Postprint: Research on Knowledge Requirement Modeling for Online Outsourcing Tasks

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Abstract

【Objective】This study establishes a method for constructing task knowledge requirement models in networked outsourcing environments.【Application Background】The method for constructing task knowledge requirement models is applied within networked outsourcing platforms to serve the online matching of tasks and talents.【Method】An expert system framework is designed, a task description model is constructed, and tasks are parsed respectively based on inference rules and text analysis techniques to obtain task knowledge requirements in a quantitative manner.【Results】Through case validation, the modeling method of this system framework demonstrates favorable effectiveness and can accurately acquire knowledge requirement models for networked outsourcing tasks.【Conclusion】The task knowledge requirement modeling method designed in this study can lay a foundation for task-talent matching in networked outsourcing.

Full Text

Research on Knowledge Requirement Modeling for Online Outsourcing Tasks*

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Abstract:
[Objective] This study aims to establish a method for constructing knowledge requirement models for tasks in online outsourcing environments. [Context] The proposed method for modeling task knowledge requirements is applied to online outsourcing platforms to facilitate the matching of tasks and talent. [Methods] We design an expert system framework and construct a descriptive model for

tasks, then parse tasks based on both inference rules and text analysis techniques to obtain quantitative knowledge requirements. [Results] Case validation demonstrates that the modeling approach of this system framework yields good results and can accurately acquire knowledge requirement models for online outsourcing tasks. [Conclusions] The task knowledge requirement modeling method designed in this study lays a foundation for task-talent matching in online outsourcing.

Keywords: Knowledge requirement; Expert system; Inference rule; Text analysis
Classification Numbers: G202; G35

Since American scholar Chesbrough proposed the concept of open innovation in 2003, online innovation outsourcing has emerged as a new model alongside rapid development of network communication facilities and evolving information technology[1]. Online innovation outsourcing can spread through the Internet to the entire society, enabling more talent to participate in market-driven innovation work. Today, online outsourcing service platforms at home and abroad are developing rapidly, such as foreign outsourcing websites like InnoCentive.com, InnovationExchange.com, and TopCoder.com, some focusing on technology and knowledge innovation while others on software customization[2]; domestically, platforms like Zhubajie.com and Taskcn.com provide networked outsourcing services[3]. Under this service model, organizations implement open innovation strategies by connecting external knowledge with internal R&D, creating more value while further promoting organizational technological development, and maximizing benefits while minimizing time and costs. Online outsourcing tasks involve diverse types, such as process outsourcing, product outsourcing, and design outsourcing from the perspective of outsourcing methods[4], or problem solving, creative design, scientific research, consulting services, and software development from the perspective of task objectives[5], covering all industries. Technical talent across various industries constitutes an important external innovation force available in the networked innovation outsourcing model, providing the most favorable external environment for solving innovative problems for enterprises and organizations, and creating value for enterprises more efficiently and rationally as key participants in online outsourcing[6]. However, online outsourcing services also face a series of practical challenges, among which efficiently finding the most suitable talent for large numbers of different types of tasks and organizations is an urgent priority[7], requiring the identification and matching of talent with corresponding knowledge backgrounds and capabilities based on task requirements.

This paper designs an expert system framework that combines rule-based reasoning and text analysis techniques to analyze and explore the professional backgrounds and knowledge structures required for talent in online outsourcing tasks from the perspective of the relationship between tasks and professional knowledge. We construct a task description model to enable standardized expression of task requirements in online outsourcing, and then identify appropriate professional course requirements for tasks by studying the relationships between tasks and professional knowledge, thereby building a knowledge requirement model for online outsourcing tasks. The model construction method provided in this study lays the foundation for task-talent matching.

Current research on task models primarily focuses on structured task requirements, such as determining program requirements in software engineering and describing modular product parameters in product development tasks. These tasks can be described using structured approaches due to their specific structures. For unstructured tasks, Duursma et al. studied the basic attribute composition of tasks and task model construction methods, where the task model mainly explores basic task content, task decomposition, and subtask description using a hierarchical structure[8]. Van Der Aalst examined the role of task models in business process analysis, covering both the model design phase and business process monitoring phase[9]. Trætteberg focused on task model construction for workflows, using task models to decompose and analyze workflows and propose optimization recommendations[10].

Wang Nan et al. proposed a model based on generalized knowledge reconstruction and abstraction, which combines task construction models to describe the general process of workflow modeling, generating simplified and abstract workflow models[11]. Eichholz et al. studied the basic definitions of task models and their definition within group collaboration contexts[12]. O' Neill investigated representation methods for task models, designing a fundamental approach for task description models under communication and cooperation frameworks[13]. However, online outsourcing tasks exhibit complex characteristics across multiple types and industries, with significant variations in requirements between different tasks and even for similar tasks across different projects. Existing models for task requirements cannot comprehensively express a specific task, and the unstructured nature of tasks makes it difficult to represent task requirements using a fixed structured model.

Regarding research on knowledge structures corresponding to task requirements, Winterton et al. summarized that knowledge results from the interaction between learning capability and learning opportunities, encompassing fundamental theories and concepts as well as experiential information gained from completing specific tasks[14]. Li Zifang proposed in his work that the knowledge structure required to complete a task consists of basic theory, basic knowledge, professional foundational knowledge, professional knowledge, disciplinary knowledge, and cutting-edge disciplinary knowledge[15]. Johnson et al. presented methods for constructing task knowledge models and knowledge decomposition, using technical approaches for task feature extraction[16]. Current research on task knowledge requirements primarily focuses on qualitative representations of knowledge structures, while automated reasoning and quantitative modeling methods for task knowledge requirements are relatively lacking, and studies on the relationships between task requirements and knowledge are not comprehensive enough.

In summary, this study proposes a method for constructing task description models and knowledge requirements, primarily aimed at identifying the professional knowledge backgrounds needed for online outsourcing tasks. Task knowledge requirements constitute a broad concept reflected in task objectives, industries, and descriptions. This necessitates describing online outsourcing task requirements in a semi-structured format, then parsing the task description model using a combination of rule-based reasoning and text analysis techniques to ultimately obtain quantitative knowledge requirements for tasks.

3 Model Construction Process

This paper designs a system framework for constructing task knowledge requirement models, as shown in Figure 1 [Figure 1: see original paper]. Figure 1 System Framework for Knowledge Requirement Modeling of Online Outsourcing Tasks. The knowledge requirements of online outsourcing tasks include demands for talent with certain professional backgrounds and relevant coursework. To address the problem of constructing knowledge requirement models for online outsourcing tasks, this study adopts the design science research methodology for expert systems[17], aiming to establish descriptive models for published tasks, then quantitatively model task course requirements based on rule reasoning and text analysis, and subsequently analyze the professional backgrounds involved in tasks to establish task knowledge requirement models, thereby laying the foundation for task-talent matching in online outsourcing.

3.1 Task Publishing and Description Model Construction

We design the system' s task database by combining the characteristics of networked outsourcing tasks and drawing on existing requirement representation methods from the software industry, segmenting task requirements into a modular description. The database design is shown in Table 1 . Table 1 System Task Database Design: Field Usage and Main Constraints. The database covers basic task information, where ID is the primary key. It records attachments serving as task prerequisites (which can be empty), defines the categories involved in tasks, defines task output products, defines the capabilities and roles of task executors, and records detailed task requirements in text format. The task publishing process employs human-computer interaction, decomposing detailed information of online outsourcing tasks and entering it into the system based on selectable prompts, then saving it to the task database. Among these, "Task Type," "Task Objectives and Output Results," and "Executor Functions" are entered via selection menus. The sources for these options are determined based on the content format recorded in each field, with the main rationales as follows:

(1) Task Type: Tasks can be classified according to different criteria. For example, by industry, they can be categorized into chemical engineering, computer science, agriculture, life sciences, etc.; by enterprise solutions, they can be divided into general business problem solving, rapid methods

and practical solutions for open innovation, and corporate strategic consulting. Classification by academic discipline is relatively more detailed and encompasses much of the information from industry classifications, which helps analyze the professional knowledge characteristics of online outsourcing tasks. This is the classification method adopted in this study.

(2) Task Objectives and Output Results: This field records the form of task output products. For instance, process outsourcing refers to the supplier completing a certain process according to requirements; product outsourcing refers to the supplier producing a final physical product; and design outsourcing refers to the supplier completing a design for a certain requirement. Different outsourcing task types produce different output products, which influences the professional selection of talent. Therefore, the options for this field need to be standardized based on mature domestic online outsourcing service platforms' definitions of task output forms.

(3) Executor Functions: This field records the capabilities that task executors should possess, which is typically related to the roles they play in their work. For example, computer-related tasks require executors with experience in positions such as software engineers, website operations managers, or system administrators. Consequently, the options for this field need to be standardized based on classifications of talent positions from authoritative job search websites.

Based on the above rationales and considering the authority and reasonableness of option sources, the sources for each option are summarized in Table 2 . Table 2 Sources of Options for Task Description Model: Task Type–Classification of tasks from two major online outsourcing platforms, ' Zhubajie.com' and ' Taskcn.com' ; Task Objectives and Output Results–Management disciplines: Information Management, Accounting, etc.; Computer disciplines: Computer Science and Technology, Brand Design, Statistical Analysis, Website Development, etc.; Executor Functions–Classifications of functions from the '51job.com' job search website: Computer-related: Software Engineer, etc.; Accounting-related: Finance, etc. http://www.zhubajie.com/. http://www.taskcn.com/. http://www.51job.com/.

Through the task publishing format and database design, the system represents detailed requirement information of networked outsourcing tasks using a semi-structured description model, facilitating further parsing of task requirements.

3.2 Rule-based Reasoning

For knowledge requirement parsing of online outsourcing tasks, it is necessary to perform reasoning analysis on the three parts of the task description model–"Task Type," "Task Objectives and Output Results," and "Executor Functions"–that are entered via selection menus, in order to identify their corresponding knowledge requirements.

(1) The prerequisite for reasoning analysis is establishing a rule base based on corresponding inference rules. In this study, the knowledge sources for the rule base are primarily built upon the "Discipline-Profession-Course Knowledge Base" and "Professional Skill Association Knowledge Base" constructed by our research team through prior text mining research.

Specifically, the "Discipline-Profession-Course Knowledge Base"is constructed by using statistical analysis methods to summarize and organize common courses offered by universities under various professional directions, and merging courses with similar teaching content using a cosine similarity algorithm to establish associations between professions and courses. The structure and key attributes of this knowledge base are shown in Figure 2 [Figure 2: see original paper].

The "Professional Skill Association Knowledge Base" is constructed by analyzing training information text objects from various universities and majors through text clustering methods, categorizing them according to different professional fields, and identifying skill indicators for each professional field category based on recognition of characteristic terms from clustering results. The structure and key attributes of this knowledge base are shown in Figure 3 [Figure 3: see original paper].

Based on the above knowledge bases, we establish the rule base for this study using the production rule representation method—a commonly used knowledge representation approach in artificial intelligence[17]. When multiple rules correspond to the same condition, they are connected using "and" or "or".

Rule Base R1: If <precondition: skill> Then <postcondition: profession>
Rule Base R2: If <precondition: profession> Then <postcondition: course>

(2) Combining the above rule bases, we use forward reasoning as the control strategy to obtain reasoning results. The forward reasoning process can be described as follows:

Identify the applicable rule base R based on requirements;
while R is not empty and the problem remains unsolved
begin
select a rule from R
if the rule' s precondition matches the problem
then use the rule' s postcondition as the solution
else move to the next rule

When performing rule reasoning on the task description model, "Task Type" and "Executor Functions" already store the professional information required by the task, so only Rule Base R2 needs to be invoked. However, "Task Objectives and Output Results" requires a two-step reasoning process, first invoking Rule Base R1 and then R2 to derive the corresponding course requirements.

(3) After performing rule-based reasoning on the three parts of the task description model, we obtain the corresponding course knowledge sets for

each part and quantitatively express the course set CT required by task T in a standardized vector form, as shown below:

CT = (N1, N2, ···, Nk)

where k is the number of course types required by the task, and Ni represents the demand frequency for the ith course type. In this course vector, if a particular value is relatively large, it indicates a stronger correlation between the task and that course, suggesting that talent who have studied that course may be better suited for the task.

3.3 Text-based Analysis

Although rule reasoning can refine a task' s course knowledge requirements, real-world tasks remain highly complex and require further parsing of the "Task Content Description" text through text analysis methods to complement rule reasoning.

(1) We perform word segmentation on both the "Task Content Description" text in the database and the course description texts in the "Discipline-Profession-Course Knowledge Base." The segmentation algorithm employs the Forward Maximum Matching (FMM) method, using the Sogou Internet Corpus as the Chinese language dictionary to divide text objects into sets of words and phrases.

(2) We then adopt the Vector Space Model (VSM), the most commonly used method for digitizing text representation, to construct a digital representation model for text objects[18]. Both task content descriptions and course description texts can be represented as vectors V(d) = (T1,W1; T2,W2; ···; Tn,Wn), where n represents the total number of feature words in the text, Tk represents the kth feature word, and Wk is the weight corresponding to feature word Tk, measuring the importance of that feature word for text d. The weight calculation method for feature words employs the TF-IDF method[19], with the calculation formula as follows:

Wij = TFij × IDFi

where Wij is the weight of term Ti in the vector of text dj, TFij is the frequency of term Ti in text dj, and IDFi is the inverse of the document frequency containing term Ti. Features of the text are represented by feature words with higher weights in the vector.

(3) We use the cosine similarity formula to calculate similarity between task content description texts and course description texts. For target texts to be compared, we obtain the union of feature words and set the weights of feature words not present in one' s own text to 0, resulting in task content description text vector Ti and course description text vector Cj. The similarity calculation formula is as follows:

Cos(Ti, Cj) = (Ti · Cj) / (||Ti|| × ||Cj||)

The closer this value is to 1, the greater the similarity between the task and the corresponding course. By calculating similarity between task content descriptions and all courses, we can obtain the corresponding course vector. The correspondence between task T and n courses is quantitatively represented in a standardized vector form CT' , where simi is the similarity between the task and the ith course, calculated as follows:

$$CT' = (sim1, sim2, \cdots, simn)$$

3.4 Task Professional Background Analysis

After obtaining the course requirement vectors for online outsourcing tasks through rule reasoning and text analysis, we can interpret the task' s demand level for various courses. On this basis, we further analyze the professional background of task requirements using task-profession similarity calculation methods to improve the task knowledge requirement model.

(1) Based on the courses corresponding to each profession in the "Discipline-Profession-Course Knowledge Base," we construct course vectors for each profession by combining the vector space model and TF-IDF algorithm, representing each profession as a quantitative form of courses and their weights. The weights of courses are calculated through a designed frequency value algorithm, with the formula as follows:

$$W = f(w, Ci) \,/\, |\{Cj \mid f(w, Cj) \quad f(w, Ci), j = 1, 2, \cdots, N\}|$$

where f(w,Ci) is the occurrence frequency of course term w in profession Ci, N is the total number of professions, and $|\{Cj \mid f(w, Cj) \quad f(w, Ci), j = 1, 2, \cdots, N\}|$ refers to the total number of professions where the frequency of w is not less than its frequency in profession Ci. The value calculated through formula (5) represents the importance degree of course term w in the corresponding profession.

(2) We then combine the task course requirement vectors obtained from rule reasoning and text analysis with the course vectors of each profession to derive similarity between tasks and professions as follows:

$$Sim(CT, CT', M) = (CT + CT') \cdot M \,/\, (||CT + CT'|| \times ||M||)$$

where CT is the course vector obtained through rule reasoning, CT' is the course vector obtained through text analysis, and M is the course weight vector of a certain profession. By calculating the similarity between the task and various professions and ranking the professions from high to low similarity, we can identify one or more professions most similar to the task. This analysis result can be used to interpret the task' s professional background, indicating which types of professions produce the most qualified talent for the task, thereby supplementing and improving the task' s course requirements.

3.5 Generation of Task Knowledge Requirement Model

The system automatically constructs a quantitative knowledge requirement model for online outsourcing tasks based on the above analysis and processing results, feeding the results back to the human-computer interaction interface for user review. The model includes the task' s professional background and related course requirements along with their corresponding demand levels, where the task' s course requirements are generated through the mutual supplementation of the rule reasoning-based course vector and the text analysis-based course vector.

The task knowledge requirement model indicates the professional knowledge background that talent capable of completing the task should possess. The establishment of this model can provide an effective basis for task-talent matching problems in online outsourcing models and

4 Application Cases and Analysis

The expert system prototype for knowledge requirement modeling of online outsourcing tasks was implemented in the Eclipse platform using Java, with SQL Server database for storing relevant information. This study selected 100 successfully completed tasks from two major online outsourcing websites, 'Zhubajie.com' and 'Taskcn.com,' as research subjects, using the system to analyze and model the knowledge requirements of these tasks. The overall modeling analysis process for the sample and analysis results for the sample task 'Face Recognition Algorithm Development for a Security Video System' are exemplified in Table 3 .

Table 3 Task Knowledge Requirement Modeling and Evaluation Results: Task Knowledge Requirement Modeling Steps | 100 Sample Tasks | Sample Task Example: 'Face Recognition Algorithm Development for a Security Video System' | Task Course Requirement Vector Analysis: Rule Reasoning - Task Attribute Course Vector; Text Analysis - Task Description Course Vector | Rule Reasoning: Data Mining, etc.; Text Analysis: Computer Graphics, etc. | Task Professional Background Analysis | Modeling Effectiveness Evaluation: General Profession Tasks, Ordinary Profession Tasks, Specialized Tasks | Course Requirement Analysis: Average F-value = 0.54; Professional Background Analysis: Average F-value = 0.68 | Computer Science, Software Engineering, etc. | Course Requirement Analysis: F-value = 0.55; Professional Background Analysis: F-value = 0.73

The 100 sample tasks involve multiple industries and types. Task information was entered and description models were constructed through the human-computer interaction interface of the expert system prototype, with automatic word segmentation performed on the "Task Content Description" text. Taking the task "Face Recognition Algorithm Development for a Security Video System" as an example, the task information entry and word segmentation process is shown in Figure 4 [Figure 4: see original paper].

The expert system separately performed rule reasoning and text analysis parsing on the 100 sample tasks, ultimately obtaining the course requirement vectors and their weights for each task. The course requirement vector for the sample task "Face Recognition Algorithm Development for a Security Video System" is shown in Figure 5 [Figure 5: see original paper], where "Task Attribute Course Vector" represents the rule reasoning results and "Task Description Course Vector" represents the text. It also proposes more specific requirements and references for other elements such as technical capabilities.

4.3 Task Professional Background Analysis

Based on the analysis of course requirement vectors for all sample tasks, the system further calculated and summarized the professional backgrounds of each task. The professional background analysis result for the sample task "Face Recognition Algorithm Development for a Security Video System" is IT-related majors such as Computer Science and Software Engineering.

During the professional background analysis of sample tasks, we found that online outsourcing tasks can be divided into three categories based on differences in professional background characteristics: General Profession Tasks, which have relatively dispersed and simple professional requirements, such as slogan design and data collection tasks with lower technical content; Ordinary Profession Tasks, which show clear demand bias toward certain professional backgrounds, such as website design and algorithm development tasks requiring comprehensive technical skills; and Specialized Tasks, which point to a specific profession, such as molecular detection and cell culture tasks with extremely high specialization. Analyzing and classifying the professional background characteristics of online outsourcing tasks helps find qualified talent more efficiently and accurately, while also providing more specific requirements and references for other elements such as the education level and technical capabilities of talent undertaking tasks.

4.4 Modeling Effectiveness Evaluation

After constructing knowledge requirement models for each of the 100 sample tasks, we obtained the professional background and quantitative course requirement model for each task. We further investigated and verified the professional backgrounds and courses studied by talent who actually undertook these tasks in practice, and used this as a basis to evaluate the effectiveness of the expert system modeling using precision, recall, and F-value metrics that represent information acquisition accuracy. The F-value is the harmonic mean of precision and recall[20], with values between 0 and 1, where higher is better. The modeling evaluation results are shown in Table 4 .

Table 4 Task Knowledge Requirement Modeling Evaluation Results: Figure 5 Example of Task Course Requirement Vector | F-value Range | Task Course Requirements | Task Professional Background

The results show that the F-values representing accuracy are basically greater than 0.5, with average F-values at a relatively high level, indicating that the task knowledge requirements parsed by the expert system align well with the professional backgrounds and courses studied by the 100 groups of talent who actually undertook the tasks. Therefore, the accuracy and effectiveness of the task knowledge requirement model construction method proposed in this study are ensured, while also achieving a quantified effect on the degree of knowledge requirements, laying a foundation for task-talent matching in online outsourcing.

This paper designs an expert system framework to study and establish a method for constructing knowledge requirement models for online outsourcing tasks. We build a task description model, then parse tasks based on inference rules and text analysis techniques to quantitatively obtain task course requirement vectors, while simultaneously constructing a knowledge requirement model for online outsourcing tasks by incorporating task-profession similarity. Case validation demonstrates that this modeling method achieves good results.

The model construction method proposed in this paper still has areas for improvement, such as research on automated updating and refinement methods for inference rules and enhancing the performance of text analysis algorithms. These issues require in-depth exploration in future studies.

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Author Contribution Statement:
Ma Tianyi: System framework design, technical solution implementation, data analysis, paper writing and final revision;
Zhang Pengzhu: Research idea proposal, research scheme design, paper revision;
Feng Haoyin: System development, data collection.

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Knowledge Requirement Model for Online Outsourcing Tasks

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Abstract:
[Objective] This study aims to build a knowledge requirement model for online outsourcing tasks. [Context] The proposed model could help us find proper personnel for each task. [Methods] We first designed an expert system framework and built a descriptive model for each task. And then, we analyzed the tasks based on inference rules and text analysis technology, with the purpose of quantifying the knowledge requirement for each task. [Results] The proposed framework successfully established the knowledge requirement model. [Conclusions] The new model laid foundation for the task-talent matching system of online outsourcing services.

Keywords: Knowledge requirement; Expert system; Inference rule; Text Analysis

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