Postprint: Multi-dimensional Characterization of Individual Experts and Balanced Recommendation of Expert Panels

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Abstract

[Purpose/Significance] This paper proposes a recommendation method for e-government project review expert panels based on multi-dimensional feature characterization of individual experts, aiming to enhance the consistency level of project reviews across different expert panels. [Method/Process] Utilizing individual experts' long-term review opinions as the data source, opinion mining techniques are employed to achieve knowledge element identification and sentiment polarity acquisition; experts' domain knowledge structures are constructed and dynamically updated iteratively; statistical analysis is used to characterize features including expert knowledge level, review profundity, sentiment style, and domain expertise, thereby realizing scientometrics-based expert feature characterization and conducting expert combination recommendations on this basis. [Results/Conclusion] The proposed method emphasizes multi-dimensional feature balance within expert panels, demonstrates strong problem relevance for e-government project review, and has achieved favorable application effects in practice.

Full Text

Preamble

Expert Individual Multi-dimensional Feature Depiction and Expert Group Equilibrium Recommendation Research

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Abstract: [Purpose/Significance] This paper proposes a recommendation method for e-government project review expert groups based on multi-dimensional feature depiction of individual experts to enhance consistency in project evaluation across different expert groups. [Method/Process] Using experts' long-term review opinions as the data source, opinion mining technology is employed to achieve knowledge element recognition and sentiment polarity acquisition. Experts' domain knowledge structures are constructed and dynamically updated through iterative processes. Statistical analysis is utilized to characterize experts' knowledge levels, review depth, emotional styles, and domain expertise features, enabling scientometric-based expert feature depiction and subsequent expert combination recommendations. [Result/Conclusion] The proposed method emphasizes multi-dimensional feature equilibrium within expert groups, demonstrates strong problem relevance for e-government project evaluation, and has achieved favorable application results in practice.

Keywords: e-government; project management; opinion mining; knowledge unit measurement; expert recommendation
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Peer expert evaluation methods based on epistemological theory [**?**] are widely employed by Chinese government departments for various project reviews. The advantage of peer expert evaluation lies in its ability to leverage expert experience for rapid quantitative estimation when sufficient statistical data and original materials are lacking. The accuracy of expert evaluation results primarily depends on factors such as experts' experience, knowledge richness, and personal emotional attitudes. While expert group evaluation methods based on independent expert assessments represent an improvement over individual expert evaluation as a group decision-making approach, they introduce the challenge of ensuring reasonable expert group composition.

In practical government project review work, randomly selecting experts to form review groups often leads to significant variations in evaluation outcomes for the same project across different groups. Therefore, research on expert group composition methods holds not only theoretical value but also practical significance for enhancing the scientific validity of project evaluations. E-government projects possess distinct characteristics of policy compliance, budget rationality, and performance evaluation feasibility. Constrained by relatively fixed management regulations, e-government project construction content and outcomes must adhere to clearly defined technical standards and implementation norms. Consequently, e-government project review activities primarily constitute group decision-making behaviors based on limited-dimensional deterministic knowledge within limited timeframes, relying on expert experience. This makes the rationality of expert group knowledge structure critically important for supporting the scientific validity of project approval conclusions.

Based on cognitive science and psychological theories, individual experts' diverse characteristics are the fundamental causes of cognitive and emotional polarity differences, which in turn lead to the objective phenomenon of inconsistent evaluation results across expert groups. As a group decision-making method aimed at balancing individual expert differences, expert group evaluation should essentially form a recommendation method that promotes multi-dimensional feature equilibrium within expert groups, thereby enhancing consistency in project review conclusions. Accordingly, defining and depicting review expert characteristics and achieving expert group recommendations based on feature equilibrium hold fundamental value for e-government project approval work.

2 Related Research

Expert recommendation research involves both scientometrics and information science, though with different emphases. Scientometrics research focuses more on selecting experts whose research expertise aligns with the evaluated project, emphasizing factors such as expert experience and authority to achieve peer and authoritative evaluation, thereby addressing cognitive differences arising from complex knowledge boundaries. Information science research, conversely, emphasizes discovering experts with specific knowledge types.

Research from Tsinghua University [?] on the "Uncertainty Principle in Talent Evaluation" demonstrates that evaluating an individual's capabilities requires scientifically selected test samples and prolonged process-based tracking to achieve reliability and validity in assessing learning and creative abilities, with results being approximate rather than precise values. This conclusion provides scientific support for using long-term, historically formed expert review opinions as the data source for expert feature depiction. Concurrently, adopting cumulative and intermittent dynamic characterization strategies aligns perfectly with the objective laws of expert cognitive development and the methodological requirements of "process-based tracking tests."

The Chinese Personality Research Group decomposes national character into five dimensions [?]: life interests, cognitive style, emotional characteristics, volitional qualities, and attitude tendencies. Life interests include traits such as intellectual curiosity; cognitive style includes objectivity, comprehensiveness, and agility; emotional characteristics include intensity and persistence. These findings establish the theoretical foundation for expert feature selection in this study.

Regarding expert recommendation research, foreign studies predominantly adopt qualitative approaches to explore scientific peer review expert supervision and management systems [?], while domestic research focuses on constructing expert evaluation indicator systems and expert identification recommendation methods: (1) In expert evaluation research, You Qinggen et al. [?] propose an expert evaluation indicator system comprising basic information, research capability, review skills, and personal credibility, which differs from Chen Yuan et al.'s [?] system focusing on research activity, review performance, and review attitude, providing reference for expert feature selection in this paper; (2) In expert recommendation methods, Zhao Qian et al. [?] construct an expert recommendation model combining paper sub-topic coverage and expert authority, while Wang Zisen et al. [?] calculate semantic similarity between expert academic expertise and project discipline concepts layer-by-layer according to project discipline tree hierarchies, achieving a multi-granularity peer expert academic expertise matching method, offering inspiration for knowledge acquisition methods in this study. However, most of these studies lack knowledgeometric analysis of individual expert evaluation conclusions, failing to support expert group recommendation research using meta-evaluation theory [?].

Scientometrics and knowledgeometrics constitute the foundational theories for expert expertise identification. Zhu Qinghua [?] analyzes knowledge element mining principles and clarifies the relationship between knowledge elements and knowledge units. Furthermore, Jiang Chunlin et al. [?] propose a scheme for academic paper evaluation using knowledge unit measurement; He Ying and Qiu Junping [?] utilize knowledge graphs and scientometric methods for interdisciplinary expert selection. These studies provide reference for defining expert knowledge features and theoretical basis for expert group composition in this paper. For expert evaluation issues, meta-evaluation theory offers methods for understanding quality deviations in expert evaluations. Meta-evaluation indicators primarily include objective indicators such as deviation coefficients and variation coefficients [?] constructed from scoring data, which constitute the basic methodology for expert feature measurement.

Based on the above summary, on the foundation of evaluation target-oriented expert feature definition, using long-term accumulated expert opinions from e-government project review processes as the primary meta-evaluation content, and employing knowledge mining and knowledgeometric methods enables multi-dimensional feature depiction of individual experts, thereby completing expert group recommendations based on multi-dimensional feature equilibrium.

3 Research Framework and Related Methods

3.1 Data Source and Knowledge Representation and Supplement Strategy for Expert Feature Depiction

E-government project review experts typically possess extensive review experience. Project management systems not only store review conclusions from multiple expert groups but also preserve individual experts' independent review results and short-text expert opinions (see Figure 1 [Figure 1: see original paper]). This data serves as the objective basis for individual expert feature depiction and, with the assistance of contextual knowledge, can meet the application requirements for expert group feature equilibrium recommendations.

Expert opinions, as cognitive results of project content, represent materialized storage of knowledge units, with ideas and viewpoints embedded within these units [?]. Through mining short-text expert opinions, knowledge elements can be extracted to form the foundation for knowledge measurement. Differences in knowledge units lie in variations in knowledge elements and their arrangement logic, which forms the basis for analogy. The essence of expert feature depiction is to achieve expert analogy. To accomplish this analogy, certain implicit attributes must first be abstracted from the analogy source (knowledge abstraction), and then the "analogy knowledge unit" must be combined with the actual problem to be solved for knowledge innovation, forming new analogical products [?].

Specifically addressing the problem in this paper, knowledge element mining from expert opinions requires two steps: (1) completing the expression and organization of knowledge units, transforming from physical-level text units to cognitive-level knowledge units; (2) completing knowledge content measurement, transforming from syntactic-level to semantic-level conversion. The difficulty in short-text opinion mining lies in sparse text features and missing context, leading to complex logical inclusion relationships in semantic features. Effective short-text opinion mining requires scientific knowledge supplementation and representation methods as support.

Using e-government project knowledge concept trees and project approval knowledge ontology to assist in knowledge acquisition and aggregation from expert opinions constitutes the technical approach for expert feature depiction in this paper. Nodes in concept trees and entities in ontologies are standardized according to national standards and relevant management policies for e-government projects [?]. Concept trees serve as representation methods for target knowledge semantic depth, addressing issues such as semantic recognition of conceptual inclusion relationships and review depth description in expert opinions. Project approval knowledge ontology can transcend concept tree boundaries, associating review knowledge semantics that cannot be mapped by concept trees through ontology to discover implicit knowledge and expand the boundaries of knowledge measurement. This combined knowledge representation method provides excellent convenience for problem-solving.

3.2 Research Framework

The research framework in this paper comprises three components: knowledge acquisition based on expert review opinions, expert multi-dimensional feature depiction, and multi-dimensional feature equilibrium-based expert group recommendation, as shown in Figure 2 [Figure 2: see original paper].

The knowledge acquisition component utilizes entity extraction technology for semantic recognition, forming an e-government domain entity lexicon. Based on syntactic analysis, expert opinions are finely segmented to extract SAO (subject-action-object) [?] structured knowledge. To achieve knowledge classification and analogy, project knowledge concept trees are used to effectively identify knowledge hierarchies in expert opinions and resolve conceptual conflicts, while knowledge ontology is employed to associate knowledge and mine implicit knowledge. This component not only performs knowledge mining and acquisition at the lexical, syntactic, and semantic levels but also utilizes RNN (Recurrent Neural

Network), LSTM (Long Short-Term Memory), and their corresponding bidirectional deep learning models—widely applied in sentiment classification—to construct sentiment classifiers for training, thereby obtaining sentiment polarity in expert review opinions.

First, the open-source tool HanLP is used for preliminary sentence segmentation, word segmentation, part-of-speech tagging, and stop-word removal of review opinion texts. Next, segmentation features X_i and part-of-speech features POS_i are integrated to enhance model recognition effectiveness. A voting method integrates four models—HMM, CRF, BILSTM, and BILSTM-CRF [**?**]—to extract entities contained in review opinions while forming a domain entity lexicon.

For opinion sentences with multiple subjects or objects in parallel, SAO structured knowledge is obtained through dependency parsing and used as basic semantic units to represent expert opinions. SAO is a triple structure extracted from text corpora that contains substantial information while effectively maintaining intrinsic relationships between information. In review opinions, intrinsic semantic relationships primarily include SA (subject-predicate), AO (predicate-object), and SAO (subject-predicate-object), typically expressing experts' views or adjustment suggestions on review objects (mostly in subject or object form). Due to non-standard language expressions in short-text opinions, this syntactic analysis yields suboptimal results, leading to SAO structured knowledge extraction errors that prevent recognition of intrinsic semantic relationships in text. To address this issue, this paper categorizes major problems in review opinions into three types and customizes rules for knowledge repositioning, with examples shown in Table 1 .

3.3 Expert Multi-dimensional Feature Selection

Expert feature selection has clear target constraints—e-government project approval knowledge constraints. Experts evaluate projects based on their knowledge structures, essentially representing a knowledge exchange activity between evaluation subjects and objects [**?**]. As information engineering for government function construction, e-government projects impose greater requirements on the breadth of expert knowledge structures. Accordingly, referencing domain concept trees and domain knowledge ontology, four constituent elements of expert knowledge structure are defined for knowledge classification, as shown in Table 2 .

Drawing on meta-evaluation theory and objective meta-evaluation indicators [**?**], knowledge level, review depth, emotional style, and domain expertise are defined as expert multi-dimensional feature depiction indicators. This definition comprehensively considers expert knowledge capabilities, psychological factors affecting expert reviews, and information availability. The intrinsic logical explanations of expert features are presented in Table 3 .

3.4 Multi-dimensional Feature Equilibrium-Based Expert Group Recommendation

3.4.1 Domain Relevance Assessment The above expert feature selection targets e-government project management objectives. By obtaining topic probabilities of projects under review through the LDA model and calculating topic similarity with expert domains, the domain relevance $Sim(V_{Pa}, V_{Ei})$ between expert E_i and project P_a under review can be obtained. A higher value indicates greater domain relevance between the expert and the project under review, calculated as shown in Formula (1). Here, V_{Pa} represents the topic feature vector of project P_a under review, and V_{Ei} represents the topic feature vector of expert E_i, calculated as shown in Formula (2), where M denotes the number of projects reviewed by expert E_i, and $T_{t,Ei}$ represents the average probability of expert E_i under topic t.

3.4.2 Knowledge Equilibrium Random Selection Equilibrium of knowledge levels among expert groups is actually achieved through knowledge aggregation of experts within each group. The specific method involves: (1) First, calculating the knowledge level and review depth means of each expert in the expert pool for the four knowledge elements in Table 2, denoted as ε_{li} and ε_{di} ($i \in$ {government knowledge, technical knowledge, management knowledge, budget knowledge}) as thresholds; (2) Incorporating the domain relevance obtained in the previous stage as weight ω into the random selection method; (3) Randomly selecting m experts ($3 \leq m \leq 9 < M$, with m being odd) from the expert pool (M experts) to form a candidate expert group, and calculating the knowledge level and review depth means of each knowledge structure of the candidate expert group. If both exceed thresholds ω_{li} and ω_{di}, the selection result is retained; otherwise, random selection is repeated.

4 Empirical Analysis

4.1 Data Source and Experimental Environment

This paper uses 1,211 review opinions from 214 provincial e-government project expert groups in 2017-2018 as the basic corpus. The domain ontology is stored in Neo4j using the Cypher language. Experiments are implemented using Python in a Windows 10 environment. The Google open-source deep learning framework TensorFlow and its high-level API Keras are used for domain entity extraction. The pyhanlp package provided by the open-source tool HanLP is utilized for dependency parsing and structured knowledge acquisition. Echarts is employed for result visualization.

4.2 Construction of Project Knowledge Concept Tree and Project Approval Knowledge Ontology

4.2.1 E-government Project Knowledge Concept Tree Based on e-government project review indicator requirements and knowledge structure definitions, the following constraints are imposed on the project knowledge concept tree in this paper: (1) The root node of the concept tree is the overall project construction scheme concept, designated as Level 0; (2) The Level 1 concepts of the concept tree are the eight elements of e-government project construction: requirements, construction objectives, technical solutions, construction content, implementation plans, assessment indicators, benefit analysis, and budget; (3) The depth weight w_{ij} constraint for nodes in the concept tree: child feature concept depth weights are greater than parent feature concept depth weights [?].

Under expert guidance, concepts are hierarchically divided and extracted top-down. Based on the Harbin Institute of Technology Synonym Forest Extension, synonyms are merged with manual adjustments. The domain concept tree is shown in Figure 3 [Figure 3: see original paper], where c_0-c_{32} represent concepts, c_0 is the tree root node, *syn* denotes synonyms of corresponding concepts, and arrows from child to parent concepts represent hierarchical relationships [?]. The breadth of the concept tree positively correlates with the richness of root node concept connotation, while depth positively correlates with semantic connotation specificity. Traversing the concept tree enables semantic recognition of different concept levels in expert opinions.

4.2.2 E-government Project Approval Knowledge Ontology The e-government project approval knowledge ontology (see Figure 4 [Figure 4: see original paper]) provides more complete representation of background knowledge. By associating knowledge elements between experts and projects, implicit knowledge such as government functions and policies/regulations that form the basis for expert reviews is acquired, supplementing project element content corresponding to expert knowledge structures and perfecting knowledge classification and aggregation. This ontology includes five categories: e-government projects, review opinions, approval stages, policies/regulations, and government functions. E-government projects include project element subclasses, while government functions contain government sub-function subclasses. Table 4 defines semantic relationships between concepts in the ontology. Using government function knowledge as an example, Formula (3) defines the knowledge association rule linking expert opinions to government functions through project elements. Subsequently, associated government function knowledge and policy/regulation knowledge are classified into government knowledge (see Table 2), supplementing project background knowledge in the knowledge structure.

4.3 Expert Review Opinion Mining and Knowledge Acquisition

An integrated model [?] is used to extract domain entities from expert review opinion texts. After manual screening and deduplication, 246 accurate domain entities are obtained, forming a domain entity library with 324 entries after synonym expansion.

Based on the domain entity lexicon, HanLP is used to analyze expert opinion syntax and intrinsic semantic relationships, finely segment expert opinions, and extract SAO structured knowledge for knowledge classification. Subjects (S) and objects (O) primarily represent reviewed objects, generally nouns or gerunds closely related to project concept semantics. Therefore, for subjects and objects, precise matching and fuzzy matching based on maximum text similarity are employed to achieve semantic recognition based on concept trees, obtaining fine-grained concept levels while being attributable to Level 1 concept nodes in the concept tree for knowledge classification.

A total of 1,752 SAO structured knowledge entries are obtained by integrating individual expert opinions and group opinions. Under expert guidance, review feature semantic concepts are manually annotated in advance. Algorithm results are compared with annotation results at different thresholds, and the maximum threshold is selected while ensuring concept accuracy, ultimately determining a fuzzy matching threshold of 0.55. To effectively test semantic recognition structures, two testing methods are defined: (1) SAO structured knowledge semantic recognition results use precision (P), recall (R), and F1-score (F1) as metrics; (2) expert group comprehensive opinion semantic recognition results use effectiveness rate (U) as the metric.

Using the proportion of projects where single-project SAO structured knowledge review feature semantic recognition accuracy (Project_S) exceeds the threshold as the indicator, the effectiveness rate of expert group comprehensive opinion semantic recognition results is calculated. Based on the characteristics of the project expert review opinion dataset and under expert guidance, the Project_S threshold is set at 0.75, with calculation methods shown in Formulas (4) and (5).

The results are shown in Table 5 , with an effectiveness rate of 81.42%, indicating that most e-government project expert group review opinion content can be mined for evaluation feature semantics using this method. Additionally, the precision P of SAO structured knowledge semantic recognition results reaches 94.18%, with F1 reaching 89.91%, effectively proving that the method can satisfactorily assign conceptual knowledge to review features. For knowledge classification results, C_P, C_R, and C_{F1} are all slightly higher than semantic recognition results, demonstrating that although the method may misidentify concepts due to fine granularity, it does not affect coarse-grained parent concept knowledge classification. The relatively low recall R and C_R result from: (1) unidentifiable project concepts in opinions that require domain ontology for recognition; (2) overly complex opinion statements forming incomplete SAO structured knowledge that can be further identified using custom rules from Table 1; (3) imperfect concept tree construction that cannot fully cover all project knowledge concepts initially, requiring dynamic expansion and maintenance to improve recall.

Using SAO structured knowledge from review opinions as data and classification accuracy as the experimental indicator, comparative experiments show RNN model at 85.37%, LSTM model at 86.79%, BIRNN model at 89.15%, while the

BILSTM model performs best with accuracy reaching 90.09%. This demonstrates that selecting the BILSTM model can effectively determine sentiment orientation in expert opinions. Partial results of review feature semantics and sentiment intensity are shown in Table 6 .

4.4 Individual Expert Multi-dimensional Feature Depiction and Visualization

4.4.1 Knowledge Level and Review Depth **(1) Knowledge Level.** Based on the knowledge level definition in Table 3, this measurement indicator is specifically designed as follows: For any expert knowledge constituent element, the relative deviation [?] between individual expert scoring opinions, sentiment, and the overall average scoring and opinion sentiment of the expert group is measured to characterize the expert's knowledge level in that knowledge constituent element. $Level_t$ represents the expert's knowledge level indicator in knowledge structure element t, controlling the importance of scoring deviation and opinion deviation through weights α_l and β_l. n represents the number of project elements corresponding to this knowledge constituent element. The scoring deviation coefficient [?] represents the relative deviation between expert score x_j and the average score $\bar{X}_j$ of all experts for project element j. O_j is the opinion deviation coefficient, representing the relative deviation between the average sentiment intensity of individual expert opinions and the overall average sentiment intensity of the expert group for project element j, where $sk1_j$ and $sk2_j$ represent the opinion sentiment intensities of individual experts and the expert group for project element j, respectively, and $K1$ and $K2$ are the numbers of individual expert and expert group opinions belonging to project element j.

(2) Review Depth. The more profound the review opinions, the more they demonstrate experts' mastery of practical knowledge required for e-government project construction. Therefore, expert review depth metrics based on the semantic hierarchy of project knowledge concept trees can depict expert knowledge depth. Expert review depth measurement is described from the following aspects [?]: (1) If expert opinions involve a large vocabulary of e-government domain feature words, the opinion content may be richer and more profound, indicating potentially greater expert knowledge breadth and depth; (2) If certain feature words appear frequently in expert opinions, experts have clearer understanding and deeper comprehension of the concepts involved; (3) The level, distribution path, and concentration (node out-degree) of feature words in the concept tree determine the specificity and clarity of reviewed feature semantic content, making the involved knowledge structure elements targeted and prominent or indicating focused knowledge composition.

(3) Visualization and Analysis. Setting both deviation weights α_l and β_l to 0.5, the overall knowledge structure level of experts is obtained by comprehensively averaging knowledge levels from each review activity. Expert review depth values are calculated through concept tree semantic hierarchy identification of all expert review opinions. Determined by domain experts, for hyponymy relationships, child concept node weights are set at 1.2 times the corresponding parent concept node weights, with both depth measurement weights α_d and β_d set to 0.5. To clearly understand the same expert's knowledge breadth and depth, both knowledge structure distributions are presented in the same radar chart. Using Expert A and Expert B as examples for illustration and analysis, Figure 5 [Figure 5: see original paper] shows Expert A's knowledge level and review depth, demonstrating strong consistency between knowledge level and review depth. Figure 6 [Figure 6: see original paper] reveals that Expert A's knowledge levels and review depth across all dimensions exceed the expert pool average, indicating outstanding review capabilities. Figure 7 [Figure 7: see original paper] shows that Expert B's technical and management knowledge levels are below the expert pool average, with correspondingly lower review depth, indicating unbalanced knowledge structure and strong capability bias.

4.4.2 Emotional Style Expert emotions are conveyed through review opinions. Based on the emotional style definition in Table 3, the calculation method for total expert opinion sentiment intensity $REmo$ is shown in Formula (12), where K is the total number of opinions from projects reviewed by the expert, and sk represents the sentiment intensity of expert opinion k.

Multiple experts' emotional styles are visualized using bar charts, as shown in Figure 8 [Figure 8: see original paper]. Experts X1, X4, X9, X11, X16, and X19 exhibit relatively strong negative emotions with more direct language, primarily adopting critical and adjustment-oriented review styles. Experts X2, X5, X7, X8, and X18 show relatively balanced positive and negative emotions with more tactful and positive language, primarily encouraging and affirming project construction while providing modification suggestions to guide project development. Verification of original expert opinions confirms these emotional style descriptions.

4.4.3 Domain Expertise The LDA model is selected due to its maturity and effectiveness. Using all reviewed project titles and material summaries as data sources, content topic analysis of reviewed projects is conducted to reflect project domains involved by experts. Main steps include: (1) Data cleaning, punctuation and number removal, stop-word filtering, and removal of common software description words to enhance LDA's representation of government, project function, and functional topics (e.g., module, business, platform, system), followed by bag-of-words construction; (2) Perplexity-based determination of topic numbers to improve model effectiveness; (3) Parsing matrix data to obtain word distribution under each topic and topic affiliation for each document, then statistically analyzing each expert's reviewed project topics.

Perplexity calculation and iterative adjustment through multiple experimental results determine the topic number as 70. After LDA model content topic analysis, the maximum probability topic for each reviewed project is statistically analyzed for each expert. Using Expert A as an example, 26 projects were reviewed, with 4 projects belonging to the “student and teacher psychological assistance and counseling” topic, 4 to the “case early warning video command” topic, and 4 to the “case law enforcement supervision and document inquiry” topic. Word clouds are displayed for topics with high frequency, as shown in Figure 9 [Figure 9: see original paper], clearly indicating that Expert A’s review domain focuses on e-government project construction related to “cases,” “early warning,” and “video.”

4.5 Expert Group Multi-dimensional Feature Equilibrium Recommendation Results

Based on the instantiated expert feature depiction method, expert group recommendations are implemented based on multi-dimensional feature equilibrium. Practical applications must fully consider factors such as multi-project simultaneous review, effective utilization rate of expert talent pools, and expert energy. To verify the effectiveness of the proposed extraction method in practical applications, multi-project parallel expert group recommendation verification is added based on single-project expert group recommendation verification. Fifty experts from the cyberspace administration expert pool are selected, with the expert group size set at 5 members.

4.5.1 Single-Project Expert Group Multi-dimensional Feature Equilibrium Recommendation To verify the results of single-project expert group recommendation based on multi-dimensional feature equilibrium, 100 simulation extractions are performed using a program, with results shown in Table 7 , where the last two columns display selected expert IDs. Under identical conditions, visualization comparison between pure random selection and multi-dimensional feature equilibrium selection intuitively demonstrates method effectiveness.

Using the 006th extraction as an example, the knowledge level means and review depth means of candidate expert groups obtained through multi-dimensional feature equilibrium selection/pure random selection are shown as short-dashed/dotted lines in Figure 10 [Figure 10: see original paper], with expert pool knowledge level and review depth means shown as solid lines. The equilibrium-recommended expert group achieves knowledge level means and review depth means equal to or higher than expert pool averages across all four knowledge constituent elements, reaching average levels. In contrast, the pure random selection group shows knowledge level means below expert pool averages in technical, management, and budget knowledge elements. Although this group’s review depth in management knowledge exceeds the expert pool average, it falls significantly below expert pool standards in the other three knowledge elements.

Furthermore, detailed data for the five experts in both candidate groups are listed in Table 8 . Analysis reveals that experts No. 6 and No. 15 obtained through equilibrium selection possess high levels and depth in technical knowledge, compensating for deficiencies in expert No. 16 in this area. Experts No. 6, No. 13, and No. 15 in management knowledge compensate for deficiencies in experts No. 5 and No. 16, achieving knowledge complementarity among experts. In contrast, experts No. 3, No. 5, No. 8, No. 10, and No. 17 selected through pure random selection exhibit uneven knowledge element levels and depth with lower knowledge complementarity and poorer intra-group equilibrium.

Additionally, pure random functions require long periods to achieve balanced selection frequency for each expert, which cannot be realized in short timeframes [?]. Table 8 observation shows that equilibrium selection incorporating review domain relevance not only improves the alignment between expert group members and review project domains but also does not associate with the number of projects previously reviewed by experts, thus mitigating frequency imbalance issues from pure random selection to some extent.

4.5.2 Multi-Project Parallel Expert Group Multi-dimensional Feature Equilibrium Recommendation Constraints for multi-project parallel selection are set as: (1) Meeting single-project candidate expert group multi-dimensional feature equilibrium recommendation requirements; (2) Selecting different candidate expert groups (with m experts) from an expert pool of M experts to review N projects simultaneously; (3) No identical review expert may appear across different projects under review.

Under these constraints, simulation experiments are conducted using the proposed method. Domain relevance between each expert and N projects under review is calculated, and selection is performed based on multi-dimensional feature equilibrium, yielding a maximum project number $N_{max} = 6$ for multi-project parallel review. This result demonstrates that the proposed method can fully satisfy practical applications of multi-project parallel review within the same timeframe while ensuring domain relevance and multi-dimensional feature equilibrium.

5 Conclusion and Outlook

Using knowledge measurement, sentiment feature extraction, and other technical methods for individual expert multi-dimensional feature depiction, and implementing expert group recommendations based on multi-dimensional feature equilibrium, brings the approach closer to the theoretical connotations of cognitive science compared to randomly composed expert groups, demonstrating stronger problem relevance and scientific validity. In practice, under conditions of relatively clear limited-dimensional knowledge boundaries, the adoption of standardized knowledge supplementation and representation methods as the technical implementation foundation supports expert group recommendations for multi-domain government projects, thereby filling gaps in existing methods. The method of knowledge extraction and measurement from long-term accumulated expert review opinions has reasonable and feasible computational complexity due to scientific knowledge representation, which has been fully confirmed in experiments.

Moreover, Chinese government departments widely adopt expert pool formats for project review implementation, providing the foundational environment for the proposed method. Finally, the method's effectiveness is constrained by the completeness and accuracy of knowledge concepts in reviewed objects and influenced by the linguistic standardization of expert review opinions, requiring continuous supplementation and improvement of domain knowledge systems in practical application. Future research will further investigate the application of this method in related fields to continuously enhance theoretical research and practical application levels.

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Hua Bin: Topic selection determination, paper revision suggestions;
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He Xin: Initial paper drafting, computer experiments involved in the paper.

Research on Expert Individuals Multi-feature Depiction and Expert Group Equilibrium Recommendation

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Abstract: [Purpose/significance] A recommendation method of e-government project review expert group based on multi-feature depiction of individual experts is proposed to improve the consistency level of project evaluation among expert groups. [Method/process] Taking the long-term evaluation opinions of individual experts as the data source, knowledge element recognition and sentiment polarity acquisition are realized using opinion mining technology. The domain knowledge structure of experts is constructed and dynamically updated. Statistical analysis is used to depict expert knowledge level, review depth, emotional style, and domain expertise features, achieving scientific measurement-based expert feature depiction and recommending expert combinations based on these features. [Result/conclusion] The method in this paper focuses on multi-dimensional feature equilibrium of expert groups, has good pertinence for e-government project evaluation, and has achieved good application effects in practice.

Keywords: e-government; project management; opinion mining; knowledge unit measurement; expert recommendation

Note: Figure translations are in progress. See original paper for figures.