulfate-to-ammonium production > salt separation > landfill disposal. In the economic dimension, most resource recovery technologies were constrained by limited product profitability and marketability. For the Ningdong Base, it is recommended to establish a centralized treatment facility and improve the quality of regenerated and mixed salts through enhanced thermal treatment and impurity removal. During

pilot-scale promotion of high-value utilization technologies, priority should be given to verifying product quality, regulatory compliance, traceability, market acceptance, and profitability.

Author Contribution

All authors contributed to the study conception and design. Yixin Cai: conceptualization, investigation, writing—original draft, writing—review and editing, visualization, formal analysis. Nianxi Wang: writing—review and editing. Jie Xu: supervision, writing—review and editing. Jun Yang: supervision, writing—review and editing. Jian Li: writing—review and editing. Yi He: supervision, resources. Yanping Liu: supervision, resources, writing—original draft, writing—review and editing.

Supplementary Information

Supplementary material associated with this article can be found, in the online version, at [Supplementary Information](#).

Declaration of Competing Interest

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

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