IDENTIFICATION AND FORMALIZATION OF THE IMPLICIT PERSONAL KNOWLEDGE OF THE EMPLOYEE ACQUIRED BY HIM IN THE COURSE OF WORK

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ABSTRACT

Article is devoted to addressing the pressing issue of developing methods for identifying the implicit personal knowledge a specialist has acquired through their production activities. The paper examines the specifics of the practical implementation of existing approaches to formalizing an employee's tacit knowledge, based on the processing of their specialized interviews' text collections using natural language processing methods. As a result of the analysis, the author concludes that the methods of thematic modelling are the most reasonable way to identify latent parameters from texts. It is proposed to solve the problem of semantic ambiguity of terms in the texts of specialized interviews of employees by using contextualized models of normalization of natural language, implying the use of unified industry dictionaries. The paper also provides a generalized pipeline for identifying implicit knowledge proposed by the author. The materials of the work are applicable to the development of practical solutions designed to formalize implicit personal knowledge for their subsequent inclusion in a single body of corporate knowledge.

KEYWORDS

Tacit Knowledge, Implicit Knowledge Formalization, Cognitive Maps, Knowledge Management, NLP (Natural Language Processing), Topic Modelling, Latent Variables, Corporate Knowledge Systems

1. INTRODUCTION

Effective identification and use of implicit personal knowledge is critically important for the competitiveness and innovative development of modern companies. This implicit knowledge, based on individual experience, plays a key role in the process of creating innovative ideas and products [1]. It is such knowledge that contributes to the uniqueness and differentiation of companies in the market [2].

Research shows that organizations that actively use implicit knowledge demonstrate higher rates of innovation and adaptability to change [3]. Effective management of implicit knowledge, which is demonstrated by such companies, contributes to the creation of a culture of knowledge sharing. This, in turn, increases the collective intellectual potential of the company [4].

In the context of globalization and increasing competition, the ability to extract value from implicit knowledge is becoming a strategic asset for organizations [5]. Therefore, the

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development and implementation of knowledge management systems focused on the identification and use of implicit knowledge is a prerequisite for achieving a sustainable competitive advantage [6].

It should be borne in mind that implicit personal knowledge is difficult to formalize and convey, since it is based on personal experience, intuition, and skills. Therefore, the process of identifying such knowledge faces several difficulties, including its subjectivity, communication difficulties, and lack of motivation among employees to share their experiences. In addition, cultural and organizational barriers can hinder the exchange of such knowledge within companies. The purpose of the work is to review existing approaches to the formalization of tacit knowledge of a specialist based on the processing of collections of texts of his specialized interviews using natural language processing methods.

Since the middle of the last century, the impact of innovation on the development of industrial technologies has increased dramatically. This has led to an increased interest among researchers in the very nature of the emergence of new technological ideas and innovations and the role of a particular employee in their creation. So, the model created by K. Arrow [7], E. Sheshinski [8] made it possible to link the process of increasing labor productivity with the accumulation of additional experience by company employees that arises when they perform their duties in the workplace. R. Lucas proposed an approach to assess the comparability of the impact of human and material capital on the innovation production process [9], and the model of R. Barro and X. Sala-i-Martin made it possible to describe the process of accumulation of human capital in a commodity product by taking into account previous technological transformations [10, 11].

At the same time, there was a process of structuring and categorizing the knowledge possessed by a particular employee. M. Polanyi was one of the first to conduct such work [2], who identified two types of employee knowledge: explicit (or traditional, understood, verbalized) and tacit knowledge (tacit knowledge), i.e. present in human activity in non-linguistic forms. A distinctive feature of implicit knowledge is that it is acquired through a person’s own experience, rather than through specialized training. Such knowledge, being at the subconscious level of the employee, is not presented verbally, is procedural and is based on a personal picture of the human world. According to Polanyi tacit, knowledge is mostly inaccessible to introspection, difficult to alienate from its bearer, and includes skills and a common everyday culture implemented by the employee in the form of uncreated behaviour. At the same time, implicit knowledge can be gradually transferred to other subjects in the process of communication and can also be acquired by the other party through personal experience. Tacit knowledge forms the basis of an employee’s creative potential and professional capabilities. Moreover, the higher the professional’s production and daily experience, the higher the proportion of implicit knowledge in his intellectual resource.

Since tacit knowledge-based skills are difficult to fully describe verbally and explain analytically, the question of mastery of such skills can cause serious difficulties. Therefore, F. von Hayek proposed that knowledge that can be used by a person in making decisions and performing actions should be classified as personal implicit knowledge in the first approximation [12]. According to F. von Hayek personal implicit knowledge cannot be formalized and therefore cannot be stored or transferred to another person, since it loses its value as the time gap between the occurrence of a choice situation and decision-making increases. However, it was this approach that made it possible to further determine the way to evaluate and formalize personal implicit knowledge through a systematic analysis of specific situational decisions of the employee using them. Based on this, the personal subjective implicit knowledge of an employee can be objectified and clarified through a systematic study of the cause-and-effect relationships of human activity and its verbal and cultural environment [13]. The resulting result of the formalization of implicit personal knowledge can be integrated into explicit scientific knowledge [14]. In this case, the methods of indirect situational assessment and correlative analysis. The methodological basis for such work can be the spiral model of information transformations proposed by I. Nonaka [15].

Researchers of corporate knowledge have developed a firm belief that a company's competitiveness is determined primarily by implicit knowledge [16], and companies are ready to spend more money on their formalization. Therefore, today one of the most pressing issues of building corporate governance systems is the search for approaches based on which it is possible to conceptualize the implicit knowledge of employees in the general structure of scientific and technical descriptions of production processes.

A significant part of the created methods for the formalization of implicit personal knowledge is based on many personal and collective interviews and tests of employees, which allow for step-by-step procedures for detecting and step-by-step clarifying elements of this knowledge. Since these procedures are quite expensive and by themselves do not guarantee a significant economic effect, the total application of methods for identifying personal implicit knowledge of employees to improve the efficiency of production processes at the turn of the 20th and 21st centuries were replaced by the introduction of highly automated technologies that gradually displace the employee from the production cycle. This meant that many companies, when switching to recent technologies, preferred to manage explicit knowledge, which was easier to accumulate and store.

The current total transition to highly automated technologies based on the widespread use of artificial intelligence elements can lead to serious staff reductions in companies and large losses of employees' personal implicit knowledge. Thus, research shows that by 2033, up to 47% of workers from the United States will be replaced by automated research complexes [17], and a comparable situation is typical for other developed countries [18, 19]. Moreover, the situation with mass displacement of workers from all spheres of production and service is typical not only for low-skilled workers [20], but also and for highly qualified specialists [21].

The possible scale of loss of personal implicit knowledge of employees being laid off during the transition to Industry 4.0 technologies is large, but not all personal implicit knowledge of employees can be applied in the context of using automated technologies. This suggests the relevance of conducting research aimed at automating the work on formalization, evaluation, and consolidation of critical personal knowledge of employees in the intellectual capital of the company.

The results of the work described in this article can be practically applied in the creation of integrated automated corporate knowledge management systems.

2. METHODOLOGY

One of the effective methods designed to identify, conceptualize, and structure implicit knowledge that often remains inaccessible to traditional methods of analysis is the creation of cognitive maps. A cognitive map is a mental map of the reality surrounding an individual, allowing them to navigate, predict the results of their actions, and choose tactics and strategies for behaviour. It contains descriptions of the elements of reality (objects, facts, phenomena) and the interrelationships and relationships between them [22]. In this regard, the cognitive map is a model of an expert's knowledge about an observed phenomenon, created in the form of an oriented graph defining causal relationships (W, F), where $W = |w_{ij}|$ the adjacency matrix of the graph; $w_{ij} \in [-1, 1]$, F is a set of specific parameters describing the phenomenon; $F = f_i$, $i = 1, ...n$; moreover, for each parameter f_i , a set of values X_i is defined.

Cognitive maps allow you to visualize individual and collective representations of knowledge. This contributes to a deeper understanding and organization of corporate knowledge [23]. A deep understanding of knowledge helps to identify the connections between different concepts, which contributes to a more rational solution of production tasks within the organization. Research shows that the formalization of knowledge in the form of cognitive maps serves as a tool for learning and knowledge transfer in teams, improving team communication processes. In addition, the use of cognitive maps helps to identify knowledge gaps and areas requiring additional training [24] and allows organizations to adapt more effectively to changes and innovations [1].

The process of identifying personal implicit knowledge using cognitive maps is based on the search, identification, and formalization of hidden (latent) objects and relationships that are unknowingly found by an employee during the performance of his work duties to facilitate his actions.

From the point of view of computer science, the process of identifying personal knowledge is based on a consistent chain of information transformations "Data→Information→Model→Knowledge→Competencies" [25] is the extraction of explicit knowledge from arrays of latent information [26, 27]. Latent is information hidden inside other information, the generalization of which is latent models described through latent variables [28, 29].

The source of raw data used to build cognitive maps of employees, suitable for building on their basis a corporate system of formalization of personal implicit knowledge, is a systematic series of interviews. In the process of interviewing employees, information text arrays are created with the aim of collecting the employee's actual knowledge about possible latent objects and relationships used by them in their activities in the form of a set of facts *F1, F2, ...Fn* and a set of observed relationships *OL1, OL2, ...OLn*.

Based on the collected facts, the most complete latent model of the phenomenon is generated, describing these facts using the identified latent objects *LO1, LO2, ...LOn* and latent connections *LL1, LL2, ...LLn* (see Figure 1).

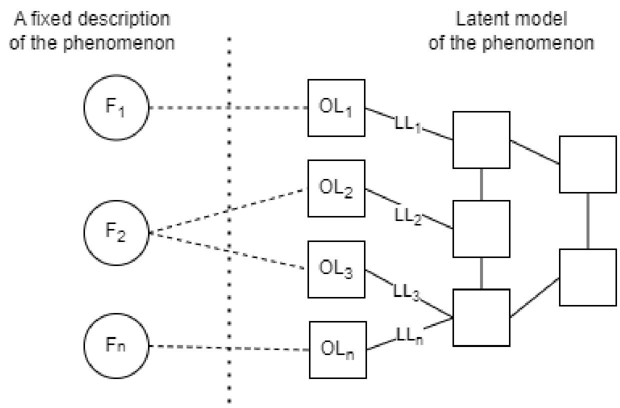

Figure 1. The scheme of the primary accumulation of facts and the creation of a latent model necessary for the extraction of implicit personal knowledge

The recorded descriptions of facts characterizing some implicit knowledge are incomplete. Therefore, the construction of a latent model based on a fixed set of descriptions of phenomena that uniformly explains various facts can be considered as one of the forms of extracting implicit knowledge. And if the set of facts F is insufficient, then it is impossible to gain new knowledge.

In this regard, when conducting interviews, they try to collect the maximum amount of information about the phenomenon being recorded. At the same time, it is necessary to try to ensure that newly identified facts containing traces of new knowledge are connected as much as possible (through objects and relationships) with the existing subject description of similar phenomena. Therefore, during the interview period, the employee tries to obtain the maximum possible amount of textual information describing elements that in one way or another define new implicit knowledge and connect this knowledge with explicit corporate knowledge previously described. Special attention is paid to information objects that describe the general essence of phenomena that contain traces of implicit knowledge and argumentation of the employee, highlighting certain innovations used by him in his work.

A generalized pipeline for detecting implicit knowledge can be described in the form of a sequence of actions shown in Figure 2.

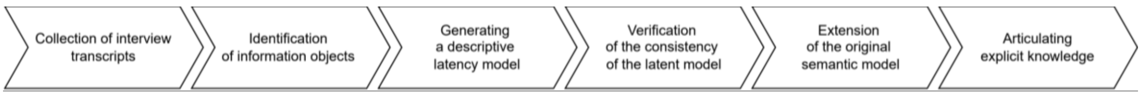

Figure 2. Generalized pipeline identification of implicit knowledge

Employee interview questionnaires aimed at formalizing implicit knowledge using cognitive maps are structured tools designed to identify and systematize knowledge that may not always be explicitly expressed. The formation of such questionnaires includes the stages of a preliminary analysis of the subject area, the definition of key topics and concepts, as well as the development of questions that contribute to the disclosure of subjective experiences and opinions of respondents. The questions can be both open and closed, which makes it possible to obtain both qualitative and quantitative data necessary for constructing cognitive maps. In the process of creating the questionnaire, it is important to consider the context of the respondents' work and the specific aspects of their professional activities. This contributes to a deeper understanding of their knowledge and experience. Testing and refining questionnaires based on feedback from pilot interviews increases their effectiveness and relevance [30]. Correctly constructed interview scenarios allow you to quickly conduct semantic localization of fragments of implicit knowledge and collect the necessary material for further analysis.

The process of further automated processing of the collected text collections is conducted using Natural Language Processing (NLP) methods and tools in terms of Natural Language Understanding (NLU), which consider texts as a system of linguistically and semantically interrelated objects (words).

Use of latent models for these purposes makes it possible to consider factors that are not directly observable. Today, an extensive mathematical apparatus has been developed for the purposes of latent analysis. Among the most effective methods used to work with latent variables are factor analysis, hidden Markov process models, and latent class models. These methods help to identify structures and patterns in data that are not obvious when using traditional analytical approaches. For example, factor analysis makes it possible to reduce the dimension of data and identify key latent factors affecting the observed variables [31]. Models of hidden Markov processes are used to analyse time series, allowing to identify hidden states of the system [32]. Latent class models help classify objects based on their similarity to latent variables.

Next step of fixing implicit personal knowledge, the process of identifying and resolving contradictions between the generated latent model and the previously constructed explicit corporate knowledge model takes place. After that, the newly identified latent model is integrated into the existing model, expanding it and creating the basis for the formulation of explicit knowledge. The data obtained is then analysed using methods of qualitative and quantitative information processing, which makes it possible to visualize cognitive maps and identify the relationships between various aspects of knowledge [24].

At the same time, it should be borne in mind that the information received from the interviewed specialist may not only contain a large amount of information about already known and actively used knowledge.

3. Results

To simplify the procedures for identifying traces of innovative knowledge acquired by an employee because of production activities, it is necessary to use approaches that make it possible to distinguish innovative personal knowledge of a specialist from already known and used in the company. It seems possible to base such actions on the premise that implicit knowledge can be characterized as a volatile mixture of practical experience, individual values, contextual information, and intuition, which creates the basis for evaluating and combining new experiences and current information [5]. This makes it possible to propose the following compositional structure of a specialist's personal knowledge (see Figure 3).

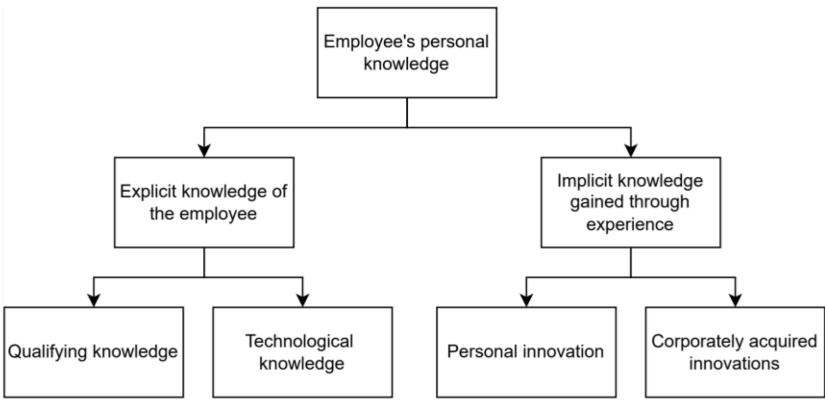

Figure 3. The compositional structure of a specialist's personal knowledge

The explicit knowledge of a specialist is the totality of all knowledge known to him about the subject of labor and methods of its production. This knowledge is acquired by him during the cycles of specialized training and by studying the necessary production documentation. They are formalized in the form of training course materials and production guidance documents. The specialist's possession of them is confirmed by passing the appropriate certification procedures necessary for admission to certain types of work conducted by an employee at his workplace. This knowledge is divided into detailed descriptions of the objects of labor on which (and with which) production operations are conducted and technological knowledge containing structured information about the chains and interrelationships of actions conducted by the employee.

Implicit knowledge is non-verbalized innovation that is consistently used by an employee in conducting production activities to optimize his production efforts. Although this knowledge is not documented, an employee can generate it personally or obtained through observation or communication with other employees.

Based on the fact that almost all elements of an employee's explicit production knowledge have a clear documentary description, it can be argued that the presence of undescribed statements in the interview texts (obtained when creating cognitive maps) may signal that these statements may be fixed descriptions of a latent model (see Figure 1), which forms the basis of the process of identifying explicit knowledge.

The methodological basis for further analysis is the understanding that texts generated in natural language assume a different (but definite) occurrence of words in the text. Moreover, the most frequent use of certain groups of words may indicate their importance for a particular document or group of documents [33]. A vector model of text representation is used for such studies [34]. VSM generation is performed by representing each word from the text being analysed as a multidimensional vector, the elements of which are the total number of words used in the entire sample [35].

In order to isolate the sets of contextual information from the interview texts that make up the statements describing the elements of the latent model, it is possible to use the basic premise of topic modelling that the presence of each specific word in a specific text document is due to the need for a detailed description in the text of a certain semantic topic, an integral part of the content of which is the word in question. At the same time, the process of analysing a document using thematic text modeling tools is based on the assumption that the occurrence of a particular word w_i in a document d_j is unambiguously justified by some topic t_k from a certain set of topics T, and does not depend on the document itself d_j, but is determined only by the general topic of the analysed text, but is determined only by the subject of the text, which can be described by a single probability distribution: $p(w|t) = p(w|d, t)$.

In this formulation of the studied collections of texts employee interviews (created with the aim of formalizing tacit knowledge) can be considered as a sample of triples (w_i , d_i , t_i), $i = 1, ..., n$ from the discrete distribution $p(w, d, t)$ on a finite set Cartesian products W DT whose elements are all possible ordered triples of the source elements.

At the same time, in each of the considered triples, the words w_i and documents di are observable variables, and specific topics from the total set of topics i are hidden (latent) variables that need to be determined. Each text analysed employee interviews can be represented as a discrete distribution on the set of the $\Theta td = pt|d$, and each topic as a discrete distribution on the set of words $\phi w|t = p(w|t)$.

In this case, according to the total probability theorem, the following expression is valid:

$$p(w|d) = \sum_{t \in T} p(w|d,t)p(t|d) = \sum_{t \in T} p(w|t)p(t|d) = \sum_{t \in T} \phi_{wt}\,\theta\mathrm{td} \tag{1}$$

Then the task of constructing a thematic model for each specific interview, considering (1), can be reduced to determining $p(wt)$ for all $t \in T$ and $p(td)$ for all $d \in D$.

After that, using the assumption that the distribution of words in a particular collection is related only to topics, and not to documents, we determine the logarithm of the likelihood functional for the probability of the joint appearance of document d and word w in the analysed collection of interview texts D:

$$L = \sum_{d\in D}\sum_{w\in W} n_{dw} \ln p(d,w) = \sum_{d\in D}\sum_{w\in W} \ln \sum_{t\in D} p(w|t)p(t|d)p(d) \to \max p(w|t), p(t|d) \quad (2)$$

in the presence of natural limitations

$$\sum_{t\in T} p(t) = 1\,; \sum_{d\in D} p(t|d) = 1\,; \sum_{w\in W} p(t|w) = 1 \quad (3)$$

To solve the problem described by expression (2), it is possible to use the iterative two-step EM (Expectation-maximization algorithm) algorithm, which is used in solving mathematical statistics problems to determine estimates of the maximum likelihood of parameters, if the analysed model has an assumed dependence on several hidden variables [36].

Having thus obtained for each analysed interview text of the employee d_j a set of topics t_k forming this document, each of which consists of a specific unchanging set of words w_i, it becomes possible to identify a set of topics t characterizing the implicit knowledge of the employee acquired with experience (see Figure 3). This set will include topics that are not involved in creating documents that characterize the employee's formalized explicit production knowledge. The set of innovative topics t that characterize implicit knowledge identified in this way can be subjected to operations to create consistent latent models for describing implicit knowledge (see Figure 1) and further formalization procedures for subsequent integration into a unified corporate knowledge system (see Figure 2).

4. Analysis of the Results

The materials presented above suggest that there is currently a wide range of computational methods that make it possible to process collections of employee interview texts in an automated manner, designed to formalize the implicit knowledge they acquired during their work.

By consistently conducting procedures for processing collections of interview texts using natural language processing methods to identify latent parameters and topics, it is possible to create consistent models of descriptions of personal innovative knowledge acquired by an employee. The resulting formal descriptions of implicit personal knowledge can be added to the general body of corporate knowledge, suitable for further use in production purposes.

At the same time, it should be borne in mind that in the formalized interview procedures conducted to create cognitive maps, we are dealing with a significant simplification and schematization of phenomena. Therefore, the description of phenomena obtained using them, based on which implicit knowledge is formalized, is not an exact copy of reality, but remains a simplified adapted reflection of it. In this regard, it can be argued that the formalization of implicit knowledge in this case occurs within the framework limited by the semantics of the issues discussed in the interview. In order to use the interview results to achieve the most adequate representation of the parameters describing the employee's implicit knowledge, it is necessary to develop an interview scenario that is most targeted at both the specific specialist being interviewed and the needs of a specific enterprise interested in obtaining personal innovative knowledge in very specific areas.

Therefore, to increase the effectiveness of using the presented approach to automated processing of employee interview results to formalize their implicit knowledge, these actions should be preceded by procedures for the semantic representation of their explicit knowledge.

The identification of implicit personal knowledge of employees formed during production activities requires a systematic approach, which can be achieved through the creation of a unified semantic description of the company. This description serves as the basis for structuring and interpreting the entire body of knowledge used by the company, ensuring their integration of the employee's formalized personal knowledge into the context of the organizational environment.

The use of a subject-specific ontological description for the purpose of systematizing corporate knowledge makes it possible to formalize corporate knowledge, which contributes to its more effective extraction and application in various business processes. According to research conducted in the field of knowledge management, the presence of a unified ontology significantly improves communication between employees and reduces the likelihood of information loss [37]. In addition, the creation of a unified semantic space contributes to a deeper understanding and interpretation of implicit knowledge [1]. It is important to note that without such a structured approach to describing corporate knowledge, the processes of identifying implicit personal knowledge of employees may turn out to be fragmented and ineffective. Therefore, the formalization and integration of implicit personal knowledge of employees within a single semantic description is a prerequisite for their successful use in the organization.

Another major problem that arises when processing employee interview collections when formalizing implicit personal knowledge is the problem of lexical ambiguity. This problem is related to the fact that different semantic meanings of words can lead to incorrect interpretation of information extracted from interview texts. Lexical ambiguity makes automatic semantic processing difficult, since computational algorithms may not consider the context in which ambiguous terms are used due to the limited volume of the analyzed content [38]. To solve this problem, it is necessary to use contextualized models of natural language normalization that can consider the specifics of professional terminology and the situation in which communication takes place. This approach will significantly improve the accuracy of interpretation of implicit knowledge, allowing models to adapt to different contexts. In addition, the introduction of a unified corporate ontological description of knowledge can help resolve ambiguities by creating structured representations of knowledge that consider the relationship between terms. Also, to solve the problem of lexical ambiguity, it is advisable to apply approaches to data annotation that make it possible to identify and clarify the meanings of terms depending on the context.

5. CONCLUSIONS

The article provides an overview of approaches to automating the processes of identifying and formalizing personal knowledge of employees based on the semantic analysis of text collections of their specialized interviews, as well as the specific features of the methods used in this process. As a result of the conducted research, the following conclusions can be drawn that are important for the further development of practical ways to formalize implicit knowledge necessary to create effective approaches to the structured description of corporate knowledge [25]:

1. the processes of identifying and formalizing implicit personal knowledge of employees can be based on the semantic analysis of collections of texts of specialized interviews using methods of detecting latent parameters using methods of thematic text modelling,
2. the greatest effectiveness of the processes of identifying implicit knowledge is achieved when conducting a preliminary semantic description of the explicit knowledge of the

employee, mastered by him during the period of preliminary training and study of working documentation,

3. solving the problem of semantic ambiguity of terms in the texts of specialized interviews of employees can be based on the use of contextualized models of normalization of natural language, implying the use of unified industry dictionaries.

REFERENCES

[1] I. Nonaka and H. Takeuchi, “The knowledge-creating company: How japanese companies create the dynamics of innovation,” Long Range Planning, vol. 29, no. 4, p. 592, Aug. 1996. [Online]. Available: http://dx.doi.org/10.1016/0024-6301(96)81509-3

[2] P. M., “The tacit dimension,” London: Routledge Kegan Paul., 1966.

[3] G. v. Krogh, K. Ichijo, and I. Nonaka, Enabling Knowledge Creation. Oxford University Press, Jan. 2000. [Online]. Available: http://dx.doi.org/10.1093/acprof:oso/9780195126167.001.0001

[4] L. Argote and P. Ingram, “Knowledge transfer: A basis for competitive advantage in firms,” Organizational Behavior and Human Decision Processes, vol. 82, no. 1, p. 150–169, May 2000. [Online]. Available: http://dx.doi.org/10.1006/obhd.2000.2893

[5] T. Davenport and L. Prusak, Working Knowledge: How Organizations Manage What They Know, 01 1998, vol. 1.

[6] R. M. Grant, “Toward a knowledge-based theory of the firm,” Strategic Management Journal, vol. 17, no. S2, p. 109–122, Dec. 1996. [Online]. Available: http://dx.doi.org/10.1002/smj. 4250171110

[7] K. J. Arrow, “The economic implications of learning by doing,” The Review of Economic Studies, vol. 29, no. 3, p. 155, Jun. 1962. [Online]. Available: http: //dx.doi.org/10.2307/2295952

[8] S. E., “Optimal accumulation with learning by doing,” Essays on the riel Theory of Optimal Economic Growth, pp. 31–52, 1967.

[9] R. E. Lucas, “On the mechanics of economic development,” Journal of Monetary Economics, vol. 22, no. 1, p. 3–42, Jul. 1988. [Online]. Available: http://dx.doi.org/10.1016/0304-3932(88) 90168-7

[10] R. J. Barro and X. I. Sala-i Martin, Economic Growth, 2nd ed., ser. The MIT Press. London, England: MIT Press, Oct. 2003.

[11] E. Mashina, “Uniform Assessment Of The Company’s Employee’s Competence Using Natural Language Processing Methods For Their Further Use In Corporate Knowledge Management Systems.” Zenodo, Nov. 11, 2022. [Online]. Available: http://dx.doi.org/10.5281/ZENODO.7368488

[12] F. A. Hayek, Individualism and economic order, F. A. Hayek, Ed. Chicago, IL: University of Chicago Press, Jun. 1996.

[13] M. Michael. Routledge, Aug. 2014. [Online]. Available: http://dx.doi.org/10.4324/ 9781315763408

[14] M. Oakeshott, Rationalism in Politics and Other Essays, 1977.

[15] I. Nonaka and D. J. Teece, Eds., Managing industrial knowledge. Thousand Oaks, CA: SAGE Publications, Feb. 2001.

[16] J. H. Dyer and K. Nobeoka, “Creating and managing a high-performance knowledge-sharing network: the toyota case,” Strategic Management Journal, vol. 21, no. 3, p. 345–367, Mar. 2000. [Online]. Available: http://dx.doi.org/10.1002/(SICI)1097-0266(200003)21:3⟨345:: AID-SMJ96⟩3.0.CO;2-N

[17] C. B. Frey and M. A. Osborne, “The future of employment: How susceptible are jobs to computerisation?” Technological Forecasting and Social Change, vol. 114, p. 254–280, Jan. 2017. [Online]. Available: http://dx.doi.org/10.1016/j.techfore.2016.08.019 12

[18] A. Sorgner, E. Bode, C. Krieger-Boden, U. Aneja, S. Coleman, V. Mishra, and A. M. Robb, The effects of digitalization on gender equaliy in the G20 economies: Women20 study, ser. Kiel E-Books. Kiel: Kiel Institute for the World Economy (IfW), 2017, additional information: This study is a joint project by the Women20 and the Think Tank 20 initiatives under the German G20 presidency, supported financially by the Emerging Market Sustainability Dialogues (EMSD) and the Deutsche Gesellschaft f¨ur Internationale Zusammenarbeit (GIZ). This study is the final report. An executive summary has been published on occasion of the Women20 summit in Berlin. [Online]. Available: https://hdl.handle.net/10419/170571

[19] K. Dengler and B. Matthes, "Folgen der digitalisierung f¨ur die arbeitswelt: Substituierbarkeitspotenziale von berufen in deutschland," N¨urnberg, IAB-Forschungsbericht 11/2015, 2015. [Online]. Available: https://hdl.handle.net/10419/146097

[20] M. Goos, A. Manning, and A. Salomons, "Explaining job polarization: Routine-biased technological change and offshoring," American Economic Review, vol. 104, no. 8, p. 2509–2526, Aug. 2014. [Online]. Available: http://dx.doi.org/10.1257/aer.104.8.2509

[21] E. Brynjolfsson and A. McAfee, Race Against the Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy. Digital Frontier Press, 2012. [Online]. Available: https://books.google. de/books?id=6O-MBAAAQBAJ

[22] E. C. Tolman, "Cognitive maps in rats and men." Psychological Review, vol. 55, no. 4, p. 189–208, 1948. [Online]. Available: http://dx.doi.org/10.1037/h0061626

[23] J. Novak and A. Ca˜nas, "The theory underlying concept maps and how to construct them," 01 2006.

[24] K. B¨orner, C. Chen, and K. W. Boyack, "Visualizing knowledge domains," Annual Review of Information Science and Technology, vol. 37, no. 1, p. 179–255, Jan. 2003. [Online]. Available: http://dx.doi.org/10.1002/aris.1440370106

[25] E. Mashina and P. Balakshin, The Influence of Descriptive Language Practices on the Process of External Integration of Corporate Knowledge. Springer International Publishing, 2023, p. 104–119. [Online]. Available: http://dx.doi.org/10.1007/978-3-031-26783-3 11

[26] R. Huang, S. McIntyre, M. Song, H. E, and Z. Ou, "An attention-based latent information extraction network (alien) for high-order feature interactions," Applied Sciences, vol. 10, no. 16, p. 5468, Aug. 2020. [Online]. Available: http://dx.doi.org/10.3390/app10165468

[27] S. Verma, C. Wang, L. Zhu, and W. Liu, "Deepcu: Integrating both common and unique latent information for multimodal sentiment analysis," in Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, ser. IJCAI-2019. International Joint Conferences on Artificial Intelligence Organization, Aug. 2019, p. 3627–3634. [Online]. Available: http://dx.doi.org/10.24963/ijcai.2019/503

[28] L. Maaløe, M. Fraccaro, V. Li´evin, and O. Winther, "Biva: A very deep hierarchy of latent variables for generative modeling," 2019. [Online]. Available: https://arxiv.org/abs/1902. 02102

[29] A. Derkach, R. M. Pfeiffer, T.-H. Chen, and J. N. Sampson, "High dimensional mediation analysis with latent variables," Biometrics, vol. 75, no. 3, p. 745–756, Mar. 2019. [Online]. Available: http://dx.doi.org/10.1111/biom.13053

[30] SAGE Publications, Inc., 2009, p. 18–47. [Online]. Available: http://dx.doi.org/10.4135/9781452230184.n3

[31] D. J. Bartholomew, Latent Variable Models and Factor Analysis, 2nd ed., ser. Kendall's Library of Statistics. London, England: Hodder Arnold, May 1999.

[32] L. Rabiner, "A tutorial on hidden markov models and selected applications in speech recognition," Proceedings of the IEEE, vol. 77, no. 2, p. 257–286, 1989. [Online]. Available: http://dx.doi.org/10.1109/5.18626

[33] E. Mashina, The use of hierarchical topic modeling methods For semantic analysis of texts generated by an employee in Order to assess his competencies. The XII Congress of Young Scientists. Collection of scientific papers. Volume 4. Part 2. St. Petersburg: ITMO University, p. 97-100, 2023.

[34] G. Salton, A. Wong, and C. S. Yang, "A vector space model for automatic indexing," Communications of the ACM, vol. 18, no. 11, p. 613–620, Nov. 1975. [Online]. Available: http://dx.doi.org/10.1145/361219.361220 13

[35] E. Mashina, The use of topic modeling to expand the possibilities of using corporate prescriptive analytics, The almanac of scientific works of young scientists of ITMO University. Volume 3. Part 2 –St. Petersburg: ITMO University, p. 59-65, 2023.

[36] R. M. Neal and G. E. Hinton, A View of the Em Algorithm that Justifies Incremental, Sparse, and other Variants. Springer Netherlands, 1998, p. 355–368. [Online]. Available: http://dx.doi.org/10.1007/978-94-011-5014-9 12

[37] T. R. Gruber, "A translation approach to portable ontology specifications," Knowledge Acquisition, vol. 5, no. 2, p. 199–220, Jun. 1993. [Online]. Available: http://dx.doi.org/10. 1006/knac.1993.1008

[38] E. Mashina, Gamification in the Personnel Management of a Self-learning Organization, 11 2023, pp. 212–230. [Online]. Available http://dx.doi.org/10.1007/978-3-031-48020-1_18

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