A term-dictionary-based technology for selecting task executors in software development projects

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Abstract: The study proposes a technology for identifying specialists, capable of performing specific tasks within software development projects. Existing models for describing professional competencies and task requirements are analyzed, showing that current approaches do not allow a direct comparison between specialists and tasks. The proposed technology builds domain-specific term dictionaries that link each term to the document in which it appears. To avoid linguistic inconsistencies, all documents are automatically translated into English prior to the term extraction. Each document model stores identified terms, technologies, and author contributions. The specialist model links authors to documents, enabling the representation of the individual competencies through associated technologies and terms. The task model represents assignments as texts containing relevant terms and technologies. A comparison mechanism determines which specialist or group of specialists best meets the task requirements. The experimental validation using the Task Distribution2 software demonstrated a 3.1-fold reduction in the time spent on task-specialist matching while maintaining accuracy. The results confirm the efficiency of the proposed decision-support technology for selecting experts in multi-project environments.

Keywords: Specialist Selection Information System, Specialist Model, Task Model, Term Dictionary, Decision Support System.

1. Introduction

The work of a project organization in software development involves performing and maintaining multiple projects simultaneously. These may include activities within separate projects, inter-project cooperation, or research into new technologies for future initiatives. A software development is divided into numerous stages or iterations, which may be executed by different specialists. A specific feature of the IT industry is the vast diversity of technologies employed. Moreover, many tasks require deep domain-specific expertise. Therefore, maintaining complete and up-to-date information about each specialist's competencies is crucial, as both the quality and timeliness of task execution depend significantly on the qualifications of the executor (Huang et al., 2023). An inappropriate assignment of a specialist may not only reduce the overall productivity by up to 5% (Nurdin, 2023) but also create tension within a development team (Thürmer & Kunze, 2022).

When the organization is large and includes many specialists, identifying the most suitable executor for a given task becomes a nontrivial problem. Thus, there arises the general problem of determining the optimal specialist who best fits the qualification and experience requirements of a specific task.

The goal of this paper is to propose an approach for determining specialists whose capabilities are best suited to a specific task. A key element of the approach is the use of a domain-specific term dictionary in the competence evaluation process.

The content of the paper is organized as follows: Section 2 reviews the approaches relevant to this study. Section 3 defines the research objectives. Section 4 presents the models and technology. Section 5 reports the experimental results, and Section 6 summarizes the outcomes and conclusions.

2. Related work

To address the problem of finding suitable specialists for specific tasks, it is necessary to define methods for both assessing a specialist's capabilities and formalizing task descriptions.

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The importance of the technical skills of a specialist for the result of the work is noted in (Bayasgalan & Nomin, 2022). However, a specific mechanism for collecting and maintaining the relevance of the necessary data is not proposed.

A number of studies have examined the problems and competencies required to address them in some detail, but the authors remain focused on narrow subject areas. For example, Padilla-Delgado, Velasco-Tafur & Ríos-Obando (2024)'s study provides a detailed analysis of the administration in the tourism industry, while Packalén & Partanen, (2025)' study examines the archival management.

With the development of the artificial intelligence in recent years, numerous attempts have been made to use it in solving some aspects of the issues investigated in this work. Numerous works on the use of the artificial intelligence in personnel management are systematized (Kaushal et al., 2023). The use of the artificial intelligence in determining the competencies of specialists is shown in Singh & Chouhan, (2023). However, further studies revealed numerous ethical problems associated with the use of AI, such as discrimination, bias and dehumanization, which are consequences of the lack of explainability of the algorithms based on the artificial intelligence (Chen et al., 2020; Charlwood & Guenole, 2022).

A domain dictionary usage proposed to represent the subject area, which largely determines the task content (Kungurtsev et al., 2020b). For the task under consideration, several such dictionaries are required. Another study presents the syntactic and semantic similarities and differences of the terms in several glossaries for project management tasks (Becker et al., 2024). Even though this task is important, conducting such an analysis is not always practical since the tasks are generally bound to a single subject area. Furthermore, the authors do not propose a technology for constructing multiple related dictionaries.

The term extraction from textual sources is well-established for major languages (Roche, 2021). Interpretation, however, generally necessitates expert participation (Kungurtsev et al., 2020a). The techniques for deriving meanings are addressed elsewhere and fall outside this scope (Widmer, 2025).

The solution to the problem of determining the specialist's availability, which invariably arises when determining the executor for a new task, is proposed in Kungurtsev & Chorba, (2023), but the approach does not consider the context of the tasks to be executed.

A literature review has shown that there are no solutions for a comparable representation of a specialist and a task, which can lead to additional time expenditure and a decrease in the quality of work when distributing tasks.

3. Research objectives

The purpose of this study is to develop a technology for task distribution based on domain-specific term dictionaries, enabling the selection of the most suitable candidates for task execution. This approach aims to reduce the task completion time and improve the overall quality of a project implementation.

To achieve this goal, the following research objectives have been formulated:

- to define a technology for constructing explanatory (term) dictionaries applicable within a project–oriented organization;
- to develop a document model that represents the competencies of specialists through their authored materials;
- to construct a specialist model;
- to create a task model;
- to design a technology for assessing the professional readiness of a specialist to perform a given task.

4. Materials and methods

A project-oriented organization may carry out development activities in multiple subject domains. Every significant activity is represented by a corresponding document. The terms extracted from a particular document may belong to one or several knowledge areas. Identically written terms across different domains may have distinct meanings and, therefore, must be stored separately in different dictionaries.

4.1. Domain-specific term dictionary

Within a project organization, it is possible to distinguish several knowledge domains, such as individual projects, prospective research directions, or specific management activities.

For term extraction from a text, appropriate software tools are required. However, such tools are not available for all languages, for instance, open-access systems for Ukrainian are scarce. To ensure consistency and high quality of the linguistic processing, it is proposed to automatically translate all documents into English before further analysis. This enables reliable translation from most languages and allows the use of a wide range of term extraction tools.

Figure 1 illustrates a simplified scheme for forming an organizational term dictionary. Each document ($Document_1$ – $Document_n$) characterizes some aspect of the organization's activities and is grouped into a corresponding domain ($Domain_1$ – $Domain_n$). Many documents are classified by domain at the moment of their creation (for instance, project documentation), while others (such as internal management papers) may require later classification. Although automated tools for generating term interpretations exist (Kungurtsev et al., 2020b), the final decision on definitions should always be validated by a domain expert, typically, one of the project developers.

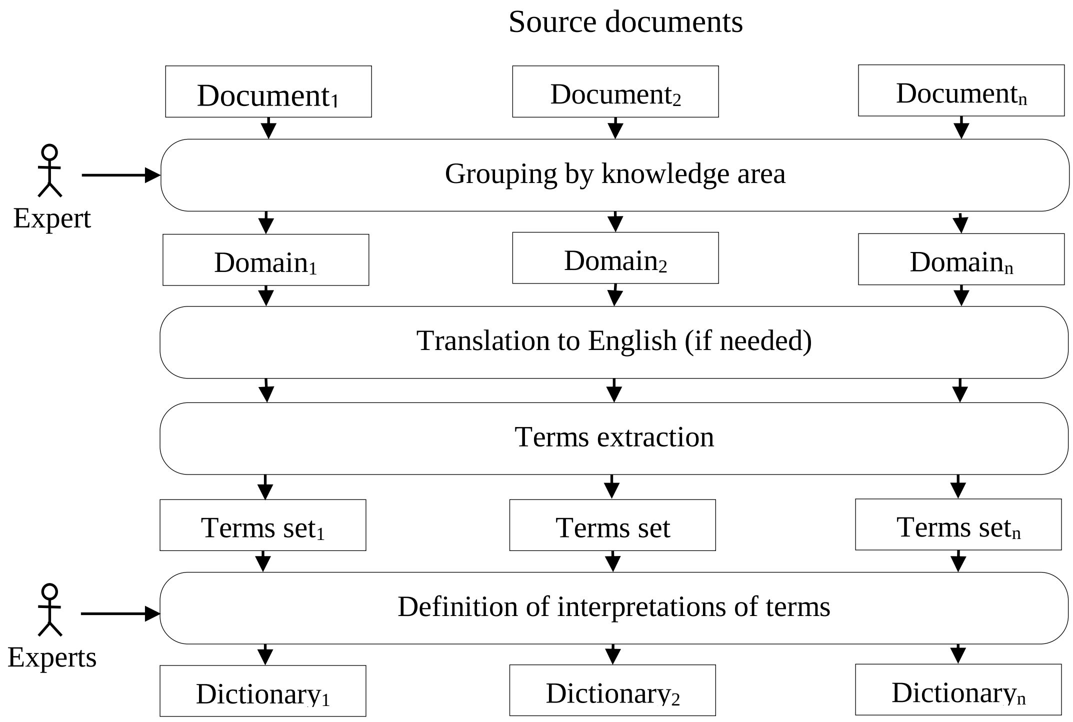

Figure 1. Structure and diagram of the organization's vocabulary formation (Authors' own research)

The organization dictionary OD can be represented as:

$$OD = \langle sSubjAreaD_i \rangle, \quad (1)$$

where – $sSubjAreaD_i$ – a subject-domain dictionary.

Each dictionary entry for a particular domain $sSubjAreaD_i$ can be represented as a tuple:

$$de = \langle termText, TermDefinition, sRefDoc \rangle, \tag{2}$$

where – *termText* is the term itself;
– *termDefinition* is the explanatory definition;
– *sRefDoc* is the set of references to documents in which the term occurs.

4.2. Document model

In project-based organizations, new documents are continuously created. It is assumed that each document undergoes an automatic term extraction upon submission.

It is proposed to treat a document as an independent informational entity that, from both organizational and informational standpoints, may belong to a certain subject area. The document is used for constructing the dictionary of a corresponding domain $Domain_i$, but it is not a part of the dictionary itself. Since the text of the document is analyzed during the term extraction process, it is proposed to simultaneously determine the document's affiliation, authors, and any technologies mentioned. The document can also be used in the specialist model but is not considered part of it.

The document model is represented as follows:

$$Doc = \langle idD, sAuthor, SubjArea_i, Date, sDocTerm, sTechnology \rangle, \tag{3}$$

where – *idD* – document identifier;
– *sAuthor* – the set of document authors;
– $SubjArea_i$ – the subject area to which the document belongs;
– *Date* – the date of document creation;
– *sDocTerm* – the set of terms extracted from the document;
– *sTechnology* – the set of technologies used in the document, if any.

Within the set of authors *sAuthor*, each author is represented as a tuple:

$$Author_i = \langle idAuthor_i, authorContrib \rangle, \tag{4}$$

where – $idAuthor_i$ – identifier of the author;
– *authorContrib* - the author's contribution to the creation of the document. It is proposed to express the contribution as a fraction of one. Defining the author's contribution, together with document terms, improves the quality of determining suitable task executors.

Within the set of terms *DocTerms*, each term is represented as follows:

$$DocTerm_i = \langle Term_i, qTerm_i, relFreqTerm_i \rangle, \tag{5}$$

where – $Term_i$ – the text of the term;
– $qTerm_i$ – the number of occurrences of the term in the document;
– $relFreqTerm_i$ – the relative frequency of the term's occurrence in the document, indicating the degree to which a particular concept is used.

Within the set of technologies Techs, each technology is represented as follows:

$$Technology_i = \langle nameTech_i, degreeOfUseTech_i \rangle, \tag{6}$$

where – $nameTech_i$ – the name of the technology;
– $degreeOfUseTech_i$ – the degree of the technology's utilization in the document.

Figure 2 shows the technology for processing a new document. As a result of the actions shown, first, a group of terms is added to the relevant section of the organizational dictionary or a new section (subject domain) is created. Second, a document model is generated, which can be integrated into the organization's document management model (this issue lies beyond the scope of the present study). Third, the specialist model receives a reference to the new document if the specialist is one of its authors.

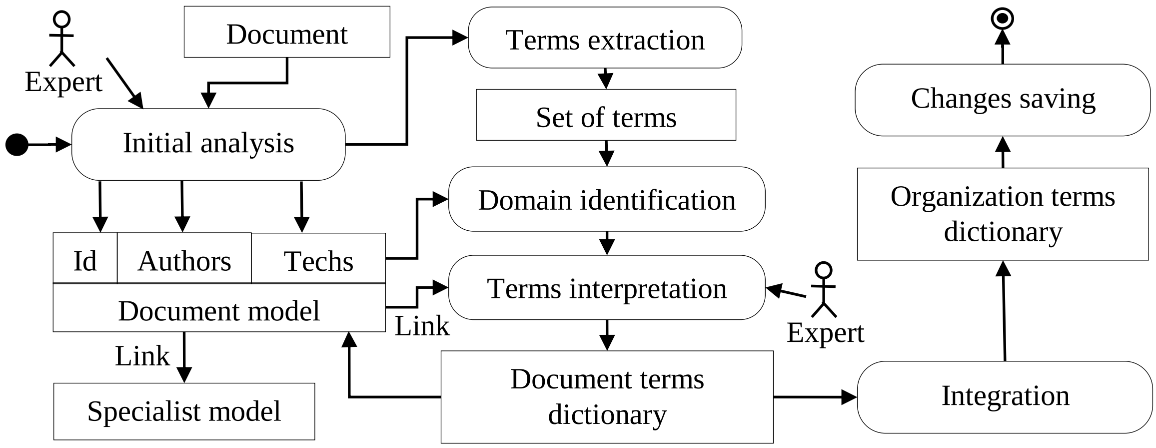

Figure 2. Document processing technology (Authors' own research)

4.3. Specialist model

The specialist model should represent the competencies of an individual specialist. It is proposed to represent the model as follows:

$$spec = \langle idSp, PersonalData, sTermSp, sTechSp \rangle, \quad (7)$$

where – *idSp* – identifier of the specialist;
– *PersonalData* – personal data of the specialist;
– *sTermsSp* – the set of terms found in the documents authored by the specialist;
– *sTechSp* – the set of technologies found in the documents authored by the specialist.

Each term $TermSp_i \in sTermSp$ is represented as:

$$TermSp_i = \langle Term_i, sRefDoc_i \rangle, \quad (8)$$

where $sRefDoc_i$ – the set of references to the documents where $Term_i$ has been found.

Each technology $TechSp_j \in sTechSp$ is represented as:

$$TechSp_j = \langle Tech_j, sRefDoc_j \rangle, \quad (9)$$

where $sRefDoc_j$ – the set of references to the documents where $Tech_j$ has been found.

4.4. Task model

The task model defines the structure and parameters of an assignment that must be executed within a project. A task can be represented as:

$$Task = \langle taskId, taskDoc, taskExecCond \rangle, \quad (10)$$

where – *taskId* – task identifier;
– *taskDoc* – task documentation;
– *taskExecCond* – task execution conditions which are represented as a tuple:

$$taskExecCond = \langle sTechnology, sTaskTerm \rangle, \quad (11)$$

where – *sTechnology* – the set of technologies required to perform the task;
– *sTaskTerm* – the set of terms that characterize the content of the task.

Each element of the set *sTechnology* is defined as follows:

$$technology_i = \langle nameTech_i, degreeOfUseTech_i \rangle, \tag{12}$$

where – $nameTech_i$ – the name of the technology;
– $degreeOfUseTech_i$ – the required degree of technology usage for successful task completion.

Each element of the *sTaskTerm* that characterizes a task is defined as follows:

$$TaskTerm_i = \langle Term_i, levelOfTermUsage_i \rangle, \tag{13}$$

where – $Term_j$ – the text of the term;

– $levelOfTermUsage_j$ – the required level of use of the term. The $levelOfTermUsage_j$ may be specified by the task author numerically (e.g., corresponding to the number of occurrences of the term in a reference document) or by predefined categorical levels established within the organization. For example, the universal levels can be defined as *lowLevel*, *mediumLevel*, and *highLevel* to indicate the relative importance of a term in the context of the task.

4.5. Technology for forming a task execution team

The proposed technology for forming a team of executors includes five stages. It ensures the systematic selection of the specialists whose competencies and experience best correspond to the requirements of a given task.

4.5.1. Stage 1: Task model formation

The task must be represented as a textual document. The set of technologies *sTechnology* is determined. The task is translated into English, and terms *sTaskTerm* are extracted from it automatically. The assigner may define priorities for both technologies and terms, specify the required team size, and provide a preliminary list of potential executors.

4.5.2. Stage 2: Searching for executors based on required technologies

Let $nameTech_i$ a technology defined in the task. Then the degree of a specialist $idSp_j$ competence in this technology can be calculated as follows:

$$dOfTechnUse_i = \sum_{k=1}^{N} degreeOfUseTech_{i,k} \times authorContrib_{j,k}, \tag{14}$$

where N – the number of documents authored by the specialist in which the technology T_i was used. The result of (14) depends on the degree of use of the technology in each document $degreeOfUseTech_{i,k}$ and the author's contribution $authorContrib_{j,k}$ to the creation of this document. The assigner of the task must establish a minimum acceptable value of $MinDegreeOfUseTech_i$ for each required technology. If for a given specialist $idSp_j$ the condition $dOfTechUse_i \geq MinDegreeOfUseTech_i$ is not met, the specialist is excluded from the list of candidates.

4.5.3. Stage 3: Searching for Executors Based on Terms

Let $Term_j$ a term included in the task description. The degree of the term usage in a document is characterized by two parameters – the number of occurrences $qTerm_{j,k}$ and the relative frequency $relFreqTerm_i$. These parameters complement each other. Therefore, two independent evaluations of the specialist's competence for the knowledge element associated with the $Term_j$ can be proposed. The first evaluation (based on the number of term occurrences) is calculated as:

$$dOfTermUse_i = \sum_{k=1}^{M} qTerm_{i,k} \times authorContrib_{j,k}, \tag{15}$$

where – M – the number of documents authored by the specialist $idSp_j$ that contain the term $Term_j$. The result depends on the number of occurrences of the specified term in each document $qTerm_{i,k}$ and on the author's contribution
– $authorContrib_{j,k}$ to the creation of the document.

The second evaluation (based on the relative term frequency) is calculated as:

$$dOfFreqTermFUse_i = \sum_{i=1}^{M} relFreqTerm_{i,k} \times authorContrib_{j,k} \div M. \qquad (16)$$

As a selection criterion for a specialist, it is proposed to use the condition:

$$\left(dOfTermUse_i \geq MindOfTermUse_i\right) \wedge \left(dOfFreqTerfFUse_i \geq MindOfFreqTermFUse_i\right). \qquad (17)$$

4.5.4. Stage 4: Determining candidate workload

After completing Stage 3, a group of candidates capable of performing the task is formed.

During the planned execution period, these candidates may already be engaged in other activities. The issue of determining the specialist's workload and task redistribution depending on task priorities is described in detail by Kungurtsev & Chorba (2023). By applying their proposed approach, the specialists who are currently assigned to high-priority tasks are excluded from the candidate list.

4.5.5. Stage 5: Final executor team formation

If, after completing the first four stages, the number of candidates exceeds the required team size, the final selection can be made based on the aggregated evaluation scores obtained in Stages 2 and 3. If the number of candidates is smaller than needed, the selection criteria can be relaxed by distinguishing between mandatory and desirable conditions. Figure 3 shows a simplified diagram of the proposed technology for determining the specialists suitable for executing a task.

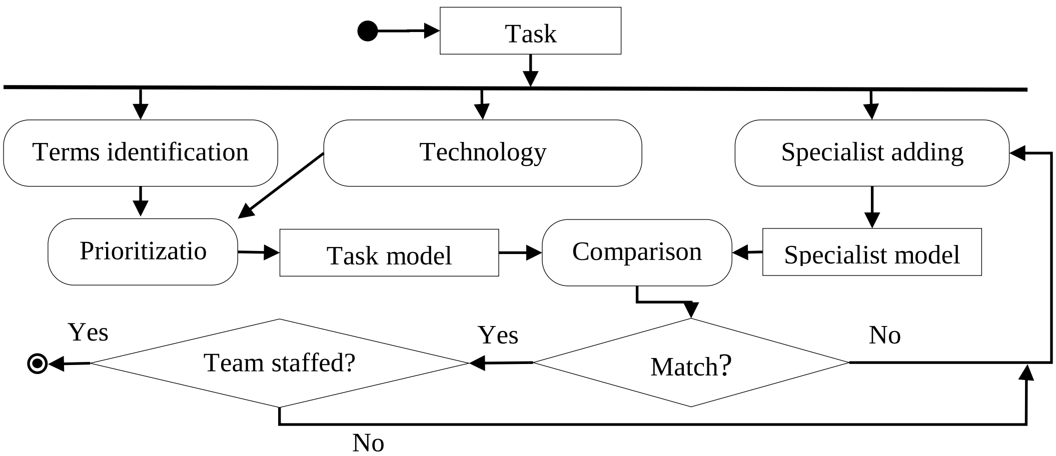

Figure 3. Technology for identifying a specialist to perform a task (Authors' own research)

5. Approbation

To implement the proposed technology, the software system Task Distribution2 was developed. This system integrates the KeyBERT as a keyword extraction tool (Buchanan, 2021) and an embedded translator that automatically translates documents from various languages into English (tested on the Ukrainian–English translation pair). The system comprises four main modules: Document, Task, Vocab, and Specialist.

The Document module accepts the text of a document, allows users to specify the contribution of each co-author, to indicate the technologies discussed in the document, and to extract relevant terms. It then offers the option to provide definitions for those terms according to the corresponding subject domain. If an author appears for the first time, a specialist model is created for him. For the already registered authors, a reference to the new document is added. The newly discovered terms are integrated into the corresponding domain dictionary within the Vocab module. The Task module processes the text of a task, its related technologies, the number of required executors, and a preliminary list of candidates (selected from the organization's existing specialist database). The terms are extracted automatically, and their definitions may be provided or supplemented from the domain dictionaries. Based on this data, a task model is generated.

Figure 4 shows the interface for determining the degree of participation of co-authors in creating a document (real author names and document titles have been anonymized).

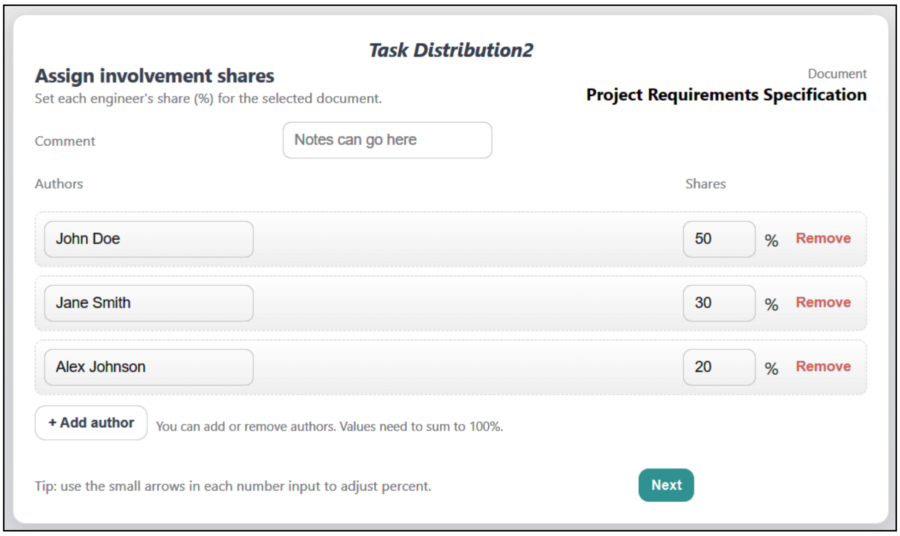

Figure 4. Determining the degree of participation of co-authors in the creation of a document (Authors' own research)

For the experimental validation, the authors collaborated with an organization which conducts multi-project software development and maintenance for several clients. Due to the organization's data protection policies, the information regarding tasks, executors, and related materials could not be shared externally. Therefore, Task Distribution2 was deployed on the organization's infrastructure. Under the supervision and consultation of the organization's staff, the necessary data were imported into the system. The dataset included technical documents from three completed projects belonging to two clients, as well as historical task data exported from the organization's task management systems. The average duration of the projects was seven months. The document size ranged from 1 to 26 pages, with 1 to 8 co-authors per document. In total, there were 39 unique co-authors and 419 documents. The total time spent by the authors of this study on data import was 23.5 man-hours (excluding 4 man-hours for expert terminology consultation). To evaluate the effectiveness of the proposed technology, the authors analyzed the time required to form teams for 20 previously completed tasks. These tasks were uploaded to the system, and the team formation results were obtained using the automated method. The average processing time per task was 0.13 man-hours.

For comparison, an experiment using the existing manual technology was conducted with the participation of four team leaders familiar with the project contexts. They were asked to analyze three newly created tasks (requiring one, two, and three executors, with estimated durations of 5–10 days each) and to select the appropriate specialists among the document co-authors. They performed this task independently, without consulting one another and without using the proposed system. The experts were allowed to communicate with document authors, review project documents, and use other available information sources. The time each expert spent on the selection process was recorded.

Next, another expert performed the same selection procedure using Task Distribution2, which automatically identified the most suitable executors according to the task requirements. The software functioned as a decision-support component. The time spent by the system and the expert's supervision time were measured. The experimental results are presented in Table 1.

Table 1. Results of the experiment on the selection of executors

Expert	Task 1 (1 specialist)		Task 2 (2 specialists)		Task 3 (3 specialists)	
	Time, man-hours	Errors	Time, man-hours	Errors	Time, man-hours	Errors
Expert 1	0.75	0	1.75	0	2	1
Expert 2	0.75	0	2	0	2.5	0
Expert 3	0.5	0	1.5	1	2.5	0
Expert 4	0.66	0	1.5	0	2.25	1
Average time spent by experts	0.67		1.7		2.3	
New technology	0.33	0	0.33	0	0.42	0

From the analysis of the experimental data, it follows that the use of the proposed technology, under conditions of sufficient documentation coverage and task relevance, reduces the time required to select an executor by a factor of 3.1, while simultaneously eliminating erroneous decisions.

The difference between the average time measured by the authors and by the experts using Task Distribution2 is explained by the experts' additional verification of the system's suggestions. This additional verification time is primarily due to their initial lack of trust in the new system, which is expected to decrease as the technology becomes established in practice. For further time-efficiency calculations, the results obtained from the expert experiment were used.

It is important to note that, to maintain accuracy, the dictionaries must be periodically updated incrementally by uploading new documents. Due to the reduced volume of documents per update, the update process is faster than the initial data import. In the experimental setting, the average effort required to upload one document was 0.056 man-hour. The update procedure can be automated, requiring minimal staff involvement for document collection and term validation. To reduce time costs, it is recommended to perform this update concurrently with software development milestones (e.g., at the end of an Agile sprint).

To analyze the impact of the data update efforts on the effectiveness of the technology, the experimental data on the 3 completed projects described above were used. Project documents for 7 months were considered. Based on the results of the documents processing for the first 6 months, dictionaries and models were created for 387 documents and 39 specialists. This process took 21.5 man-hours (Figure 5, initial data import). 15 tasks were selected from the project materials of the 7th month. Experts provided time estimates for selecting executors for the selected tasks. For the same tasks, the selection of executors was performed using the Task Distribution2 program. After completing the 10th task, the dictionaries were updated due to the accumulation of new documents (Figure 5, incremental data update). Data updating took 2 man-hours. Time consumption during this process is demonstrated in Figure 5.

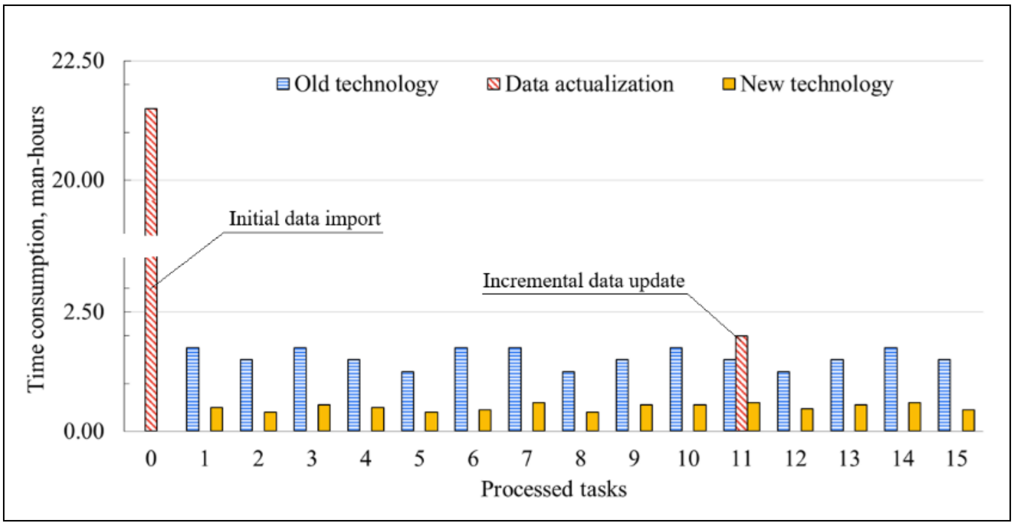

Figure 5. Time costs in the cyclic use of the technology (Authors' own research)

From Figure 5 it follows that the effectiveness of the proposed technology is determined not only by the time saved on the processing of the specific tasks but also by the time spent on the actualization of the dictionaries. To determine the general effect of the proposed technology, depending on the number of performed tasks, the graph in Figure 6 is provided.

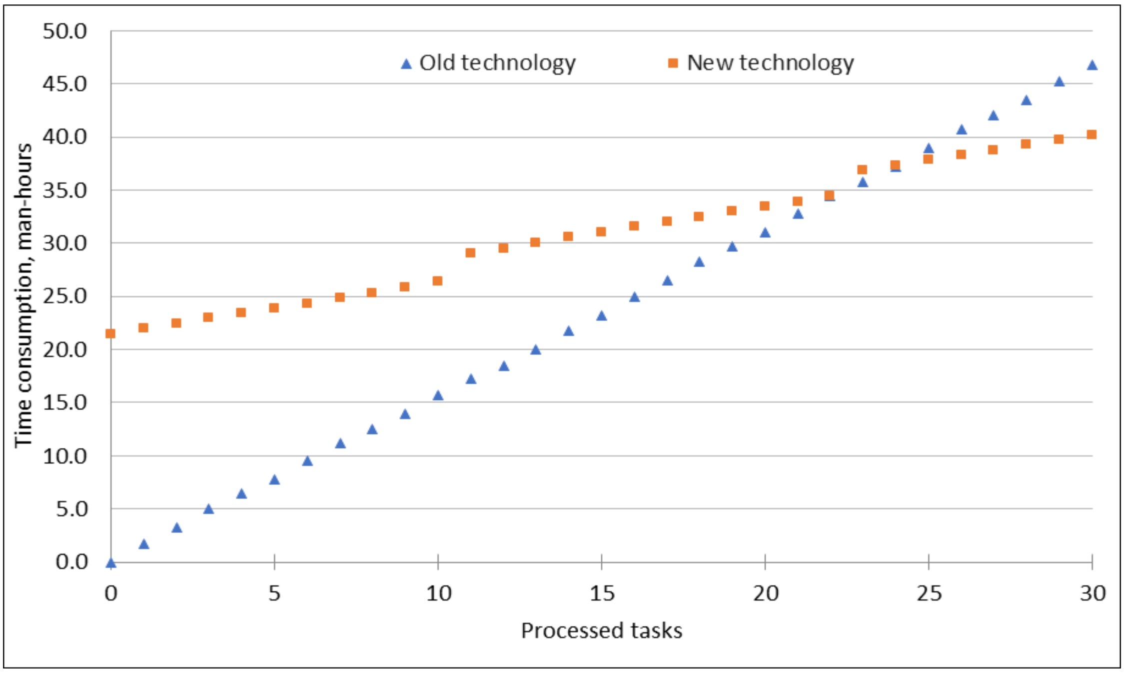

Figure 6. Cumulative time spent using the traditional and the proposed technology (Authors' own research)

According to Figure 6, the use of the new technology would have reduced time costs on the 25^{th} task execution.

The systems which allow an automated executor selection and consider the task context, reviewed in this article, are based on AI. Unlike these systems (Kaushal et al., 2023; Singh & Chouhan, 2023), the proposed term-dictionary technology provides transparent, linguistically grounded reasoning without ethical bias risks. While the AI-based approaches require periodical models re-training, the proposed approach requires certain efforts for the dictionaries updates. On the other hand, handling the situation when the same term has different meanings needs separate analysis in the AI-based system, while the proposed technology provides a clear approach for this case.

The identified limitations of the technology include its inapplicability to tasks that are irrelevant to the existing document base, due to the high probability of errors caused by insufficient data. It is also not advisable to use the technology for trivial or short-term tasks, where time savings on decision-making are negligible. Both limitations require separate experimental research.

6. Conclusions

A technology for constructing explanatory dictionaries within a project-oriented organization has been developed. The proposed approach ensures that the relationship between each term, the document in which it was discovered, and the document's author is preserved. This structure allows the representation of a specialist's competencies through the set of terms and technologies associated with their authored documents.

A document model has been developed, which contains information about the terms and technologies identified in the document, as well as about the contribution of each author to its creation. The set of terms and the relative frequency of their occurrence indicate the depth of elaboration of a particular topic within the document.

A specialist model has been created that, through references to authored documents, enables the identification of competencies in specific technologies and thematic areas.

A task model has been designed that defines the content of the assignment in terms of required technologies and terms. It also allows assigning weights to individual task components to improve the quality of the candidate selection.

A technology for assessing the professional readiness of a specialist to perform a task has been developed. Several methods for evaluating specialist competencies have been proposed, based on measurable document-derived indicators.

The experimental validation has shown that the application of the proposed technology enables the effective preliminary selection of the task executors, reducing the time required for this process by at least a factor of 3.1 compared to the traditional manual methods. The results confirm that the developed solution can serve as a foundation for decision-support systems in the software project management, facilitating a more objective, data-driven selection of specialists for tasks execution.

Author contributions

Conceptualization: O.K and R.C.; Data Curation: O.K and R.C.; Supervision:O.K. Validation: R.C.; Writing–original draft: O.K and R.C.; Writing–review and editing: O.K and R.C. All authors have read and agreed to the published version of the manuscript.

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