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POSSIBILITIES TO EVALUATE EMPLOYEE KNOWLEDGE AS A COMPONENT OF KNOWLEDGE SYNERGY AT ORGANISATION

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Abstract
Knowledge evaluation and management is one of the key tasks in any organisation aiming to improve the efficiency of its activities, create an environment in which employees are unconditionally willing and are able to share their knowledge and generate new knowledge, thus creating a higher added value and a modern, synergy processes-based and sustainable organisation. Employee knowledge – a component of organisational knowledge synergy – is multifaceted and consists of different content factors with quantitative and qualitative expressions. A comprehensive evaluation of this object requires multi-criteria evaluation methods to transform data, build a hierarchy of indicators and get an aggregated estimate. The article analyses the employee knowledge evaluation process and characteristics of multi-criteria evaluation methods, explaining why they are used in employee knowledge evaluation.
KEY WORDS: knowledge, employee knowledge, evaluation, multi-criteria evaluation methods.

Introduction

With advancing information technology and knowledge as a key economic resource, humanity has entered into a complex and diverse world of knowledge society. When dealing with today's problems and socio-cultural situations, the emphasis is put on the concept of a harmonious man. Management theories actualise a systematic approach and focus on professionalism, where knowledge is an integral part (Katinienė, Skačkauskienė 2014). Environmental uncertainty and technological developments make every organisation to focus on the management of employee's basic and exclusive competence, create an environment favourable to sharing knowledge and promote new knowledge creation processes.

By sharing their knowledge employees create preconditions for synergy, the components of which are explicit and tacit employee knowledge and relations among employees (Skačkauskienė et al. 2017). Evaluation of knowledge synergy and its components is an essential prerequisite in organisational knowledge management. The object of this research is one of the knowledge synergy components – employee knowledge. According to Giroux, Taylor (2002), Peters, Maruster, Jorna (2010, 2011), employee knowledge evaluation allows us to measure the input of knowledge in added value creation as well as the scope of and need for knowledge in an organisation. Employee knowledge is not evaluated by universally recognised methods. Some researchers (Dave, Dave, Shishodia 2012, Moradmand, Datta, Oakley 2013) evaluate employee knowledge by competence analysis, others (Fink 2005, Park, Lee, Kwon 2010) by expert evaluation.

Evaluation of employee knowledge as a component of organisational knowledge synergy should take into account many complex factors and consolidate them. Multiple methods have been proposed to combine partial indicators of a complex phenomenon into a single aggregated indicator. Many different multi-criteria methods have been created to evaluate complex processes: from a simple sum of positions (ranks) to methods based on complex mathematical calculations. These methods evaluate alternatives according to their characteristics and common goals. Many socio-economic phenomena and complex processes are evaluated by multi-criteria evaluation methods. They are increasingly popular among foreign researchers (Li et al. 2011, Liu et al. 2013, Oztaysi 2014, Rajesh, Ravi 2015, Şengül, Eren, Eslamian Shiraz, Gezder, Şengül 2015, Lupo 2015, Bouyssou, Marchant 2015, Mir et al. 2016) as well as Lithuanian researchers (Zavadskas, Turskis 2010, Beležentis, Beležentis 2011, Slavinskaitė 2012, Poškas et al. 2012, Zavadskas, Turskis, Kildienė 2014, Simanavičienė, Cibulskaitė 2015). In the article about the application of multi-criteria methods, Mardani et al. (2015) mentions 393 articles published between 2000 and 2014 in 19 fields. Limited research of knowledge evaluation is revealed by the fact that only five (or 1.27%) articles apply multi-criteria methods to analyse knowledge management problems. No cases have been found where knowledge synergy and employee knowledge as its component are evaluated using multi-criteria evaluation methods. Thus, the aim of this research is to analyse multi-criteria evaluation methods, identify employee knowledge evaluation methods and, if possible, propose a set of relevant methods. To achieve this aim the following objectives have been set: analysing the evaluation process, providing an employee knowledge evaluation technique for a complex employee knowledge evaluation, examining the methodological potential of multi-criteria methods and justifying the use of these methods in employee knowledge evaluation. The article applies comparative and critical analysis, synthesis and modelling.

Modelling an employee knowledge evaluation model

Alkin (2004) claims that evaluation should be understood as a process of determining the value of a certain object. To ensure a smooth evaluation of all or certain organisational activities, this process is structured. For example, Patton, Sawicki, Clark (2012) suggest that evaluation should be conducted consistently and provide a six-step evaluation cycle (Fig. 1).

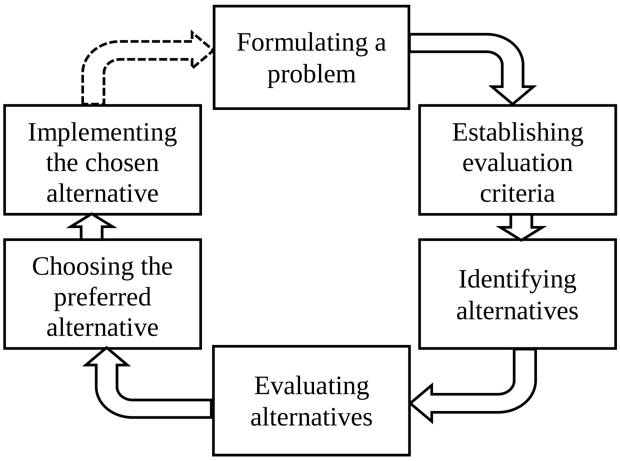

Fig. 1 Classical evaluation cycle (Patton, Sawicki, Clark, 2012)

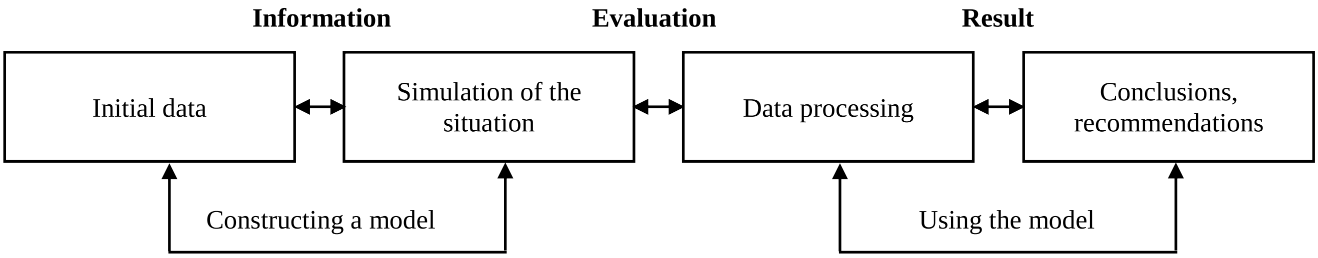

Fig. 2 Multi-criteria evaluation scheme (Guitouni, Martel 1998)

The classical evaluation cycle provided by Patton, Sawicki, Clark (2012) is suitable for the evaluation of different objects. However, Beležentis and Beležentis (2011) identify original steps in multi-criteria evaluation methods applied to complex tasks: (1) developing a system of goals and related indicators, determining their weight; (2) developing a response matrix and normalising it using multi-criteria decision-making methods; (3) interpreting the findings and making decisions. The application of multi-criteria evaluation methods has been systematised by Guitouni, Martel (1998): using the available data for simulating the situation, processing data and getting the evaluation result (Fig. 2).

Andriušaitienė et al. (2008) proposes to start multi-criteria evaluations with the identification of the research object and end them with decision-making to improve the phenomenon at issue (Fig. 3). Slavinskaitė (2012) agrees with this order, but merges the first stage and the second stage into one. Sarraf, Mohaghar, Bazargani (2012) use four steps in multi-criteria evaluation: (1) formulating the object and problems; (2) identifying alternatives and evaluation criteria; (3) applying the model and (4) choosing the best solution.

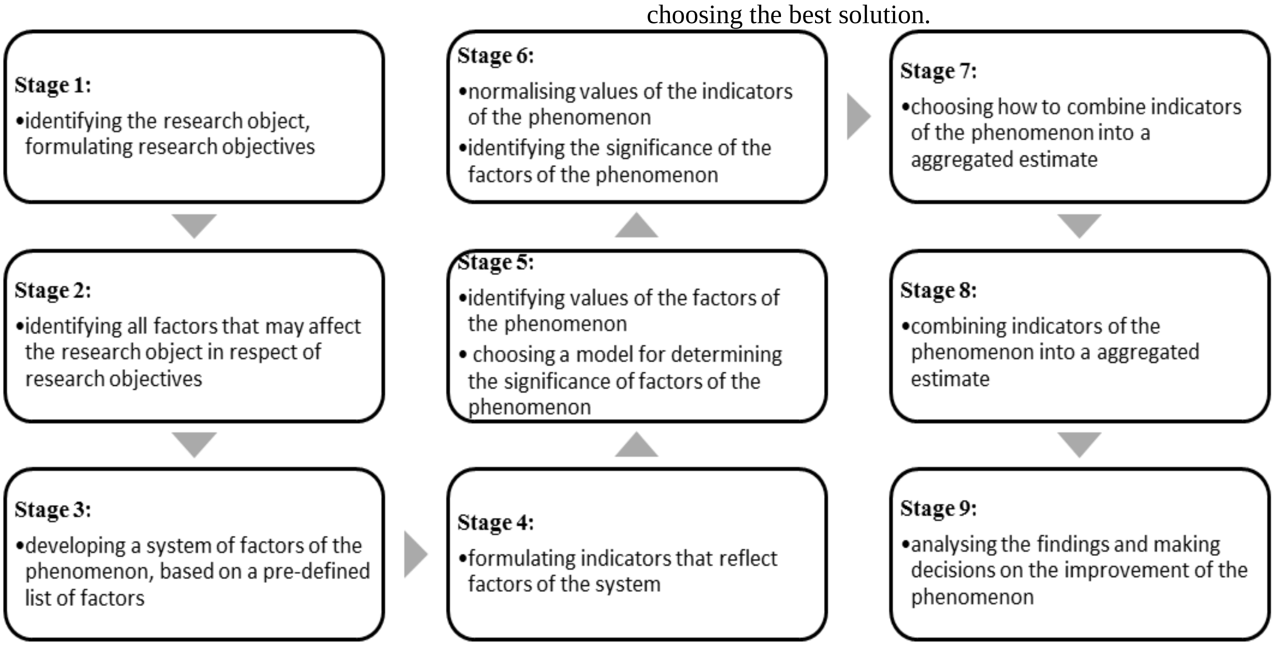

Fig. 3 Stages of multi-criteria evaluation according to Andriušaitienė (made by the authors)

Podzvesko (2008) claims that irrespective of the task subject to multi-criteria methods, the researcher examines the following key stages of a complex task (not necessarily all of them):

- developing a system of partial indicators with complex quantities;
- preparing evaluations of statistical data of the indicators applied or expert evaluations;
- transforming and normalising data;
- determining the significance of indicators – calculating their weight;
- analysing the characteristics and limitations of different multi-criteria methods, choosing specific relevant multi-criteria evaluation methods, analysing the compatibility of individual results;
- establishing a hierarchy of complex quantities and carrying out qualitative evaluation of the hierarchical structure;
- conducting a complex evaluation of indicators of the main hierarchical level;
- measuring the effect of data uncertainty on multi-criteria methods, establishing intervals for changing model parameters.

Comprehensive evaluation of complex objects consists of certain stages of evaluation. As a rule, it starts with the formulation of the research problem, the development of a system of partial indicators and a hierarchical structuring of components and ends with the determination of the aggregated estimate of the phenomenon at issue and the verification of the stability of the models applied. To summarise stages of multi-criteria evaluation distinguished by many researchers, the authors of this article used a linear algorithm and developed an employee knowledge evaluation technique (Fig. 4). The article further analyses stages 1 and 2 in more detail.

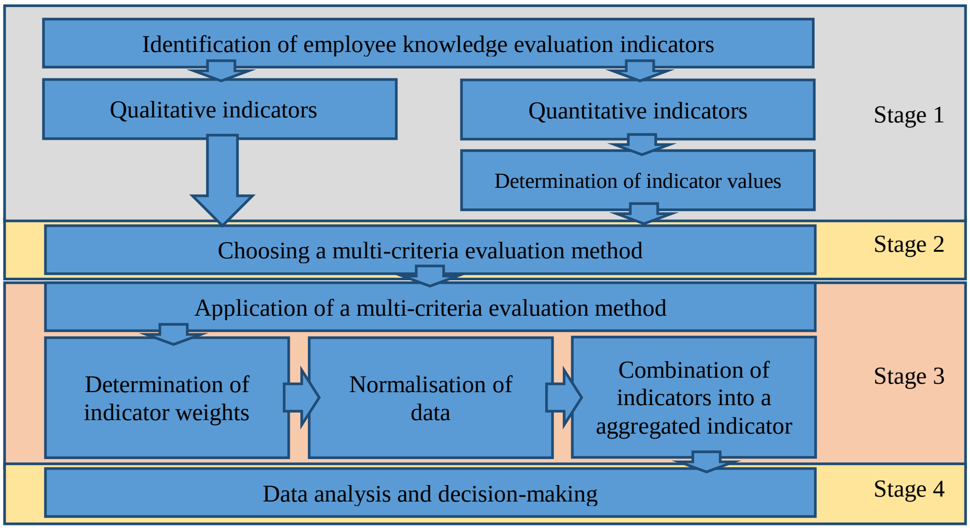

Fig. 4 Employee knowledge evaluation algorithm (made by the authors)

The system of employee knowledge evaluation indicators consists of two subsystems. Employee knowledge is divided into two blocks: explicit knowledge and tacit knowledge (Skačkauskienė et al. 2017), and these consist of relevant factors (Fig. 5).

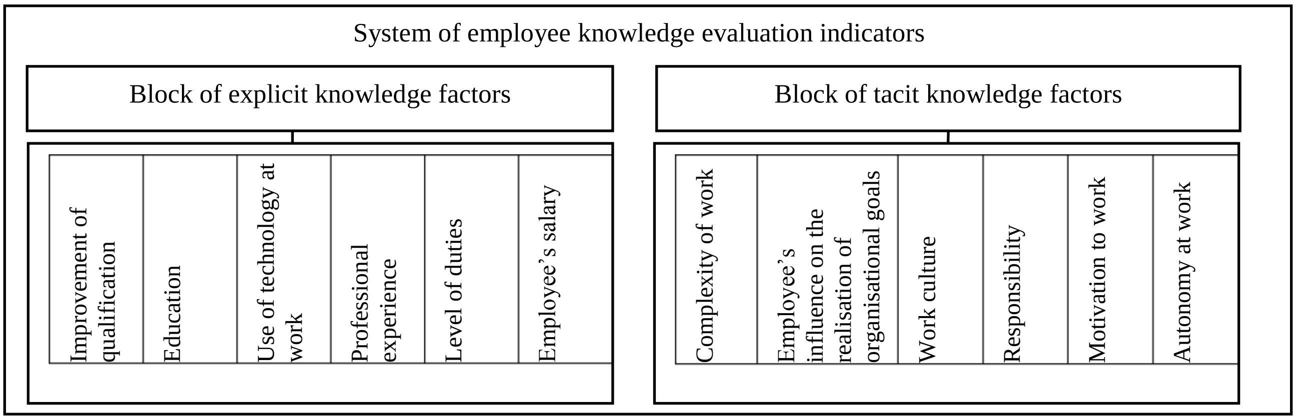

Fig. 5 System of employee knowledge evaluation indicators (made by the authors)

Factors of the explicit knowledge block have both quantitative and qualitative expressions. Their content is specified in Table 1.

Table 1. Quantitative and qualitative factors of the explicit knowledge block (made by the authors)

Factors		Components of the factor	Unit of Measurement
Type	**Name**		
Quantitative	Improvement of qualification	*Number of courses:* Per year. Computer literacy certificate (ECDL) Language certificates	 hour unit unit
	Professional experience	*Work experience:* (1) all work experience (2) work experience by profession	 year year
	Employee's salary	Post Hourly wages (before tax) or Monthly salary (before tax)	unit currency currency
Qualitative	Education	*Level of education:* primary	 1 point
		progymnasium (basic)	2 points
		gymnasium (secondary)	3 points
		professional education or secondary special	4 points
		higher education or higher non-university education (professional BA)	5 points
		higher university education (BA)	6 points
		higher university education (MA)	7 points
		doctoral degree	8 points
	Use of technology at work	Neither technology nor computer is used	0 points
		Only computer is used at work	3 points
		Operating machinery that requires technological knowledge	7 points
		Work includes using a computer and developing technology	10 points
	Level of duties	Level 1: manager, deputy, head of unit	3 points
		Level 2: foreman, brigade leader	5 points
		Level 3: administration, employee, civil servant	8 points
		Level 4: auxiliary worker, janitor, cleaner, security guard	10 points

Factors of the tacit knowledge block are of a qualitative nature. They should be evaluated using components describing their content (Table 2). Components of qualitative employee knowledge factors are measured in points. The number of components that describe factors varies, therefore evaluation points also vary. For example, if the employee does not deal with any strategic objectives and does not have any influence on the realisation of organisational goals, he/she gets 0 points, but if the employee participates in various working groups, performs various complex tasks and finds partners, i.e. influences the realisation of organisational goals, he/she gets 10 points.

Table 2. Tacit knowledge factors (made by the authors)

Factors		Components of the factor	Points
Type	**Name**		
Qualitative	Complexity of work	Easy physical work	3
		Physical work that sometimes causes stress	5
		Work related with constant mental activity	8
		Work causing much metal and nervous tension, related to constant concern for all activities in the organisation	10
	Employee's influence on the realisation of organisational goals	No influence	0
		Weak influence	3
		Average influence	5
		Strong influence	8
		Very strong influence	10
	Work culture	Does not listen to other opinions, often engages in conflicts	0
		Has his/her own opinion, but engages in conflicts	3
		Acknowledges opinions of their own and others	5
		Willingly shares data, information, knowledge and experience	8
		Creates a positive micro-climate in the organisation	10
	Responsibility	Does not make any decisions	0
		Makes decisions when problems are identified	3

		Makes individual decisions when problems are not identified, but the result is under control	5
		Makes individual decisions when problems are not identified; decisions determine the performance of the whole division	8
		Leads a collective management body when dealing with issues related to key strategic issues	10
	Motivation to work	No motivation to work	0
		Average motivation to work	5
		Strong motivation to work	10
	Autonomy at work	Routine work defined by rules	3
		Tasks are defined, but require external information	7
		Individual tasks for creativity, innovation, intuition, higher education, internal and external communication	10

Standard employee survey data are sufficient for determining values of all qualitative factors. Weights of factors are determined by expert survey. Data of qualitative factors are usually stored in the organisation's information system. The key factors affecting employee knowledge and expressed in quantitative and qualitative terms are combined into one indicator (D_i). It helps to calculate the sum of components of explicit (m_i) and tacit (n_j) employee knowledge factors and the sum of factors of explicit (I_i) and tacit (N_j) employee knowledge (formulas 1, 2 and 3).

$I_i = \sum_{i=1}^{6} \gamma_i \, m_i$ (1)

$N_i = \sum_{i=1}^{6} \delta_i \, n_i$ (2)

$D_i = I_i + N_i$ (3)

where I_i is a sum of explicit employee knowledge factors; γ_i is weights of components of explicit employee knowledge factors; m_i is estimates of components of explicit employee knowledge factors; N_j is a sum of tacit employee knowledge factors; δ_i is weights of components of tacit employee knowledge factors; n_i *is* estimates of components of tacit employee knowledge factors; *i* is a number of the indicator; D_i is employee knowledge index.

Another step after developing a system of knowledge evaluation indicators and identifying key factors that affect the formation of employee knowledge is choosing a proper multi-criteria evaluation method.

Characteristics of multi-criteria evaluation methods

Scientific literature offers many multi-criteria evaluation methods for complex tasks: from a simple sum of positions (ranks) to methods based on complex mathematical calculations (Ginevičius, Krivka 2009). They all evaluate alternatives according to their characteristics and common goals and help to make the best decisions (Table 3).

Table 3. Classification of multi-criteria methods (made by the authors according to Ustinovichius et al. 2007, Brauers et al. 2008, Keršulienė et al. 2010)

Method group	Name of the method	Description	Author, year	Application
Rank correlations	Rank correlation	Based on rank generalisation. Calculates a coefficient to verify the compatibility of expert results (Kendall).	Spearman 1904; Kendall 1970	Dealing with issues of contingency
Comparison of ranks	ELECTRE	Eliminates alternatives with less favourable characteristics. Alternatives are prioritised in accordance with concordance and discordance indicators.	Roy 1968; Ulubeyli 2009	Selecting indicators
	PROME-THEE	Uses indicators characterising the objects being compared, statistical data (or expert evaluation) matrix and weights of indicators. Indicators are evaluated by experts. Requires participation of the decision-maker. Possible partial, full, continuous and interval classification.	Brans 1982; Behzadian et al. 2009; Podvezko 2009, 2012	Comparing alternatives
Qualitative evaluations replaced by quantitative evaluations	AHP	Hierarchical data breakdown based on a pairwise comparison matrix. Experts compare all indicators.	Saaty 1980	Qualitative methods are transformed into quantitative methods, thus solving a wide range of tasks
	Methods based on the theory of	The theory of fuzzy numbers is focused on the rationalisation of uncertainty. Experts evaluate indicators in external and internal	Liang 1999; Chou 2008; Stein et al. 2013	Tasks with the indefinite

	fuzzy numbers	interval points. Qualitative criteria are converted into fuzzy numbers, i.e. calculations use triangular fuzzy numbers, trapezoidal fuzzy numbers and Gaussian membership functions.		number of possibilities
Methods based on the measuremen t of distances from the reference point	TOPSIS	Technique for order performance by similarity to ideal solution. Uses vector data normalisation. The final step determines the relative distance between each alternative to the “ideally best (worst)” alternative. Experts evaluate criteria weights. Maximising (minimising) indicator values do not need minimisation (maximisation).	Hwang, Yoon 1981; Lin 2008; Antuchevičienė et al. 2010	Finding how to distance alternatives from the ideal solution
	COPRAS	Multi-criteria complex proportional assessment. Alternatives are compared in a relative way (positive and negative characteristics).	Zavadskas, 1996, 2008; Kaklauskas 1996	Comparing alternatives
	VIKOR	Linear normalisation and measurement of distances from the hypothetical best alternative. No expert evaluation.	Opricovic, Tzeng 2002, 2004	Comparing alternatives
	MOORA	The ratio system helps to normalise data and harmonise different indicator measurement systems, therefore requires an external normalisation mechanism. The reference point theory uses ratios calculated by the ratio system method The principle of the method of calculation: the sum of criteria evaluations of maximising normalised alternatives minus the sum of minimising normalised criteria values. Indicators are divided into groups with the same weights. No expert evaluation is required.	Brauers, Zavadskas 2006	Comparing alternatives
	MULTIM-OORA		Brauers, Zavadskas 2010	Comparing alternatives
Additive methods	SAW	The sum of products of indicator values and weights. The weights of indicators are determined by experts and these values are normalised. Alternatives are subject to ranking.	MacCrimmon 1968; Hwang, Yoon 1981	Comparing alternatives and ranking indicators
	ARAS	Additive ratio assessment, i.e. alternatives are assessed by a ratio of additive indicators. Expert evaluation is required.	Zavadskas, Turskis 2010	Comparing alternatives

Every multi-criteria evaluation method has its own peculiarities, strengths and limitations. When choosing a specific method, it is important to take into account requirements for the transformation of indicator values, normalisation and the reorganisation of negative values, the weighting effect on evaluation, the nature of evaluation criteria (maximising and minimising), etc. (Podvezko 2008).

Each of these methods has a characteristic evaluation process. When comparing SAW and COPRAS, Podvezko (2011) found that COPRAS gave a more accurate assessment of the calculation results. COPRAS and TOPSIS may be used to evaluate the same probability (Antucheviciene, Zakarevičius, Zavadskas 2010). Simulation of the stability of multi-criteria methods, performed by Vinogradova (2015), found that the more simulations there were, the more accurate evaluation of the stability of the multi-criteria method at issue was. After one million simulations, the percentage of stability is as follows: PROMETHEE – [65.8–65.9%], TOPSIS – [58.46–58.54%], SAW, COPRAS – [53.43–53.45%], MOORA – [44–58%]. A method that is in a larger percentage range is more stable.

The ARAS method helps to measure the effectiveness of alternatives compared to the optimal alternative, parameters of which are determined by the evaluator. It shows the best alternative for the interested group. Due to outranking with a complex logic, PROMETHEE and ELECTRE are rarely used. These methods use values of specially selected functions (priorities, concordance and discordance) rather than the usual normalised criteria values. A decision-maker must participate in setting function parameters (Podvezko 2012).

The practice of many researchers (Ginevičius et al. 2006, Podvezko 2008, Ginevičius, Krivka 2008, Simanavičienė 2011, Vinogradova 2015) shows that the subjectivity of the multi-criteria evaluation method applied has a lower impact, if the phenomenon is evaluated by several methods. The final result is an arithmetic mean of the results obtained by the multi-criteria evaluation methods.

Data of multi-criteria methods are stochastic. Their uncertainty affects the results of the methods applied. Any mathematical method may be used in practice, if it meets the stability requirement (Žukauskienė 2011). A mathematical method is considered stable when minor fluctuations of parameters correspond to minor developments of the results. Employee knowledge should be evaluated by a method which gives stable results, has low time costs and is simple and easy to apply in the organisation (Table 4).

Table 4. Criteria of evaluation methods (made by the authors)

Criteria / **Methods**	**Stability of results (Stable (2)/ Average (1)/ Unstable (0))**	**Times costs (Low (2)/Medium (1)/High(0))**	**Easy to apply (Easy (2)/Moderate(1) /Complex(0))**	**Expert survey (Not required (1)/ Required (0))**	**Total evaluation**
AHP	1	1	2	0	4
ARAS	1	1	1	0	3
COPRAS	1	1	1	0	3
ELECTRE	2	0	0	0	2
PROMETHEE	2	0	0	0	2
MOORA	1	1	1	1	4
SAW	1	2	2	0	5
TOPSIS	2	1	1	0	4
VIKOR	1	1	1	1	4
Preferred evaluation	*2*	*2*	*2*	*1*	*7*

It should be noted that all methods can evaluate alternatives expressed in quantitative and qualitative indicators, whereas criteria may be of different measurements. It is beneficial to evaluate employee knowledge by the SAW method. It has low time costs, it is easy to use and it gives moderately stable results. SAW requires expert evaluation to weigh indicators of the employee knowledge block of factors. It allows the organisation to prioritise certain factors of employee knowledge. AHP, TOPSIS, MOORA and VIKOR meet the stability requirement and their joint application could minimise the subjectivity of results. AHP allows experts to evaluate structured employee knowledge and the priority of indicators. Moreover, if the significance of the factors is regarded taking into account the specifics of the organisation's activities, i.e. if the organisation needs employees with higher education, experts will be able to give more weight to this factor than to other factors. The TOPSIS method stands out with stable results, but its methodology is rather difficult to apply in an organisation. The methodology of MOORA and VIKOR does not include expert evaluation, therefore there is no subjectivity caused by different competence, value systems and experiences of experts.

Conclusions

An employee evaluation algorithm has been created to evaluate employee knowledge. It consists of four stages: stage 1 – the identification of employee knowledge evaluation indicators; stage 2 – choosing a multi-criteria evaluation method; stage 3 – multi-criteria evaluation; stage 4 – data analysis and decision-making. A system of employee knowledge indicators has two subsystems: explicit knowledge and tacit knowledge. It is proposed to describe factors using indicators with quantitative and qualitative expressions. Standard employee survey data are sufficient for identifying components of qualitative factors. Weights of factors are determined by expert survey and components of quantitative factors by data stored in the organisation's information system.

The analysis of multi-criteria evaluation methods has showed that a lot of methods can be used for complex tasks. To summarise the results of the analysis, it may be claimed that ELECTRE and PROMETHEE are not widely used due to their complex logic, even though PROMETHEE has many modifications. AHP compares criteria in pairs, while VIKOR and MOORA do not need expert evaluation, which allows them to avoid any subjectivity. SAW gives stable results and is one of the easiest to use, therefore widely used.

For complex tasks with many parameters it is wise to use methods which meet the stability requirement, i.e. when minor fluctuations of parameters corresponds to minor developments of the results. Employee knowledge should be evaluated by a method which gives stable results, has low time costs and is simple and easy to apply in the organisation. The SAW method meets the requirements the best. AHP is also suitable for employee knowledge evaluation. It allows experts to evaluate structured employee knowledge and the priority of indicators. TOPSIS is characterised by stable results, but its methodology is rather difficult to apply in an organisation and therefore is not recommended. The methodology of MOORA and VIKOR does not include expert evaluation, therefore there is no subjectivity caused by different competence, value systems and experiences of experts. SAW, AHP, MOORA and VIKOR allow for a complex employee knowledge evaluation and evaluation results contribute to the improvement of human resources management. If possible, SAW, AHP, MOORA and VIKOR should be used as a set, thus avoiding any subjectivity. Moreover, results of such evaluation would give additional useful information about organisation's strengths and weaknesses.

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