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INTELLIGENT MODEL FOR RANKING IT SPECIALISTS BASED ON COMPETENCIES, TEAM ROLES, AND RESOURCE WORKLOAD INDICATORS

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Abstract. The article presents the results of developing and formalizing a conceptual model of an intelligent information system designed to optimize human resource management processes in the IT industry. The relevance of the study stems from the need to overcome the fragmentation of data involved in forming project teams, where traditional methods often overlook the interdependence between technical competencies, psychological compatibility, and the actual workload of personnel. The author proposes a comprehensive approach to the automated ranking of specialists based on the integration of multidimensional input data, including professional competencies (Hard Skills), soft skills, team roles according to the Belbin methodology, and dynamic administrative indicators. Particular attention is devoted to the formalization of evaluation criteria, among which the level of autonomy, domain expertise, and specific parameters of resource availability are of critical importance. The scientific novelty of the work lies in the development of a mathematical framework for calculating an integral indicator of candidate effectiveness that accounts for nonlinear organizational constraints, including a maximum workload threshold of 85% and the risks of professional burnout assessed through the analysis of vacation and sick leave usage dynamics. The model implements a «logical filter» mechanism based on project roles, enabling the system to instantly exclude irrelevant candidates and concentrate the analysis on a targeted group of specialists. The practical significance of the study is demonstrated through the description of operational scenarios for the system's intelligent core, which is capable of automatically balancing team composition by prioritizing missing behavioral roles even in cases of minor deviations in technical qualifications. The proposed model also incorporates technical and legal constraints, including compliance with data protection requirements under the General Data Protection Regulation (GDPR), making it a robust foundation for designing highly reliable web applications in the field of human resource management. The results of the study establish a foundation for transitioning from subjective personnel selection to intelligent talent management based on objective metrics and predictive analytics.

Key words: IT resources, IT teams, IT projects, specialist ranking, team formation, hard skills, soft skills, conceptual model, information system, intelligent system.

Introduction. The dynamic growth of the IT sector and the increasing complexity of software products present management with the challenging task of forming project teams both quickly and effectively. However, traditional human resource management approaches often struggle with fragmented data: information regarding technical skills (hard skills) is typically stored separately from employees' psychological profiles and their actual workload metrics. This results in situations where specialists are assigned to projects because they formally match the technology stack, yet they may be incompatible in terms of team roles or on the verge of professional burnout due to excessive workloads.

The problem is further compounded by a lack of integrated tools that allow for the real-time tracking of not only professional qualifications but also dynamic parameters, such as remaining vacation days, the frequency of sick leave, and current project allocation percentages. Insufficient attention to organizational constraints – specifically exceeding a workload threshold of 85–90% – critically reduces operational efficiency and leaves no resources for employee training and development. Furthermore, the processing of large volumes of confidential information while maintaining compliance with GDPR and national data protection laws remains a pressing issue.

Analyzing previous research indicates that the effectiveness of team formation in IT and Data Science projects depends on numerous interconnected factors. One study, which focused on an algorithmic approach to forming Data Science project teams based on an analysis of approximately 30 student groups, demonstrated that project success correlates most strongly with the level of trust between members, shared professional backgrounds, domain expertise in programming and machine learning, and individual behavioral traits such as optimism and openness to cooperation [1]. Another study explored the application of deep learning methods to form effective teams by analyzing personality traits based on the OCEAN (Big Five) model. The BERT model was utilized to identify participants' psychological characteristics, while team formation was carried out using an optimized algorithm that accounts for both professional skills and individual personality metrics [2].

Several studies examine a systemic approach to human resource management using SWOT analysis to evaluate environmental factors and formulate comprehensive HR development strategies. It has been shown that implementing artificial intelligence technologies allows for the automation of recruitment processes, reduces decision-making bias, and increases the efficiency of data-driven personnel management [3]. To improve the objectivity of assessment and resource selection, it is proposed to formalize criteria and weighting factors using Qualimetry theory and to utilize expert decision-support systems in HR [4].

Leadership style is also a vital factor in team efficiency. Research has shown that transformational and democratic leadership styles are significant predictors of project success, explaining approximately 63% of the variation in teamwork outcomes, while organizational culture and team diversity act as moderators of leadership effectiveness [5]. Additionally, a decision-support information system was developed for managing large Agile teams in IT projects, ensuring effective communication, coordination, and process adaptability. The scientific novelty lies in the integration of the Cynefin Framework into the system's conceptual model, enabling adaptive team management based on the complexity level of the project environment [6; 7; 8].

Studies also demonstrate that a high level of emotional intelligence (EI) in managers positively affects the performance of cross-cultural teams by improving communication, conflict resolution, trust, and productivity. To achieve maximum impact, EI should be combined with knowledge of cultural norms and organizational structures, alongside the implementation of specialized training, feedback systems, and policies for performance evaluation and leadership competency development [9]. Team building is regarded as a vital element of personnel policy in modern organizations and public administration to enhance teamwork efficiency. It has been proven that successful team formation depends on defining shared goals, mutual accountability, managerial competence, and systemic support from human resources departments, all of which contribute to improved management quality and the achievement of collective objectives [10].

A key factor in increasing the productivity of management teams is effective time management. The implementation of digital tools – such as project management platforms, cloud-based collaboration systems, and AI-driven assistants – together with the development of leadership competencies and Agile practices, helps optimize processes and reduce cognitive load [11; 12; 13]. Research shows that cognitive diversity positively impacts team performance both directly and through the mediator of team efficacy, while team learning further strengthens this connection. A practical conclusion is the necessity for the systemic development of collective efficacy and the implementation of continuous learning practices to maximize the benefits of cognitive diversity [14]. Furthermore, meaning-based leadership indirectly influences the execution of team strategy through the alignment of team values with top management. A higher level of such leadership from an immediate supervisor amplifies this effect, making value congruence a key mechanism for implementing organizational strategy [15].

Consequently, there is an objective need to create an intelligent model capable of consolidating these disparate information flows into a unified basis for decision-making. This requires the development of a conceptual approach to building a system that automatically ranks candidates by considering both direct qualification assessments and indirect behavioral and administrative factors. The problem statement lies in the need to formalize input parameters, monitoring processes, and a system of constraints that will serve as the foundation for developing an intelligent web application for IT resource management.

In light of the above, the purpose of this work is to develop and formalize a conceptual model for an intelligent information system for human resource management in IT teams. This involves creating a comprehensive approach to automated specialist selection and ranking by integrating multidimensional input data: professional competencies, psychological characteristics based on the Belbin methodology, and dynamic metrics of personnel workload and availability. A vital component of this objective is the substantiation of a mathematical framework for calculating a candidate's integral performance indicator, taking into account established organizational, technical, and legal constraints. This approach aims to minimize the risks of professional burnout and optimize the project team formation process.

Research implementation. To implement the proposed intelligent model, it is necessary to structure the information flows. Below is a detailed description of the input parameters that ensure objective specialist evaluation.

Within the development of the intelligent human resource management information system for IT teams, clearly defining input and output data is a key stage that ensures the functioning of the conceptual model. The input data forms the system's informational basis, which is divided into several functional blocks.

The first block of input information consists of direct professional qualification metrics. these include ratings of programming language and framework proficiency on a ten-point scale, data regarding previous industry experience, and code quality assessment results.

The second block covers behavioral and psychological characteristics, such as testing results based on the Belbin methodology, soft skills proficiency, and the degree of autonomy in decision-making.

The third block of input data is dynamic in nature and is retrieved from integrated project management and time-tracking systems. This provides information on an employee’s current workload percentage, the number of vacation days used, and the frequency of temporary disability (sick leave) incidents.

Additionally, specific project parameters are fed into the system, namely requirements for project roles and the necessary technology stack, which serve as the benchmark for subsequent comparison.

The input data forms the system's informational basis, which is categorized into several functional blocks (Table 1).

Table 1. Input data structure of the intelligent model

Model block	**Model sub-blocks**	**Elements included in the sub-block**
Input data	Employee DATA	1) ID. 2) Last name. 3) First name. 4) Middle name. 5) Phone number. 6) Email address. 7) Hire date. 8) Termination date.
	Vacations and sick leaves	1) ID. 2) Number of vacation days. 3) Number of sick leave days. 4) Number of vacation/sick leave days in the last quarter.
	Current employment	1) Employment percentage (workload %). 2) Project IDs (to which the employee is assigned).

The processes specified in Table 2 ensure the dynamic, real-time updating of information regarding the status of human resources.

Table 2. Functional modules and data processing

Model Block	**Modules**	**Functionality**
Processes	Employee selection for project engagement	1) Extracting a list of all employees based on selected parameters (filters), ranked by utilization level. 2) Automated selection of employees based on chosen criteria (filters such as number of roles, engagement level, and estimated duration). 3) Generating the final list of employees for the project.
Monitoring and Updates	Monitoring and data actualization	1) Automated updates of remaining vacation and sick leave balances after each transaction in the HR module. 2) Recalculation of employee workload percentage (once per day).
Data Management	Data management	1) Automated updates of employee data (e.g., % engagement). 2) Manual adjustment of employee data (e.g., soft/hard skills).
Reporting	Report generation	1) Generating resource utilization reports (actual vs. planned) to identify bottlenecks. 2) Generating vacation and sick leave utilization reports (to analyze burnout indicators).

The composition of the system's output data and reporting is presented in Table 3.

Table 3. Composition of output data and system reporting

Model block	**Model sub-blocks**	**Elements included in the sub-block**
Output data	Project data (by employees)	1) Project ID. 2) Project name. 3) Updated employee workload percentage.
	Employee data	1) Updated engagement percentage, 2) Added project ID, 3) Updated vacation and sick leave balance.
	Reports	1) Updated resource utilization reports (once per day).

Accounting for the constraints outlined in Table 4 is critical for ensuring the high reliability and legal compliance of the web application.

Table 4. System of organizational, technical, and legal constraints

Model block	**Model sub-blocks**	**Elements included in the sub-block**
Input data	Organizational constraints	1) The employee's workload level cannot exceed 90% (10% is allocated for training and development). 2) An employee cannot have more than 10 sick days (3 ABAPS and 7 certified), except in cases of manual overrides. 3) Employee training.
	Technical constraints	1) Backup generation (once per day). 2) Integration with current project management systems (Jira/Trello, Confluence). 3) Data management tools for the initial MVP stages.
	Legal constraints	1) Compliance with GDPR and the Law of Ukraine on personal data protection.

As a result, by refining the input/output data, as well as the information regarding processes and constraints, we are able to compose and design the conceptual model for the future web application (Fig. 1). Conceptual modeling of information systems using both systemic and process-oriented approaches was utilized based on the research found in [16; 17; 18; 19].

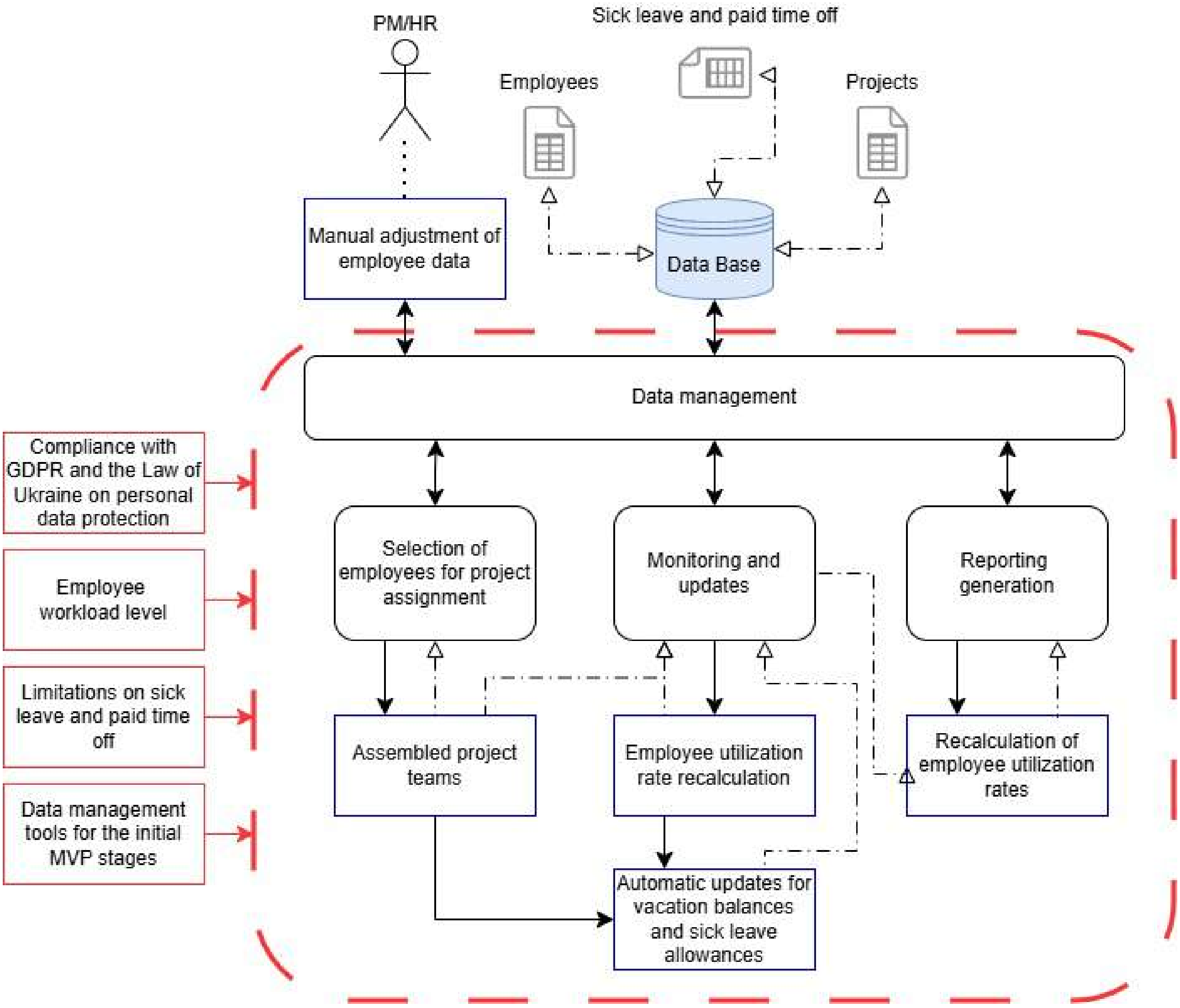

Figure 1. Conceptual model of the information system

An example of applying this model is a standard team formation scenario for a FinTech project. In this case, the project manager initiates a request within the system, specifying the necessary technical parameters – such as Python proficiency and experience in FinTech development – along with constraints regarding the specialist's current workload for the upcoming quarter.

The system's intelligent core queries the AWS Data Lake to retrieve information on employees who match the selected filters. Subsequently, the comparison module generates a ranked list. The system may recommend a specialist with a slightly lower hard skills rating but with a zero-workload percentage and relevant domain experience, ensuring a rapid project start without the need for extensive onboarding.

Once the candidacy is finalized, the personnel management module initiates the data update process for the employee, adjusting their workload status. This process is a prime candidate for future full automation.

Each employee in the system can be represented as an object E_i (Employee). The set of input data for each employee D_i, which includes the last name, first name, middle name, contact information, and other details from the employee's records, is described as a tuple of parameters:

$$E_i = \{D_1, D_2, D_3, \dots, D_n\}, \qquad (1)$$

where E_i – is the employee, and \$i\$ is the unique index of the employee within the overall personnel pool; D_i – is a unique dataset for the employee (full name, contact information, etc.).

For each project P_i , the employee selection function E_i is defined by the formula:

$$L_i = f\{F, T, C\}, \qquad (2)$$

where L_i – a generated list of candidates based on: F – set of filters and selection parameters (role, experience, domain expertise); T – available workload volume in man-days (based on 8 hours per day on weekdays); C – the list of candidates from the database.

The system's output data after team formation can be represented as an updated tuple of the project state S_P and the employee E_P:

$$S_P = \{D_i, U_i\}, \qquad (3)$$

where D_i – updated employee data based on workload; U_i – total team workload.

For any model to function correctly, it is necessary to have a list of parameters, characteristics, and weights.

To ensure the model operates correctly, a list of parameters, characteristics, and their corresponding weighting coefficients has been defined (Table 5).

Table 5. Comprehensive system of specialist assessment criteria

Name	Criticality	Description	Rating	Weight
Hard Skills level	High	Technical skills (languages, frameworks). Determines whether an employee can perform the task.	Scale of 0-10	0,25
Soft Skills level	Medium	Communication, emotional intelligence, and teamwork. Affects the team climate.	Scale of 0-10	0,2
Belbin team role	Medium	Behavioral role (leader, implementer, monitor evaluator). Important for team balancing.	Scale of 0-10	0,05
Project role	High	The employee's specific project role (analyst, engineer, etc.).	N/A	Filter
Number of vacation days	High	Remaining available rest days. Helps plan release schedules and prevent burnout. Total number of sick days. A key marker for assessing resource availability.	Calculation algorithm	0,15

Name	Criticality	Description	Rating	Weight
Autonomy level	Medium	Ability to work without detailed supervision. Determines the workload on the Team Lead.	Scale of 0-10	0,1
Project experience	High	Experience in a specific business niche (e.g., FinTech). Reduces onboarding time for the project.	Scale of 0-10	0,2
Current workload	High	Percentage of engagement in other projects. Prevents overloading.	Value in %, where 85 is the realistic maximum out of 100	0,15

To determine Hard Skills (Table 6), it is necessary to describe the specific skills required by the team, such as knowledge and proficiency in programming in Python/Java/C#.

The following set of parameters is provided to describe each individual specialty.

Table 6. Assessment parameters for professional skills (Hard Skills)

Criterion name	Criticality	Assessment description	Rating	Weight
Theoretical knowledge	Medium	Level of understanding of technology principles, algorithms, and architectural patterns.	Scale of 0-10	0,15
Practical experience	High	Number of years/months of experience working with the technology on real-world commercial projects.	Scale of 0-10	0,4
Code quality	High	Adherence to coding standards (Clean code, SOLID) and the absence of critical errors.	Scale of 0-10	0,3
Task resolution speed	Medium	Ability to meet time estimates when performing technical tasks.	Scale of 0-10	0,1
Certifications	Low	Verification of knowledge by external vendors (AWS, Google, Oracle, etc.).	List	0,05

The corresponding analysis for Soft Skills is presented in Table 7.

Table 7. Soft Skills assessment criteria

Criterion name	Criticality	Assessment description	Rating	Weight
Communication quality	High	Ability to articulate thoughts clearly, active listening, and providing constructive feedback.	Scale of 0-10	0,35
Team collaboration	High	Willingness to help colleagues, participation in group discussions, and absence of toxicity.	Scale of 0-10	0,3
Stress tolerance	Medium	Maintaining productivity during deadlines or sudden changes in project requirements.	Scale of 0-10	0,2
Autonomy	Medium	Ability to find solutions without constant guidance from management.	Scale of 0-10	0,1
Mentorship	Low	Willingness and ability to train less experienced colleagues (relevant for Senior/Lead levels).	Scale of 0-10	0,05

It is worth separately defining an algorithm for calculating leave days, which also includes sick leave (ABAPS – unverified sick leave of up to 3 days, and company-paid medical leave of up to 20 days that must be certified by a physician).

Certain parameters do not use a numerical score; instead, they function as filters and strict rules for selecting candidates for a project team:

1. Project role – a non-scoring criterion. It serves exclusively as a filter to select employees of a specific specialty. For example, if a search is conducted for a DevOps Engineer, only employees identified as «DevOps» in the database will be displayed, regardless of other criteria (Hard Skills, Soft Skills, etc.

2. Vacation and sick leave data calculation algorithm – the following principle is proposed for this model: if an employee's number of unused or unplanned vacation days exceeds 14 calendar days and their sick leave count for the last quarter is fewer than 5, they receive a minimum score of «0». Conversely, if the allotted vacation and sick leave days have been fully exhausted, the score is 10.

3. Current workload – in alignment with global time management practices, most companies aim for a maximum employee workload of 85% of total working hours, leaving the remaining 15% for professional development. Therefore, a threshold of 85% will be used to assess an employee's available capacity.

The overall employee rating (R) for selection for a specific project can be calculated using the following formula:

$$R = \sum_{i=1}^{n} (\mathrm{Score}_i * w_i), \quad (4)$$

where Score_i is the normalized score on a scale of 0 to 10; w_i is the weight of the corresponding criterion from the table.

Thus, the expanded scoring formula for each set of criteria individually will be as follows (I_{hr}):

$$I_{hr} = \sum (S_i * w_i) = S_1 * w_1 + S_2 * w_2 + S_3 * w_3 + S_4 * w_4 + S_5 * w_5 + S_6 * w_6, \quad (5)$$

where S_i is the normalized criterion score; w_i is the criterion weight.

To incorporate «Workload» (S_{load}) and «Time off» (S_{vac}), into the formula, they must first be converted into scores:

Since an employee's maximum possible workload is 85% of their working hours, we use the following system of equations:

$$S_{load} = \begin{cases} 1 - \frac{\mathrm{CurrentLoad}}{85}, & \frac{\text{Якщо Load} < 85}{\text{Якщо Load} > 85}, \\ 0, & \end{cases} \quad (6)$$

The lower the employee's workload, the higher their score.

A reduction coefficient is applied to calculate sick leave. If an employee has few vacation days remaining (risk of burnout) or a high number of sick days (risk of absence), their score decreases.

$$S_{vac} = \frac{\mathrm{DaysRemaining}}{\mathrm{TotalYearPolicy}} * (1 - \mathrm{Penalty}_{sick}), \quad (7)$$

The candidate's final rating R is calculated as the product of the integrated indicator I_{hr} and the logical filter for project role alignment.

The resulting data is summarized in Table 8.

Table 8. Parameters for calculating the integrated performance indicator I_{hr}

Parameter	**Weight (w)**	**Calculation type in the model (S_i)**
Hard Skills	0,25	Direct value (Score / 10)
Domain experience	0,20	Direct value (Score / 10)
Current workload	0,15	Inverted value (85% equals 0 points)
Time off / Sick leave	0,15	Resource availability Coefficient
Soft Skills	0,10	Direct value (Score / 10)
Level of autonomy	0,10	Direct value (Score / 10)
Belbin team role	0,05	Alignment with required role (0 or 1)

The «Project role» filter serves to eliminate redundant results and narrow down the scope of the output. This parameter is not included in the total sum; instead, it functions as a logical multiplier:

$$R = I_{hr} \cdot P_{match}, \quad (8)$$

where $P_{match} = 1$, if the employee's role matches the project role; $P_{match} = 0$, if the employee's role does not match the project role.

The system utilizes an integral indicator I_{hr} for the instantaneous ranking of candidates for a specific project: the intelligent model filters the database by «Project role» and generates a top-tier list of specialists with the highest scores. If the system detects that a team already consists of two «Plants» (idea generators) but lacks an «Implementer», it will automatically increase the priority of a candidate with the corresponding role, even if their hard skills are slightly lower.

The utilization and indication of available, planned, or unused vacation and sick leave provide the project manager with a more accurate understanding of the employee's availability. As a future enhancement to the model, an analysis of employee leave/sick days over a previous period (e.g., one year) could be implemented to establish individual attendance trends.

Furthermore, another compelling direction for the development of this intelligent model lies in integrating KPIs and other performance metrics. It is possible to collect and update these metrics based on project outcomes to either reward an employee or, conversely, adjust their internal rating downward.

Conclusion. Throughout this study, a pressing scientific and practical challenge was addressed: the automation of the IT team formation process through the development of a conceptual model for an intelligent specialist ranking system. The proposed approach overcomes data fragmentation in HR management by integrating professional competencies (Hard Skills), psychological profiles based on the Belbin methodology, and dynamic personnel workload and availability metrics into a unified informational framework. The scientific novelty of this work lies in the formalization of a comprehensive evaluation criterion. Unlike existing approaches, this criterion accounts for not only static qualifications but also nonlinear parameters of organizational constraints – specifically, the critical workload threshold of 85% and the risks of professional burnout identified through the analysis of remaining vacation balances and sick leave frequency. The practical value of these results is confirmed by the development of a mathematical framework for calculating an integral performance indicator. This allows for the automated selection of the most relevant candidates, minimizes onboarding time, and ensures a balanced distribution of team roles within projects. The resulting model serves as the foundation for the development of an intelligent web application that guarantees compliance with GDPR and national data protection laws, providing high-precision management decisions within the dynamic environment of the IT industry.

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