# PRESERVING EMPLOYEES' PERSONAL KNOWLEDGE DURING THE TRANSITION TO AUTOMATED PRODUCTION

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***ABSTRACT***

*This article is devoted to analysing ways of identifying and preserving the personal knowledge acquired by employees in the course of their work in the context of the introduction of highly automated production, as well as determining the most acceptable technologies for this process. The paper examines the practical implementation of existing approaches to the transfer of employees' personal knowledge, based on the consistent formalization of employees' personal knowledge and controlled organizational forgetting. As a result of the analysis, the author concludes that the transfer of individual employee knowledge for further use in automated systems should be based on the use of semantic models of corporate knowledge built using industry ontologies. The article describes the author's proposed process for creating semantic knowledge models for the transfer of employee knowledge. The materials of the work are applicable for the development of practical ways and methods for identifying, further preserving, and effectively using the personal knowledge of employees during the transition to Industry 4.0 technologies.*

***KEYWORDS***

*Knowledge Alienation, Knowledge Transfer, Automated Production, Semantic Model, Industry Ontology*

## 1. INTRODUCTION

The current stage of development of public production represents a widespread transition in manufacturing and services to Industry 4.0 technologies [1]. This process is characterized by the widespread introduction of highly automated systems. The defining features of this process are the use of automated cyber-physical systems, the introduction of artificial intelligence, the regular use of big data, virtual and augmented reality (VR/AR) technologies, active use of the Internet of Things (IoT), additive technologies, and qualitative changes in the nature of the organization of workers' labour activities.

The resulting changes in the structure of employment lead to a redistribution of labour resources between individual industries and specialties. This makes the issue of minimizing potential losses for companies associated with the risk of losing significant corporate knowledge when qualified specialists are dismissed or move to other jobs particularly relevant.

The aim of the study is to analyse ways of identifying and preserving the personal knowledge of employees acquired in the course of their work in the current conditions of increasing automation, as well as to determine the most acceptable technologies for this process.

Since the middle of the last century, models have been developed that allow the role of production experience and personal knowledge of employees to be formally linked to the growth rate of production. Thanks to the work of R. Solow, K. Arrow, E. Sheshinski, R. Lucas, N.

Rosenberg, D. Teece, T. Davenport, L. Prusak, and other researchers, the role of employee knowledge in innovative development has been demonstrated and possible ways of taking it into account when determining the production potential of companies have been described. At the same time, thanks to the work of A. Maslow and C. Rogers, it has been shown that the accumulation and creation of new personal knowledge by an employee during his professional activity should be considered not only as the result of the development of optimal personal practices that facilitate his work, but also as an incentive to satisfy the highest degree of human needs, naturally leading to the formation and development of personality.

Based on previous developments at the turn of the 20th and 21st centuries, K. Wiig, I. Nonaka, K.-E. Sveiby, and their followers created a unified concept of corporate knowledge management, which included issues of formalization, alienation, use, and accounting for employees' personal knowledge in companies' capital.

Today, the range of tools designed to record and analyse employee knowledge has expanded significantly. It may include: specialized modules of automated information systems for knowledge management (including through the recording of best practices in the use of automation tools), tools for workplace standardization using universal approaches to assessing the skills of specialists and describing job requirements (such as the pan-European project for describing occupations and employee competencies ESCO [2] or the ICDL certification project, which implements procedures for certifying the practical skills of specialists in the field of computer technology [3]) .

At the same time, several processes caused by the Fourth Technical Revolution taking place today raise the question of the need for a significant modernization of traditional systems for identifying and formalizing the personal knowledge of employees, an important part of which are extremely time-consuming individual and group interviews, testing, and brainstorming.

The introduction of automation tools is proceeding very rapidly and may lead to large-scale job losses soon. Studies conducted [4], have shown that at the current rate of automation, up to 47% of jobs in the US could be replaced by automated systems by 2033. A similar trend (albeit with less impressive figures) is also characteristic of other developed countries [5, 6]. In this context, given the relatively low productivity of the systems currently used to formalize corporate knowledge, there is a real danger of irreversible loss of employees' personal knowledge that is not fully recorded.

At the same time, widespread automation is already causing polarization in the labour market in developed countries, leading to a growing demand in all sectors of the economy for positions that require a high level of education and involve solving complex problems, while at the same time increasing the number of jobs that boil down to performing simple operations by low-skilled workers [7]. This is causing the labour market to lose many medium-skilled workers, who are the bearers of the bulk of essential personal professional knowledge that may be lost. In addition, the widespread introduction of artificial intelligence into production and business processes has a significant impact on the group of the most highly skilled specialists [8], who possess a large amount of unique expert knowledge.

In this regard, it can be argued that there is a real threat today of losing a large amount of personal knowledge of medium- and highly skilled workers amid the ongoing structural restructuring of the labour market caused by the advent of Industry 4.0.

Since the processes of widespread automation are happening very quickly, the question of how the structural changes in the labour market caused by it will affect the overall volume of corporate knowledge of companies remains unexplored today, as well as what changes in the processes of identifying, preserving, and further using the personal knowledge of skilled workers will result from the processes described. In this regard, the objectives of this work are a comparative analysis of existing approaches to solving the problem of retaining employees' personal knowledge, the development of proposals for implementing the most acceptable solution to the problem, and a description of the specific methods used in the solution.

## 2. METHODOLOGY

Today, the scientific community is conducting an unprecedented amount of research related to structuring data arrays and transforming them into knowledge ready for practical use. One of the effective tools for identifying significant connections between the processes under study from the vast space of scientific literature is key trend identification technologies [9]. It should be borne in mind that the extreme relevance of the topic under consideration significantly increases the number of publications on the subject, reducing the relevance of some of them. On the other hand, consulting companies engaged in real work on knowledge transfer due to the transition to Industry 4.0 technologies are not always interested in fully publishing their know-how regarding work methods.

To increase the efficiency of the preliminary selection of the most relevant sources for the research topic and those that complement each other, it is advisable to use automated methods of semantic evaluation of materials based on thematic modelling methods in this work.

Latent Dirichlet Allocation was used as the basic method for preliminary processing of literary sources, which provides effective tools for identifying hidden themes in large volumes of text data, allowing for high-quality systematization and interpretation of information [10].

The method assumes that each document discusses several different topics, described by a specific (and document-independent) distribution of words. In this representation, texts are viewed as the result of probability distributions over hidden topics, and the topics themselves are viewed as probability distributions over words. LDA is based on a probabilistic model that assumes that documents consist of mixed topics. This makes the LDA method particularly useful for analysing complex text structures. Unlike other methods of preliminary semantic analysis of texts, such as clustering or the k-means method, LDA provides a more accurate distribution of topics across documents, which provides a better understanding of the content of specific texts [11].

The theoretical basis of LDA relies on the use of the concept of interchangeability (de Finetti's theorem [12]), which can be used to obtain an intradocument statistical structure through a mixed distribution. As a result of the LDA calculation algorithm, a matrix is obtained, each row of which represents a probability distribution defined by topics for each document.

The practical implementation of the method consisted of a preprocessing stage of the set of analysed text data, its vectorization in the form of a "bag-of-words" using the specialized tool CountVectorizer (part of the scikit-learn open-source machine learning library), and the direct implementation of the LDA calculation algorithm using the scikit-learn library (LatentDirichletAllocation class). The result of the described solution is a list and content of latent topics that form the desired trends, as well as a set of the most relevant documents, based on which we build a set of scientific topics and studies in the analysed field that are most popular among researchers and are characterized by the greatest significance. Using the described method allows us to significantly improve the quality of semantic search for sources for further analysis.

## 3. Results

Most authors writing about the transition to Industry 4.0 technologies are unanimous in their assessment of the danger of the irreversible loss of a significant number of employees' personal knowledge during the transition to total automation technologies.

This can manifest itself in the loss of previously informal experience and skills of employees, the breakdown of informal connections they used in their work, missed opportunities from undiscovered innovations, threats to the company's intellectual property, the need for radical retraining of employees, and several other similar factors [13]. At the same time, the material damage from such losses per specialist can reach, according to various estimates, from 50% to 200% of his annual salary, depending on the level of qualification and the specifics of his work.

Such a high level of damage forces companies to look for ways to effectively transition to Industry 4.0 technologies. At the same time, the entire existing set of methods can be placed between two extreme approaches: the method of sequential formalization of employees' personal knowledge and the method of controlled organizational forgetting.

Method of sequential formalization of personal knowledge is based on the spiral model of information transformation SECI (socialization-externalization-combination-internalization) (see Figure 1), proposed by I. Nonaka [14].

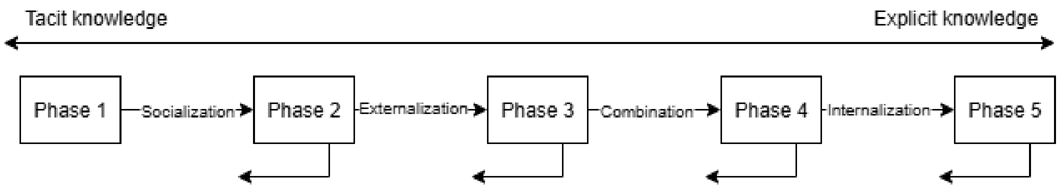


Figure 1. Diagram of the SECI spiral model of information transformation

When it comes to turning employees' implicit personal knowledge into something explicit that can be separated from the person who has it and used later, the SECI process has a few steps. In phase 1, the possible existence of specific knowledge in an employee is recorded and identified. In phase 2, the recorded knowledge is initially formalized using available means of description. In phase 3, the identified and preliminarily formalized knowledge is checked for accuracy, uniqueness, and integrity. Phase 4 involves actions to structurally integrate the verified knowledge into the existing corporate knowledge system, associated with the creation of an archetype that can take the form of an organizational element (e.g., a process or structure). In phase 5, processes are carried out to prepare the identified knowledge for practical application and its use in conjunction with the company's existing knowledge.

Using the SECI model of information transformation, many productive techniques have been created for identifying, recording, and further using tacit knowledge in an organization's business processes [15–17].

It should be noted that despite significant differences in implementation, most methods for identifying and preparing for corporate application of employees' tacit personal knowledge use many methods of group and individual interaction between employees whose tacit knowledge is being extracted and the specialists of the team carrying out this work (see Table 1).

Table 1. Forms of interaction used during the formalization of tacit knowledge and preparation for its use

| Phase | Applicable methods |
|---|---|
| Phase 1 | Interviews and informal conversations<br>Assessment tests, case studies<br>Group discussions and brainstorming sessions<br>Observation of work in typical production processes<br>Study of successful projects and achievements<br>Collection of informal feedback from colleagues |
| Phase 2 | Joint documentation of knowledge elements by the employee and the coach<br>Discussions within the framework of mentoring and coaching<br>Webinars on self-documentation of knowledge<br>Joint development and analysis of specific examples with the coach<br>Regular feedback from colleagues<br>Organization of a centralized database |
| Phase 3 | Additional testing to verify understanding of the issue<br>Conducting case studies or simulations for practical assessment<br>Collecting feedback from other employees on the identified innovation<br>Evaluating the results of using the innovation in tasks or projects<br>Comparing the innovation with existing best practices<br>Keeping logs of the practical use of innovations |
| Phase 4 | Updating the company's centralized knowledge base<br>Conducting regular training events to share experiences<br>Assigning more experienced employees to transfer new knowledge<br>Updating existing work processes and standards<br>Regularly receiving and processing feedback from employees<br>Forming specialized innovation implementation groups |
| Phase 5 | Creating training materials and developing guidelines<br>Implementing pilot projects in real-world conditions<br>Updating the company's knowledge management system<br>Creating cross-functional implementation teams<br>Organizing regular events for sharing experiences<br>Implementing mentoring and peer learning procedures |

The implementation of such diverse and large-scale measures to identify employees' personal knowledge, which is taking place during the transition to Industry 4.0 technologies, requires virtually all structural divisions of the organization to take coordinated action according to a single scenario (see Figure 2).

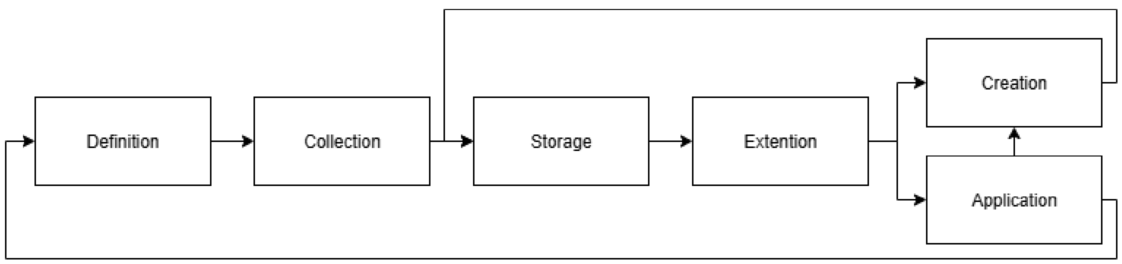


Figure 2. A unified corporate process for identifying, formalizing, and preparing for the use of employees' personal knowledge

Consistent implementation of the above steps means that the total cost of the work required to identify and preserve the personal knowledge of a single employee can vary from several thousand to tens of thousands of dollars, depending on the level of involvement of external consultants and the internal time of employees. The process can take from several weeks to several months (some studies show that it can take 40 to 200 hours to fully document the knowledge of a single specialist). In addition, it should be borne in mind that many employees' personal knowledge, gained because of their active participation in outdated production processes, may not be applicable in the context of new technologies.

At the same time, in the context of the transition to new, more productive but also capital-intensive Industry 4.0 technologies, the need for a quick return on investment necessitates a reduction in associated costs. As a result, when transitioning to highly automated production, many companies decide to abandon systematic efforts to preserve the personal knowledge of their employees and opt for a strategy of controlled organizational forgetting [18]. This approach involves the controlled loss of the company's competencies to carry out certain activities because of technological or other transformations. At the same time, the company focuses its actions solely on the introduction of advanced automated technologies, deliberately accepting the loss of knowledge and production culture associated with the previous technology [19].

By choosing the path of controlled organizational forgetting, the company significantly reduces the financial and time costs of formalizing past knowledge and shortens the time required to start up new production facilities. At the same time, it is proposed that all missing knowledge, including that held by employees, be identified and used as necessary. Obviously, this approach inevitably leads to the loss of a large amount of valuable knowledge and a significant increase in social tension among employees who lose their jobs or are forced to retrain. This is a strong disincentive for employees to share the knowledge that the company needs with them in the future. In addition, the company's dependence on the developer and owner of the advanced technology being implemented increases, which is fraught with higher costs in the future.

Understanding the potential losses of moving towards complete knowledge preservation and transitioning to organizational forgetting, it is preferable to take a "middle" path of corporate knowledge management when transitioning to Industry 4.0 technologies, which would allow for maximum preservation of employees' personal knowledge and significantly reduce the cost and time expenses of this process. In this regard, many intermediate methodologies are currently being developed to preserve the personal knowledge of employees during the transition to automated production and business processes [20].

However, as the results of the analysis show, modern approaches to the transfer of employees' personal knowledge to automated systems are often based solely on the principle of expediency, which can lead to incomplete integration of critical information and, as a result, reduced efficiency. To develop an optimal knowledge transfer process, a systematic theoretical examination of the problem is necessary to identify the key factors influencing the success of this process and to develop methodologies that consider the specifics of various [21].

## 4. ANALYSIS OF RESULTS

To find ways to theoretically justify the optimal transfer of employees' personal knowledge to automated systems, let us consider the information transformation diagram (see Figure 3), which represents a model diagram of the relationship between corporate data, information, and knowledge. The diagram describes the levels that "raw data" passes through on its way to becoming a set of employees' personal competencies.

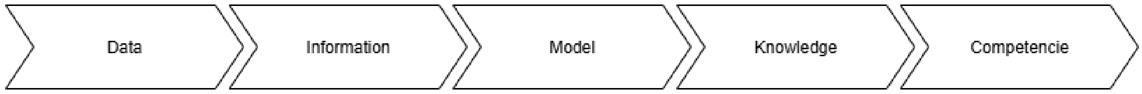


Figure 3. DIMKC information transformation scheme

In the DIMCS scheme, the “Data” level represents a set of empirically obtained and recorded facts characterizing the properties of objects in the external world. The “Information” level operates with the results of primary data transformation, which includes verification of truthfulness and integrity, as well as ranking and primary systematization. At the “Model” level, the object under study is described by objects of another system, which is necessary for studying the object itself or its interaction with other objects. At the “Knowledge” level, generalizations are made and patterns and interrelationships in a specific subject area are established. The “Competence” level describes the ability to independently solve specific problems using a specific set of knowledge. It should be noted that all stages of the transition from the data level to the competence level in the DIMKC model are characterized by an increasing complexity of information structures with each level, as well as the emergence of additional connections and restrictions between them.

From the DIMKC diagram, when transitioning to automated processes, an employee’s existing competencies cannot be used in the updated technological process without additional processing. This is because the sets of competencies of an employee involved in the “old” and “new” production cycles will be based on two different sets of knowledge. And the greater the differences between technologies, the greater the gap in the required employee competencies will be.

At the same time, an attempt to transfer the full set of employee competencies according to the SECI scheme (Fig. 1) will, in fact, represent a complete cycle of information transformations according to the DIMKC model and may lead to unnecessary costs. Unnecessary costs can be significantly reduced by using processes to coordinate the amount of an employee’s personal knowledge that needs to be transferred to updated technological processes, comparing the knowledge models of the “old” and “new” technological processes. The result of the comparison will show which part of the employee’s personal knowledge will be immediately required in the automated system, and which part will become the company’s “innovative potential,” requiring consideration and use in the next stages of the transition to automated systems.

With this approach, the most effective approach to ensuring the successful transfer of competencies to automated systems is the use of semantic knowledge representation models. Semantic knowledge representation models provide a more flexible and contextualized understanding of information, which contributes to the effective transfer of employee competencies to automated technological systems. Unlike logical and production models, semantic approaches allow for the integration of heterogeneous data sources and ensure their interoperability [22]. This is especially important in dynamically changing work processes where rapid adaptation of knowledge is required [23] in addition, semantic models support a higher degree of automation in knowledge extraction and processing, which reduces the likelihood of errors in the transfer of competencies [24]. They also contribute to the creation of more intuitive interfaces during their generation and use, which facilitates the training and adaptation of employees to new technologies [25]. Thus, the use of semantic knowledge representation models is the most effective approach to ensuring the successful transfer of competencies to automated systems.

The creation of semantic knowledge models for the transfer of employee competencies to automated technological systems requires the consistent implementation of a series of steps (see Figure 4).


Figure 4. The process of creating semantic knowledge models for the transfer of employee competencies

The first stage involves analysing existing knowledge and identifying key competencies that need to be transferred. This is followed by the development of ontologies that formalize this knowledge and ensure its structured representation. Next, various data sources are integrated to ensure interoperability and accessibility of information. The fourth stage is the implementation of knowledge extraction and processing mechanisms, which contributes to the automation of the competence transfer process. At the end of the process, it is necessary to test and validate the created model to ensure its effectiveness and applicability in real conditions. Thus, the sequence of these steps ensures the successful transfer of employees' personal competencies to automated systems.

In this process, RDF/RDFS (RDF Schema) technologies [26] and OWL (Ontology Web Language) [27]. RDF/RDFS allow to formalize the simplest facts about objects, classes, and properties. OWL describes complex relationships between classes and properties.

It should be borne in mind that when creating a model of knowledge and competencies that exists in a company before starting work on the transition to the use of a particular automated system, one should not focus entirely on the knowledge model used in the automated system being implemented. Such a step can significantly limit and complicate future technical modernization. Therefore, when creating a knowledge model designed to transfer the personal knowledge of employees during the transition to the use of automated systems, it is necessary to focus on industry knowledge models.

The use of industry knowledge model templates provides significant advantages, including data standardization, which improves interoperability between different systems [28]. In addition, the application of industry standards contributes to improving data quality and reducing duplication of information, as confirmed by successful cases in sectors characterized by a high diversity of data. At the same time, the specific semantic content of the corporate knowledge model description can be obtained through semantic analysis of documents describing the technological processes performed in the workplace.

## 5. CONCLUSIONS

The results obtained indicate that the creation of effective means of transferring employees' personal knowledge during the transition to highly automated production systems is one of the most pressing tasks for the successful deployment of Industry 4.0 technologies, and the set of methods proposed in the article for performing these actions is promising for carrying out the specified work.

The following conclusions can be drawn from the study, which are important for the further development of practical ways and methods for identifying, preserving, and effectively using employees' personal knowledge during the transition to Industry 4.0 technologies:

- Transfer of employees' individual knowledge for further use in automated systems should be based on the use of knowledge models
- Preferable to use semantic models based on industry ontologies as the basis for structuring and preserving corporate knowledge
- Preliminary semantic content for the corporate knowledge model can be obtained through semantic analysis of production documents.

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