UDC 004.9
DOI: 10.15587/1729-4061.2026.365174

ADAPTATION OF KNOWLEDGE MANAGEMENT MODELS IN PROJECT AND OPERATIONAL ACTIVITIES OF AN ORGANIZATION FOR SOFTWARE IMPLEMENTATION

Denys Robotko
PhD Student*
ORCID: https://orcid.org/0009-0003-7301-0509
Olena Kovalenko
Corresponding author
Candidate of Technical Sciences, Associate Professor*
E-mail: ok@vntu.edu.ua
ORCID: https://orcid.org/0000-0003-2864-9058
*Department of Information Technologies and Computer Engineering
Vinnytsia National Technical University
Khmelnytske highway, 95, Vinnytsia, Ukraine, 21021

This study investigates knowledge management processes involving highly qualified personnel at enterprises engaged in project and operational activities. The task addressed is to adapt knowledge management models for further implementation in software modules of an information system. Special attention has been paid to intellectual projects, which include software development at software engineering enterprises and knowledge management during their project and operational activities.

At the meso level, a dynamic model was built, based on a system of differential equations, which describes the rate of change in the integrated level of knowledge by the project team. At the microlevel, a model for assessing the effectiveness of corporate training was constructed. A special feature of the models is the transition from a descriptive description (such as the SECI model) to an analytical calculation of cognitive processes by integrating pure rates of knowledge exchange and formalized digital traces of specialists.

The results of model construction for assessing learning outcomes are attributed to the combination of the classical Ebbinghaus forgetting exponent and a linear function of the level of practical activity intensity, in which the cognitive memory fading indicator decreases inversely proportionally through performing verified operations in various instrumental environments.

Conditions for the practical application of models are their implementation in specialized HR analytics software modules with REST API support for automated metric collection. Analytical solution of models based on open industry data confirmed their adequacy. Thus, the calculation results indicate that under the condition of active internal learning, the developer approaches the target expert level in less than a year. Experimental modeling of learning outcomes for conditions of lack of practice recorded a degradation of skills up to 22% after 6 months, while regular performance of operations ensures the preservation of competencies at the level of 98%.

The constructed mathematical and visual models of knowledge management ready for implementation could lay the groundwork for developing special software and practical cases for knowledge management specialists

Keywords: knowledge management; automation of personnel management; software engineering; knowledge retention; IT project knowledge monitoring; forgetting curve

Received 30.03.2026
Received in revised form 05.06.2026
Accepted 16.06.2026
Published 30.06.2026

How to Cite: *Robotko, D., Kovalenko, O. (2026). Adaptation of knowledge management models in project and operational activities of an organization for software implementation. Eastern-European Journal of Enterprise Technologies, 3 (3 (141)), 21–28. https://doi.org/10.15587/1729-4061.2026.365174*

1. Introduction

Modern enterprises actively use technology and require highly qualified employees. This leads to a constant need to improve enterprise management and, in particular, knowledge management to preserve intellectual assets. The implementation of modern knowledge management processes requires the active use of software for automatic monitoring of the level of knowledge and support of management processes. Such software modules could allow real-time tracking of the dynamics in accumulation and loss of knowledge by personnel, analysis of the intensity of training, taking into account the peculiarities of communication processes and factors of personnel turnover.

Scientific and practical research should be focused on the construction of models for knowledge management in the organization within the framework of project and operational activities for the preservation and generation of knowledge. It is this part of the intellectual capital of the organization that actively influences the results of the implementation of strategic and operational development goals, the implementation of new projects. The use of mathematical models in such research makes it possible to structure input data, determine the procedures for their processing, and ensure the quality of preservation and generation of formal and informal knowledge.

Knowledge management systems support the procedures for making managerial decisions [1], in particular in the processes of personnel management and training. The result of implementing knowledge measurement models is to provide HR managers with tools for assessing employees, which is necessary for the effective formation of project teams and determining the quality of corporate training over different periods. Software using mathematical models makes it possible to automatically generate recommendations for advanced training or retraining, offering personalized training trajectories; determine the level of knowledge for project implementation. An important practical aspect is that when the system detects a high concentration of knowledge in one specialist, it can initiate the process of documenting knowledge, creating internal instructions, or transferring competencies to other team members. This reduces the level of dependence of the enterprise on individual specialists and increases the level of organizational stability. In addition, models for assessing the results of distance courses or trainings (immediately after completion and through certain periods of practical work) make it possible to develop special algorithms for determining the needs for further training and formalizing the accumulated expertise in the form of knowledge.

The combination of mathematical and visual modeling with the subsequent implementation of knowledge management software makes it possible not only to predict training needs but minimize the risks of loss of intellectual capital of the enterprise as well. One of the most intellectual areas of development is the Information Technology industry and software engineering enterprises, the peculiarity of which is the use of modern information and management technologies. For such enterprises, knowledge management is an operational process, the result of which is the reproduction of intellectual resources. Therefore, software engineering enterprises, on the one hand, can develop and implement software for knowledge management, on the other hand, they need special software modules to implement effective knowledge management. Unfortunately, well-known knowledge management models are not implemented in software and need to be adapted [2, 3].

Therefore, it is a relevant task to construct knowledge management models for the project and operational activities involving highly qualified personnel.

2. Literature review and problem statement

Our analysis of results from scientific research can be divided into two areas; one of them, related to knowledge management models, including models at different levels (macro, meso, micro) and in different areas – monitoring knowledge at the level of intellectual capital of the organization, monitoring the knowledge of a specific specialist based on the results of training, etc.; the second – software for automated knowledge management systems. A number of studies consider the development of digital technologies for the implementation of known models. Analysis of work [1] reveals a close connection between the macro model of enterprise knowledge management and the micro model of training. However, to design software modules for knowledge management, it is necessary to clarify calculation formulae.

Analysis of known models of knowledge management allows us to assert that the key theoretical basis is the SECI model (Socialization, Externalization, Combination, Internationalization) [2, 3]. It visualizes the process of designing organizational knowledge through four interrelated phases: socialization, externalization, combination, and internalization. This model provides a conceptual understanding of knowledge dynamics but is qualitatively descriptive and does not allow for quantitative assessment of the speed of knowledge exchange, losses due to staff turnover, or the effectiveness of internal communications. In addition, this model does not take into account the differentiation of personnel by level of qualification and roles in knowledge flows. That is why such a general model must be specified and detailed for implementation in a software module.

A more recent direction is stochastic and dynamic approaches, in particular the model of Knowledge Flow Dynamics (KFD) [4]. In this model, the process of knowledge exchange is considered as a multi-scale stochastic system, which takes into account random interactions between agents, the lifetime of knowledge, and the effect of network structures. Agents include both specialists and software modules. But the model still remains general and does not adapt to automated knowledge management of specific enterprises, groups of highly qualified personnel, projects. That is why there is a need to study procedures for assessing the level of knowledge by preparing mathematical and visual models for implementation in a software module.

The components of knowledge management model described in [5] are aimed at increasing the effectiveness of knowledge flows. The work provides an example of using collective knowledge using the Wiki environment of the organization. But the author does not offer an applied mathematical apparatus for calculating knowledge management indicators. While acknowledging that in [6] not only a knowledge management model is reported but also the use of digital technologies for monitoring the development indicators of intellectual capital, the problem of implementing a model for forming a knowledge management software module has not been solved. The study reported in work [7] indicate the evolutionary development of the introduction of digital innovations into modern knowledge management systems. The authors focus on various tools for fixing knowledge and spreading experience. But the model does not contain calculation algorithms for implementation within the project.

Work [8] indicates that knowledge management should use quantitative methods that make it possible to predict future skill shortages in the organization, introduce talent management methods through point training. But the authors do not provide a clear mathematical apparatus for quantitatively assessing the experience of individual personnel profiles and collective experience. To clarify the mathematical apparatus in knowledge management models at the micro level, it is advisable to use formulae that take into account knowledge loss along the forgetting curve [9, 10]. The proposed mathematical apparatus could be used to calculate the parameters of individual forgetting. But for the implementation of computational models, it is advisable to build complex models in accordance with current practical cases at enterprises and in project groups. Using the Heike formula to assess the increase in knowledge can provide an opportunity to more clearly calculate indicators of learning control and, even, the presence of personnel competencies [10]. But the analysis of the use of such mathematical apparatus for the implementation of complex models requires more detailed research.

The example given in [11] indicates the relevance of determining the educational trajectory for highly qualified personnel but does not take into account the indicators of the intensity of knowledge exchange.

According to the authors of [12], analysis of the evolution of knowledge management information systems reveals that such systems include various data repositories, messaging tools, corporate websites, etc. But to implement models in software modules, it is necessary to determine the target parameters of each of the knowledge management tools, as well as consider practical cases for enterprise and project managers.

Our review of related literature demonstrate that the known knowledge management models are not actively implemented at the macro-, meso-, and micro-levels because they are mainly descriptive in nature and are not adapted to possible technological implementations of an automated knowledge management system. The lack of a mathematical apparatus for a comprehensive and quantitative assessment of the dynamics of knowledge flows at the project or unit level remains an unresolved issue. Also, the assessment of the effectiveness of training of highly qualified personnel with the possibility of algorithmization and programmatic implementation of recommendations has not been studied in detail.

The above allows us to argue that it is advisable to conduct a study aimed at adapting knowledge management models for implementing calculation modules in software. Solving this task requires the formalization of parameters for knowledge assessment, training, exchange of experience, preservation of accumulated and generation of new knowledge within the framework of a specific activity.

3. The aim and objectives of the study

The purpose of our study is to adapt mathematical models for assessing the knowledge dynamics of highly qualified personnel in project and operational activities at the meso level (assessing the dynamics of knowledge flow in a unit, project) and the micro level (based on the results of personnel training) for further implementation in the knowledge management software module. Such models will reduce the gap between the theoretical description of knowledge management processes and the development of software modules for automated knowledge management in an organization and in individual projects. This will make it possible to store existing and generate new knowledge of the organization in formal and informal forms.

To achieve the goal, the following tasks were set:

– to build a mathematical model of knowledge management at the meso level (within a project);

– to perform calculation operations in accordance with open data for knowledge management;

– to construct a mathematical model for assessing the level of knowledge based on the results of knowledge management training at the micro level using an example (assessment of learning outcomes).

4. The study materials and methods

The object of our study is the knowledge management processes involving highly qualified personnel engaged in project activity at an enterprise.

The principal hypothesis assumes that active activity in a certain professional direction is a technique for preserving, using, and generating knowledge; its non-use leads to forgetting and reducing the level of knowledge.

The following simplifications were adopted when performing the study. Knowledge management processes are considered within the framework of one project (or department activities). To formalize the relationships between the level of knowledge of employees, the team structure and the effectiveness of the project, the model is built on certain criteria for analyzing the level of qualification of personnel, existing knowledge, predicting the effect of training or personnel rotation.

For the micromodel of assessing learning outcomes, a mathematical apparatus for assessing the level of forgetting and the lack of experience in using the acquired knowledge in practice is used.

In addition, the procedure for documenting knowledge is also productive for preserving its formal part. But for knowledge management it is necessary to adapt known mathematical models involving the apparatus of differential calculus and design visual models to describe dynamic processes of knowledge management. Mathematical formalization is carried out by building models that describe the rate of change in the level of knowledge depending on the controlled parameters of learning and communication, taking into account the stochastic influence of staff turnover. To verify the adequacy of the theoretical provisions used, the method of calculating the level of knowledge based on statistical data from industry reports and the results of monitoring the educational trajectories of personnel is used. The information base of our study is open statistical reports, internal data from IT companies on staff turnover, and the results of testing the distance learning system, data on the need to measure residual knowledge of the results of studying previous related disciplines.

5. Results of construction and practical testing of mathematical models for knowledge management

5. 1. Construction of a general mathematical model of knowledge management using a project as an example

A general mathematical model of knowledge management on the example of a project can be formed on the basis of scenarios of the manager's work and the processes of generation and preservation of knowledge. Let's consider a typical scenario of personnel selection for a new project in an IT company. The manager, together with the HR department, form a team that must ensure the successful implementation of the task – the development of new software. To do this, they analyze the existing knowledge and competencies of employees, as well as the corporate knowledge base, which contains documentation, standards, code fragments, internal instructions, and results of previous projects.

In this process, the task of assessing the relevance of each employee's knowledge to a specific project arises. For example, programmers and testers have a high impact on the result because their knowledge directly determines the quality of development. Supporting staff (for example, cleaning specialists, material supply) has less impact on the success of the task. Figure 1 shows a visual model of personnel recruitment for the selection of specialists for a new project.

The manager and HR must make a decision on the recruitment of specialists to the team, determine what knowledge needs to be strengthened, how complete the knowledge base is for effective interaction between participants. In the process of personnel recruitment, a number of practical issues arise:

– how to quantify the level of knowledge of each employee;

– how to determine the degree of compliance of professional competencies with project requirements;

– how to take into account the existing corporate knowledge base in the decision-making process;

– how to predict the impact of the loss of key employees or lack of knowledge on project risks.

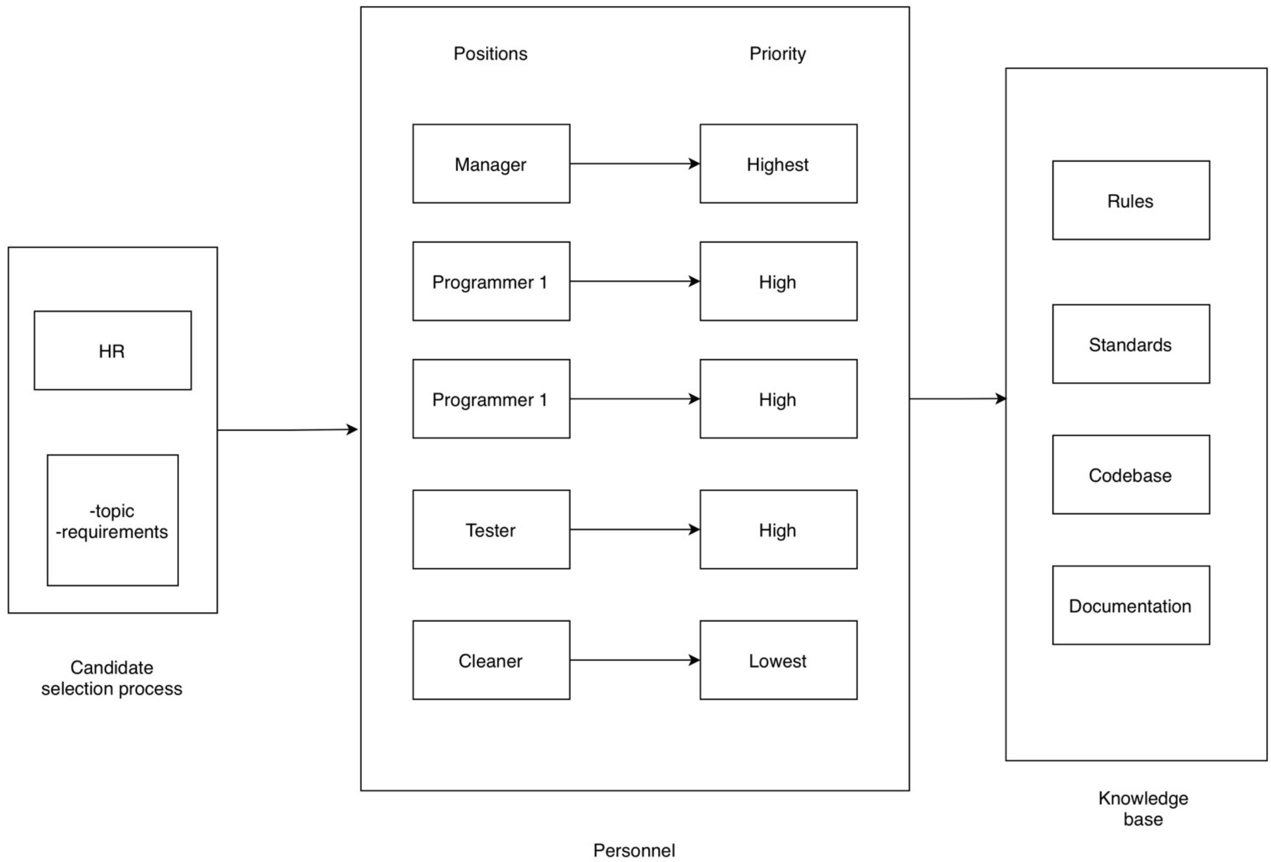

Fig. 1. Visual knowledge management model for project team selection

The considered scenario demonstrates that without a formalized approach to knowledge assessment, the HR department and management are forced to make decisions intuitively. The proposed mathematical model and a working automated knowledge management system will allow for more objective decisions on personnel selection, knowledge preservation and generation at both the strategic and operational levels.

To implement a knowledge management software module, it is advisable to consider a mathematical model that makes it possible to formalize the dynamics of learning, communication, and forgetting processes. The mathematical model was built on the basis of the reviewed literature [1–10].

For this purpose, variables were introduced that describe the key aspects of the system:

– $K(t)$ – integrated level of knowledge by highly qualified personnel at time t (can be estimated to the limit from 0 to 100 points);

– $I(t)$ – intensity of training and advanced training (controlled parameter) (hours/month per employee, number of trainings, budget/month, etc., it reflects the total amount of relevant competencies accumulated in the team);

– $A(t)$ – level of communication activity (speed of knowledge exchange between employees; number of technical sessions, workshops, pair activities, etc.);

– α – coefficient of training effectiveness (determination according to the last term of training, compliance with the project topic, competencies);

– β – coefficient of knowledge exchange (publishing messages, wiki, documentation);

– γ – coefficient of knowledge loss (dismissal, forgetting, information obsolescence).

The task is to build a model that describes the change in the level of knowledge $K(t)$ over time, taking into account the above processes – accumulation through learning and exchange, as well as knowledge loss for various reasons. Based on this model, it is necessary to devise an approach to choosing the optimal strategy for managing parameters $I(t)$ and $A(t)$, which ensures the maximization of the collective level of knowledge in the long term.

Knowledge is considered as a dynamic resource that grows through learning and communication, performing actions to maintain competencies and skills, but is gradually lost due to forgetting, staff turnover and technological obsolescence.

The general model can be represented as a function of maximizing the integrated level of knowledge at a certain time $K(t)$ by increasing coefficients α (learning efficiency) and β (knowledge exchange), decreasing coefficient γ (the level of loss of acquired knowledge).

The analysis horizon is set by the time interval $t \in [[0, T]$, which usually corresponds to several months or quarters of active work of the team.

The model is built on the interaction of three key elements:

– system state – knowledge level $K(t) \geq 0$;

– controlled parameters – learning intensity $I(t)$ and level of communication activity $A(t)$;

– system constants – coefficients of learning efficiency, knowledge exchange and losses.

Controlled variables have natural limitations

$$0 \leq I(t) \leq I_{\{max\}},\ 0 \leq A(t) \leq A_{\{max\}}.$$

Constant parameters determine the nature of the system:

– $\alpha > 0$ – learning efficiency (how many units of knowledge unit I provides per unit of time);

– $\beta > 0$ – exchange efficiency (how much communication accelerates the multiplicative spread of knowledge);

– $\gamma \geq 0$ – knowledge loss (forgetting, fluidity, obsolescence of technologies).

The basic equation of knowledge dynamics can be represented as follows (1)

$$\frac{dK}{dt} = \left(\alpha I(t) - \gamma I(t)\right) + \left(\beta A(t) - \gamma A(t)\right) * K(t), \quad (1)$$

where additive growth of knowledge through learning $\alpha I(t)$ is carried out even in the absence of communications if the staff is actively learning. But knowledge is also forgotten if it is not constantly used and updated.

Multiplicative growth through communications $(\beta A(t))K(t)$ enhances the overall level of knowledge and characterizes the intensity of exchange between employees as each unit of knowledge has a "spreading effect". But this component also takes into account forgetting and obsolescence of knowledge.

For convenience, a pure rate of change of knowledge during communications was introduced

$$r(t) = \beta A(t) - \gamma A(t), \quad (2)$$

and the net rate of change of knowledge in the implementation of learning

$$n(t) = \alpha I(t) - \gamma I(t), \quad (3)$$

and then the model takes on a compact appearance

$$\dot{K} = n(t) + r(t)K. \quad (4)$$

If $r(t) > 0$, that is, knowledge exchange prevails over losses, the level of knowledge grows exponentially. If $r(t) < 0$, training is the only source of maintaining competencies. The model is linear with respect to $K(t)$, which ensures the integrity of the solution under standard continuity conditions.

From a managerial point of view, the interpretation of the model can be represented as follows:

– coefficient α determines how effective investments in training are (if low, the quality of training should be improved and their focus on the necessary knowledge of the personnel should be more clearly defined);

– β shows the team's ability to share knowledge (increases due to joint sessions, mentoring);

– γ reflects the loss of competencies (they are reduced by motivation, staff retention, documentation).

The resulting model makes it possible to describe how the level of knowledge changes depending on the parameters of training, communications, and staff losses. It is a quantitative addition to the conceptual SECI model, allowing us to move from a qualitative description of processes to their analytical analysis and forecasting of results over time.

The considered mathematical model of knowledge management of a project (department) makes it possible not only to formally describe the processes of accumulation and loss of competencies but also to quantitatively assess the effectiveness of training, communications, and personnel decisions. To demonstrate its practical use, let's consider a conditional scenario of personnel selection for a new project in a company operating in the field of information technology.

In the process of team building, the manager together with the HR department should assess the current level of knowledge of employees using testing, surveys, and results of performing special tasks, as well as determine the need for additional training. For this purpose, the model makes it possible to calculate the integrated indicator of knowledge $K(t)$ of highly qualified personnel taking into account the intensity of knowledge and training $I(t)$, the level of communications $A(t)$, the efficiency of knowledge transfer β, losses γ, and the efficiency of training α.

To perform the calculations, assumptions were adopted regarding constant values of controlling influences. Assuming the stationarity of controlling influences $I(t) = \text{const}$, $A(t) = \text{const}$ within a certain time interval. The solution to the inhomogeneous differential equation (1) by the method of separation of variables makes it possible to obtain an analytical dependence of the level of knowledge in the following form (5)

$$K(t) = Ce^{Pt} + \frac{Q}{P}, \quad (5)$$

where

$$Q = I(\alpha - \gamma),$$

$$P = A(\beta - \gamma).$$

C is an arbitrary integration constant, that is, the transformed value of the initial level of knowledge.

5. 2. Estimated results of the knowledge level assessment model based on open data

Our calculations used open data for 2023, published by Training Magazine; the average number of training hours per employee is approximately 57 hours per year, which corresponds to $I = 4.75$ hours/month [13]. The personnel turnover in the technology sector, according to open analytical reports, is about 13% per year [8, 9], that is, $\gamma = 0.011$ per month, taking into account additional knowledge losses due to forgetting. The parameters of the effectiveness of training and knowledge exchange are taken at the levels of $\alpha = 0.3$ and $\beta = 0.04$, and the communication index is $A = 2.0$. The initial level of knowledge is taken as $K_0 = 35$ arbitrary units (on a scale from 0 to 100).

Using the above values, it was found that with the specified level of training and communication, staff knowledge grows exponentially – from 35 to about 85 units in 12 months (Fig. 2).

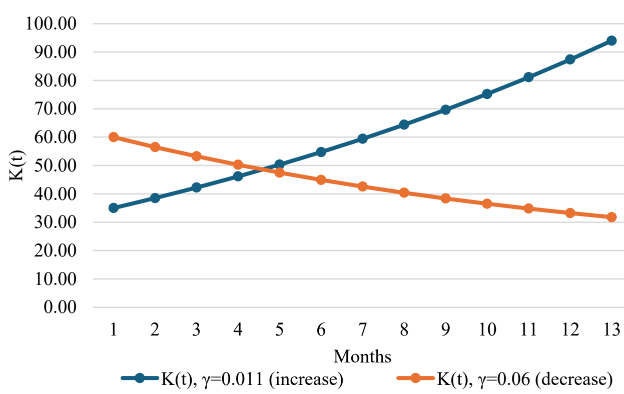

Fig. 2. Dynamics of knowledge level in the cases of changing parameters

This result indicates that the interaction effect $(\beta A > \gamma)$ prevails over the losses, and therefore the organization's knowledge system evolves in a self-reinforcing way. From a practical point of view, this means that even moderate investments in training (I) have a significant effect provided that there is active internal knowledge exchange (A). That is, the manager can estimate how many hours of training or how many internal communication activities are needed to achieve the target level of competence.

However, if the exchange rate decreases or staff turnover increases, knowledge begins to decrease, and even significant training efforts do not guarantee sustainable development. Therefore, the model can be used for sound planning of HR strategies, identification of training needs, and for managing the risks of losing critical knowledge.

For example, assuming $K_0 = 60$, $I = 4.75$, $A = 2$, $\alpha = 0.3$ and $\beta = 0.02$, $\gamma = 0.06$, a steady decrease in the level of knowledge was obtained over 12 months (from 60 to 31) (Fig. 2).

A practical example of using the proposed model for decision-making in the process of selecting employees will make it possible to determine the optimal ratio between the level of knowledge of a new candidate and the intensity of his/her training within the organization. This makes it possible to predict how quickly an employee will reach the required level of competence and what effect his/her integration into the team will have.

For illustration, a scenario of the work of an enterprise implementing a new information system is considered using the example of the work of a specific specialist. The initial level of knowledge of the employee is taken to be $K_0 = 0$ (on a scale from 0 to 100), the intensity of training $I = 0.5$, the activity of interaction with colleagues $A = 0.6$, the coefficients of the model are $\alpha = 0.075$, $\beta = 0.2$, $\gamma = 0.1$.

Then, according to the analytical solution, a forecast of the dynamics in the employee's knowledge level during the first 12 months of work is obtained.

The calculation shows that after 6 months $K(6) \approx 0.65$, and after a year $K(12) \approx 0.9$. This means that with active internal training, the employee approaches the expert level in less than a year.

Thus, the model makes it possible not only to assess dynamics in the growth of knowledge of a particular candidate but also to use the results to optimize the recruitment strategy. An enterprise can choose between quickly hiring a less experienced employee with high learning potential or a more expensive candidate with already formed competencies. For example, for an enterprise that invests in personnel, such a model demonstrates the need for spending on training, knowledge exchange, and mentoring with a forecast of obtaining an expert level of knowledge in almost a year.

The mathematical model is a tool for predicting the effectiveness of integrating new personnel into project or other production activities, which reduces the risks of erroneous personnel decisions and increases the effectiveness of knowledge management in the organization. Moreover, its use as part of a software product makes it possible to automatically track the progress of new employees, identify gaps in the expected trajectory of competence development, and offer personalized recommendations for training or mentoring support. This approach turns the model into a practical tool for operational knowledge management that enhances personnel decisions with data and increases their accuracy.

An information system built on the basis of the proposed model will be able to evaluate the effectiveness of training activities, compare the intensity of knowledge in different departments, and generate analytical reports for management. Thanks to this, the model becomes not only a theoretical tool but also the basis for building a practical solution that supports strategic knowledge management at an enterprise.

5. 3. Construction of a mathematical model for assessing the level of knowledge of employees based on the results of training

One of the important procedures for supporting the knowledge of personnel and in the organization is training. That is why a mathematical model for assessing the level of knowledge of employees based on the results of training in the course of distance or blended learning (training) was considered. The input data of such a model are the results from testing, the time of passing test modules, the number of attempts, the results of practical tests. For blended learning, the model should be expanded, taking into account not only tests but also the activity of the employee in the learning environment.

The mathematical model for assessing and predicting the effectiveness of corporate training is based on the synthesis of the theory of knowledge increment and the Ebbinghaus exponential forgetting model, adapted to the conditions of an active practical environment [9, 10]. The assessment of the effectiveness of an educational event at the first stage is determined through the normalized increase in knowledge, which makes it possible to neutralize the influence of the respondent's previous experience

$$g = \frac{S_{post} - S_{pre}}{S_{\max} - S_{pre}}, \tag{6}$$

where S_{pre} and S_{post} denote the scores of the input and output testing, respectively. The value of $g \geq 0.7$ is categorized as a high level of efficiency of material assimilation. However, for long-term prediction of competence within the information system, the dynamic coefficient of knowledge retention R is used, which takes into account the time interval t and the intensity of practical application of skills Iw. The classical differential equation of Ebbinghaus's memory fading [10] can be represented as a dynamic function of knowledge stability, which linearly varies according to the volume of practical operations and the multiplicative coefficient of complexity of the technological stack

$$R(t) = S_{post} * e^{-\frac{t}{S*(1+\beta*\ln(N_p+1))}}. \tag{7}$$

In the given model, S reflects the basic stability of memory, N_p is the number of verified practical operations (for example, closed issues in Jira (Australia) or commits in GitHub (USA), and β is the complexity factor of the technological stack.

Such a model can be empirically considered using the example of a case study of a specialist for an IT project on the implementation of microservice architecture. For example, a developer studied and received S_{post} 90 points based on the results of the workshop. In the absence of practical tasks ($N_p = 0$), after 6 months ($t = 180$ days) at $S = 30$, the predicted knowledge balance will be

$$R(180) = 90 * e^{-\frac{180}{30}} \approx 0.78. \tag{8}$$

This indicates a degradation of competence by 22% from the initial level. On the contrary, under the condition of active development (N_p = 100 operations) and the coefficient β = 0.4, the knowledge reproduction indicator will be

$$R(180)=90*e^{-\frac{180}{30*(1+0.4\ln(101))}}\approx 0.98. \quad (9)$$

Thus, the proposed model makes it possible to determine the level of knowledge to confirm the competencies of specialists and teams with changes in time characteristics and the level of activity of the specialist.

The models built are the basis for automated calculations when implementing the functions of monitoring learning outcomes and the level of knowledge for a specific specialist in the project. The first version of the software module for accumulating data on knowledge management and forming profiles of highly qualified personnel is the basis for further modeling changes in the volume of knowledge and determining the need for training in accordance with the competencies of personnel. To do this, it is necessary to form catalogs of competencies for monitoring and forecasting. Data collection for further adaptation of the constructed mathematical models is carried out by assessing learning outcomes, the level of activity of specialists.

Functional requirements for software imply the implementation of automatic integration with learning, personnel and project management systems, which will make it possible to use data on learning outcomes, monitor turnover and practical activity of specialists in projects. The visualization dashboard should reflect the trajectories of knowledge development and their correspondence to competencies over time. In addition, the forecasting system should generate notifications about the risk of losing critical knowledge in cases of low activity levels of specialists, dismissals, changes in paradigm and development technologies, etc. The system is implemented as a web-based service using a representational state transfer application programming interface (REST API) to interact with the corporate information ecosystem. It is advisable to use the procedure for exporting reports in Microsoft Excel format (USA) for further analysis and making management decisions.

6. Discussion of results based on investigating mathematical models and indicators of knowledge dynamics

Our results make it possible to track quantitative indicators of the processes of accumulation and loss of knowledge within the project and according to the results of training. The growth of knowledge dynamics is observed when the intensity of knowledge exchange and professional training exceeds the level of personnel losses and forgetting of information. This dependence is described by formula (4), which reflects the change in the integrated level of knowledge over time. The results of the experimental assessment of the micro-level of knowledge are justified by formula (6), which determines the normalized increase in the knowledge of employees. In addition, the use of formula (7) demonstrates the influence of the intensity of practical activity on the preservation and maintenance of professional competencies.

Our results confirm the hypothesis that the level of knowledge of personnel depends on active professional interaction and continuous learning. The visual model (Fig. 1) is generalized for understanding the relationship between formal and informal knowledge and its preservation in the form of documentation, code, notes, discussion notes, etc. Fig. 2 demonstrates scenarios of knowledge generation under the condition of developed communications, professional activity and knowledge exchange (upper curve) and a decrease in the volume of knowledge under the condition of the absence of active professional communications. Such graphic interpretation could be the basis for analyzing the level of influence of professional activity and communications of personnel on their level of knowledge.

A feature of the adapted models and performed calculation examples is the use of mathematical metrics for quantitative assessment of the volume of knowledge of personnel. Unlike general models of knowledge management presented in [2, 3], the meso level model formed based on the results of the study takes into account not only the general level of knowledge but also the processes of its accumulation, loss, and preservation, as well as assessment of learning outcomes.

Thanks to the model for assessing the results of a specialist's training, talent management systems [8] or personnel in a project can be detailed to quantitative indicators that allow for a more accurate measurement of the need for specialist training.

The results of our study make it possible to construct mathematical apparatus for its practical use in automated procedures for monitoring user activity and assessing their level of knowledge. The introduction of the proposed models allows for transition from the concept of passive knowledge storage using various information systems to dynamic procedures for assessing the level of knowledge.

A limitation of the study is the use of averaged indicators for groups of employees based on open data, without taking into account individual characteristics of perception and assimilation of information. In addition, the model is used mainly within individual projects or organizational units, which may require additional adaptation for other areas of activity, as well as additional methods for assessing the organization's knowledge as intellectual capital.

The disadvantage of the procedures for adapting and implementing the model is the need for constant collection of accurate data on personnel activity, which can increase the load on managers and information systems of the enterprise. In addition, the quantitative indicators of access to documentation and knowledge bases may be overestimated due to the low quality of the content, its complexity, and the incompleteness of the volume for independent study and learning. In the future, such shortcomings should be eliminated.

Further studies involve designing automated systems for monitoring the intellectual assets of the organization in the form of knowledge. The plans for further research include the detailing of visual models and metrics for assessing knowledge, taking into account the level of completeness of documentation, and using the experience of implementing similar projects. The main difficulties are the fixation of informal contacts and the transfer of hidden knowledge, which is difficult to measure only by technical means.

7. Conclusions

1. A general mathematical model has been built, to be implemented, which describes the dynamics of knowledge in an organization (using the example of a project). The model takes into account the intensity of learning, the processes of knowledge dissemination through communication, and natural

losses (forgetting or staff turnover), which makes it possible to predict the intellectual potential of the team at different stages of the project life cycle. Analysis of the model reveals the following pattern – if the net rate of knowledge change $r(t) > 0$, that is, knowledge exchange outweighs their losses, then the integrated level of knowledge grows exponentially. In the opposite case, when $r(t) < 0$ – learning remains the only source of knowledge maintenance.

2. By analytically resolving the model based on open data and performing calculations, weaknesses were identified (reduced level of knowledge exchange and use, inconsistency of training, etc.). Maintaining the specified indicators makes it possible to generate new knowledge to compensate for losses, which is the basis for making management decisions regarding the intensity of personnel training. The result of the calculations is the conclusion that, under the condition of active internal training, an employee approaches the expert level in less than a year. The results of the analytical solution indicate that to achieve an almost expert level of knowledge (maximum value = 1), a specialist needs 12 months ($K(6) \approx 0.65$, and after a year $K(12) \approx 0.9$) under the condition of active training and knowledge exchange.

3. A model for assessing learning outcomes at the end of a distance or blended course has been built. Case studies on learning outcomes have shown that the level of knowledge loss is 22% when knowledge sharing and use of learning outcomes are reduced and increases to 98% when knowledge is actively used.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study and the results reported in this paper.

Funding

The study was conducted without financial support.

Data availability

All data are available in the main text of the manuscript.

Use of artificial intelligence

The authors confirm that they used artificial intelligence technologies only to standardize the presentation of the list of literary sources. The language model Gemini 3.1 was used.

Acknowledgments

The authors thank VNTU management for using the JetIQ system and its services to implement the learning outcomes assessment model.

Authors' contributions

Denys Robotko: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Investigation, Visualization; **Olena Kovalenko**: Conceptualization, Methodology, Writing – review & editing, Investigation, Formal analysis.

References

1. King, W. R. (2009). Knowledge Management and Organizational Learning. Springer. https://doi.org/10.1007/978-1-4419-0011-1
2. Nonaka, I., Takeuchi, H. (1995). The Knowledge-Creating Company: How Japanese Companies Create the Dynamics of Innovation. Oxford University Press.
3. Bratianu, C., Bejinaru, R. (2020). Knowledge dynamics: a thermodynamics approach. Kybernetes, 49 (1), 6–21. https://doi.org/10.1108/k-02-2019-0122
4. Huang, J.-J., Chen, C.-Y. (2025). Knowledge Flow Dynamics in Organizations: A Stochastic Multi-Scale Analysis of Learning Barriers. Mathematics, 13 (2), 294. https://doi.org/10.3390/math13020294
5. Cress, U., Kimmerle, J. (2008). A systemic and cognitive view on collaborative knowledge building with wikis. International Journal of Computer-Supported Collaborative Learning, 3 (2). https://doi.org/10.1007/s11412-007-9035-z
6. Alvarenga, A., Matos, F., Godina, R., C. O. Matias, J. (2020). Digital Transformation and Knowledge Management in the Public Sector. Sustainability, 12 (14), 5824. https://doi.org/10.3390/su12145824
7. Di Vaio, A., Palladino, R., Pezzi, A., Kalisz, D. E. (2021). The role of digital innovation in knowledge management systems: A systematic literature review. Journal of Business Research, 123, 220–231. https://doi.org/10.1016/j.jbusres.2020.09.042
8. Gurusinghe, R. N., Arachchige, B. J. H., Dayarathna, D. (2021). Predictive HR analytics and talent management: a conceptual framework. Journal of Management Analytics, 8 (2), 195–221. https://doi.org/10.1080/23270012.2021.1899857
9. Yadav, R. K. (2025). Modeling Memory Retention with Ebbinghaus's Forgetting Curve and Interpretable Machine Learning on Behavioral Factors. https://doi.org/10.36227/techrxiv.174495325.58680708/v1
10. Hake, R. R. (1998). Interactive-engagement versus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics courses. American Journal of Physics, 66 (1), 64–74. https://doi.org/10.1119/1.18809
11. Pelánek, R. (2016). Applications of the Elo rating system in adaptive educational systems. Computers & Education, 98, 169–179. https://doi.org/10.1016/j.compedu.2016.03.017
12. Tyndale, P. (2002). A taxonomy of knowledge management software tools: origins and applications. Evaluation and Program Planning, 25 (2), 183–190. https://doi.org/10.1016/s0149-7189(02)00012-5
13. 2023 Training Industry Report. Available at: https://trainingmag.com/2023-training-industry-report