Comparison of the Use of Decision-Making Methods in Czech Companies as a Result of the Covid-19 Pandemic

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Abstract: To quickly address the changes that have significantly affected our lives in the last two years, it is crucial for organisations to be able to use more sophisticated tools in their work processes. The paper aims to compare changes in the application of individual decision-making methods within Czech companies, focusing on tools based on data analysis. This comparison is created from the results of pilot research (conducted just before the outbreak of Covid-19 in February 2020) and a targeted questionnaire survey, which also dealt with decision-making methods in detail and emphasised the use of business intelligence (conducted in May 2021). The paper evaluates the position of data analysis compared to other methods between two groups of employees: managers and specialists without subordinates. Results show a growing trend in the utilisation of data analysis and MCDM methods, especially among managers. However, the application of MCDM is not as yet widely implemented by employees.

Keywords: Decision-making, Decision-making methods, Data analysis, MCDM

JEL Classification codes: C44, D81, D91

INTRODUCTION

While in the run-up to the Covid-19 pandemic managers had the opportunity to make decisions based on lessons learned and past data and trends, they were subject to different decision-making requirements during the pandemic than they had previously been accustomed to. The new problems and threats (which after the first wave of panic could be turned into opportunity) caused significant changes in current management practice, and not only in the decision-making process itself.

This paper aims to map changes in the use of decision support methods in work processes of Czech employees in relation to the Covid-19 pandemic. Data for this comparison was obtained in two questionnaire surveys. The first pilot research was conducted just before the pandemic outbreak in February 2020. In general, it dealt with decision-making habits in Czech companies, emphasising supporting decision-making methods based on data analysis, processing large amounts of data and its conversion into information. As a part of quantitative research, the targeted questionnaire survey, conducted in May 2021, was based on lessons learned from the pilot research. Again, the main goal was to reveal the respondents' approaches to decision-making and applied methods with a more detailed focus on business intelligence tools.

Data-based decision-making is an essential part of managerial work, but at the end of the solution process it is the managers who make the final decision (Pranjić, 2018). As some research shows, "the essence of big decision-making is a balance between instinct and analytics" (Carucci, 2016).

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1. LITERATURE REVIEW

The following literature review presents the fundamentals of a rational decision-making process and the possibilities of decision support if the manager has (or doesn't have) relevant information available.

1.1 Models of decision-making process

The decision-making process describes the general procedure for solving the selected decision-making problem in detail. The individual activities and their content are closely connected with the structure of the decision-making process; they follow in time and can be divided into individual stages. The concept of individual phases and their division within relevant literature differs according to author. This approach to the decision-making process is characterised by the so-called rational model, which is described as a multi-stage analytical process built on logic, extensive use of information and determination of variants based on data. Users of this model strictly follow the defined phases (Eisenführ et al., 2010).

The rational model of decision-making is therefore based on the following assumptions: maximisation of return, perfect availability of information, measurability of variables having cognitive, time and resource expectations for the evaluation of each phase of the decision-making process (Pranjić, 2018). Data-based decision-making methods or MCDM are highly applicable in this type of modelled scheme.

Herbert Simon made a major contribution to a better understanding of the decision-making process in general. He is considered a pioneer in decision support systems. In his independent work (Simon, 1960), and its later additions (Newell & Simon, 1972), he was the first to propose an individual decision-making model and divided it into three basic phases (Nirmalya, 2010):

Intelligence (problem identification and data collection): is the first stage in the decision-making process. In this step, the decision-maker identifies the problem or opportunity. A problem in an organisational context is the detection of anything that is not following the plan, rules or standard.

Design (generation of alternative solutions): in the second phase, alternative ways to solve the given problem are presented. The evaluation of each variant is performed based on criteria defined to facilitate the identification of positive and negative aspects of each solution. Quantitative tools and models are used. At this stage of the decision-making process, the variants are only outlines of the actual results and are only defined for further suitability analysis.

Choice (selection of the optimal alternative): this is the last stage of the process, in which the potential solutions are compared with each other to find the optimal solution.

However, this decision-making model does not take into account the following factors that can potentially affect the quality of decision-making: variables that cannot be quantified, personal feelings, prejudices, emotions, intuition, and personal preferences (Pillai, 2014). The opposing decision-making model is defined by the so-called bounded rationality (Newell & Simon, 1972). The manager does not have enough information available, which, therefore, cannot be analysed according to a predefined process. The effort of the responsible employees is to make the best possible decision with limited access to information and the impossibility of using it properly (Pillai, 2014). And it is in these cases that managers resort to decisions based on previous experience or consultation with colleagues.

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1.2 Decision-making methods

Countless publications dealing with decision-making in the corporate environment can be found in literature and professional journals. Some resources only deal with a selected group of tools; others offer a summary. The classification below offers a general view of possible ways to solve a problem, presenting several ways to proceed efficiently. A decision can be made (Grünig & Gaggl, 2006):

- purely intuitively without careful consideration of the nature of the problem,
- through previous routines,
- based on expert recommendations,
- random selection,
- based on rational thinking supported by relevant information.

Applied techniques can also be divided according to external decision-making conditions: in certainty, at risk or in uncertainty (Blažek, 2011). Šubrt (2015) deals with methods working on mathematical foundations. He further divides quantitative methods into these categories (Šubrt, 2015), unless otherwise stated):

- **Linear programming:** every decision problem is associated with several assumptions that define real solutions. When solving these problems, the restrictive conditions must be fully respected and, at the same time, the best solution must be found within these conditions. If only linear functions, equations and inequalities are used for its mathematical formulation, it is a model of linear programming.
- **Decision-making models:** the author classifies decision-making trees in this category, and the division of instruments according to the future state of conditions is repeated here: in certainty, at risk or in uncertainty.
- **Game theory:** modelling cases where the outcome of the decision-making process is influenced by several participants who are either interested in the outcome of the decision or influence the outcome of the decision, but are not interested in it (Gros, 2003).
- **Multi-criteria decision-making models:** multi-criteria decision-making (MCDM) refers to decision-making in the presence of multiple, usually conflicting criteria. MCDM problems can be broadly divided into two categories: multi-attribute decision making (MADM) and multi-objective decision making (MODM) (E. K. Zavadskas & Turskis, 2011).
- **Data envelopment analysis:** models based on the principles of this theory calculate efficiency coefficients as a ratio of the weighted sum of outputs to the weighted sum of inputs (Štědroň et al., 2015).
- **Structural analysis (balance models):** the basis of the analysis is the balance between consumption and production; each deviation of the balance in one part of the chain causes a change in the next part.
- **Graph theory:** real situations are rewritten into a graph with the help of a set of points and connections between them; this presentation is often more understandable and clearer for the layman than the classical outputs from mathematical models.
- **Stochastic models:** most decisions are made at risk; we assign probabilities of realisation to individual quantities in the real world. Data analysis is based on available data and the average values of random variables are fit to the models (Gros, 2003).

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Recent studies also tend to select and classify methods based primarily on automatic data processing and more complex, computer-aided tools. The following breakdown can serve as an example: multi-criteria decision-making, mathematical programming, artificial intelligence and integrated methods (Chai & Ngai, 2020; Hoang et al., 2019).

If it is impossible to find the optimal solution using the above tools, heuristic decision-making methods can help speed up the whole process. Heuristics rely on mental acronyms that reduce cognitive burden in decision making. The principles of heuristics are evident when applying the trial-and-error method, educated estimation, intuition or common sense (MacKay et al., 2020).

Principles representing heuristic methods often ignore the otherwise emphasised importance of information. Contrary to the widely held view that a lower level of information processing reduces the accuracy of a decision, a study of heuristics shows that its accuracy can in fact be improved through less information, calculations and time. (Gigerenzer & Brighton, 2009). Computer simulations have even shown that despite limited processing requirements, heuristics provide very accurate predictions (Goldstein & Gigerenzer, 2002).

2. METHODOLOGY

First, the individual methods for decision support were examined within the literature search. Further, they were assigned to individual models of the decision-making process according to their nature. Subsequently, two research surveys were conducted, which are characterised in the next section.

2.1 Questionnaire surveys

The pilot survey was conducted in February 2020. In the analysis, 75 of the 90 addressed respondents were included. The initial set of questions in the questionnaire focused on obtaining demographic information about each employee (see Table 1). The aim was to classify respondents according to the company's size, business sector, departments and the utilization of information systems within the company, not only in the decision-making process. In the next section, the current level of use of business intelligence in Czech companies compared to other decision-making methods was determined. Based on the obtained data, it was then possible to verify the relationship between the use of BI and the system settings available in the organization and determine the factors affecting the involvement of more complex methods in the decision-making process (Kašparová, 2020). Three basic types of questions were included in this research. Respondents answered yes / no questions, selected from a limited number of alternatives, and a Likert scale (a five point one) representing the degree of agreement with the statement was also used.

Targeted quantitative research, partially based on the results of pilot research, was carried out in May 2021, and 152 respondents could be included in the analysis. In the beginning, basic facts about each respondent were monitored, including demographics and essential information about the type of employment. The second part of the survey focused on the most commonly used methods to support decision-making and business intelligence tools in general. It aimed to verify the model based on The Unified Theory of Acceptance and Use of Technology (UTAUT 2) concerning on utilization of BI in companies. The questionnaire in this section consisted of the following types of closed questions: dichotomous, enumeration, and Likert scale. In contrast to the pilot research, a seven-point scale was used for greater scalability, with respondents expressing a degree of agreement for individual statements: 7 stars represented absolute agreement, 1 star outright disagreement.

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A set of questions dealing with decision-making methods was part of both of these surveys, so it is possible to make the above-mentioned comparison. In the presented research, decision support tools are divided into four major groups: intuition and previous experience, peer consultation, data analysis and multicriteria decision-making methods (MCDM). In the pilot research, respondents could choose consultations with external experts as well, but this option was excluded for further study due to low frequency. In both surveys, the addressed employees could also add any other method to support their decision-making in the "other" column. From the obtained data, it is possible to evaluate the position of data analysis as a tool to support decision-making compared to other methods. The application of selected methods is further examined according to the nature of the respondent, regardless of whether their job position is managerial or a specialist without subordinates.

The elementary characteristics of both research files are summarised in Table 1.

Tab. 1 Demographics and basic characteristics

Distribution by…	Pilot research (out of 75)	Quantitative research (out of 152)
Gender		
Male	49	113
Female	26	39
Enterprise size		
Micro- and small-sized enterprises (0-49 e.)	7	110
Medium-sized enterprises (50 to 249 e.)	15	21
Large enterprises (more than 250 e.)	53	21
Job level		
Management	32	101
Specialists	43	51
Business sector		
Automotive	40	19
Information technologies	10	72
Finance and insurance industry	9	11
Accommodation (hotels, etc.)	2	5
Agriculture, forestry, fishing	1	45
Other	13	0

Source: own processing

More respondents working in large companies took part in the pilot survey, while more respondents from smaller companies appeared in the targeted questionnaire survey. In the first case, respondents were most often contacted through the LinkedIn job network, where many employees of large companies can be found. This method was chosen as the simplest to obtain a relevant number of responses in the pilot research phase. The distribution in the follow-up survey is given by targeting companies from specified sectors of the economy that

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were contacted by random selection. There was a greater willingness to answer and react among the employees of smaller companies.

Regarding the distribution of respondents in individual fields of business, in both cases most of them worked in sectors that show the highest long-term involvement of decision-making methods based on data analysis (Statista, 2018): automotive, information technology, finance and insurance. The involvement of these tools in the decision-making process, according to the field of business, was subjected to a detailed analysis in previous research. The follow-up research, presented in this paper, focuses on the differences in the approach and application of individual methods between respondents according to their job position. The presented outputs therefore evaluate the application, not only of data analysis, among managers and specialists without direct subordinates.

3. RESULTS AND DISCUSSION

Individual respondents could indicate any number of methods; on average they chose 2.5 from the offered list. The results in Table 2 summarising the application of selected methods to all respondents already indicate behavioural changes in the decision-making process. There was a decrease in the application of intuition and previous experience among the respondents, while consultations with colleagues increased and methods based on data analysis and MCDM were also more significantly applied. While data analysis, which includes processing of available data and its transformation into information using business intelligence tools, is already applied in the decision-making process by more than 2/3 of respondents (69%), while techniques based on multicriteria decision-making are used by only a third of respondents (32%). The complete results are summarised in Table 2.

Tab. 2 Most used decision-making methods

Method(s) based on…	**Pilot research (out of 75)**		**Quantitative research (out of 152)**	
	Absolute frequency	Relative frequency	Absolute frequency	Relative frequency
Intuition and previous experiences	61	81%	115	76%
Consultation with colleagues	50	67%	111	73%
Data analysis	47	63%	105	69%
Multi-criteria decision-making (MCDM) methods	19	25%	48	32%
Consultation with experts outside of the company	14	19%	not included	not included
Others	2	3%	10	6%

Source: own processing

A comparison of the results of the two surveys shows a growing trend in the use of more complex decision support techniques. At this point, it is necessary to draw attention to the need to ensure the high quality of information provided by systems based on large-scale data processing, as mere regulation of inclusion in the work process by management can ultimately be counterproductive (Visinescu et al., 2017). A wide range of statistical and non-statistical decision-making techniques can be found in literature, among which MCDM has recently enjoyed great popularity and offers a wide range of applications for modelling complex

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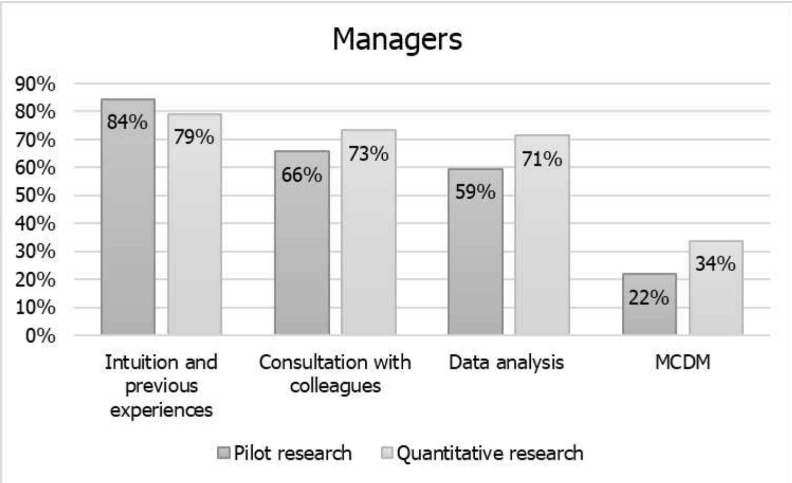
business processes (E. Zavadskas et al., 2019). However, as the outputs obtained in Czech companies suggest, their transfer to practice is still in its infancy. Nevertheless, the rising trend of their usability can be assessed positively.

Any extension of managerial experience with tools providing broad data analysis should lead to streamlining the complete decision-making process (Seddon et al., 2012). Figure 1 presents a comparison of managerial behaviour in decision-making in both surveys.

Fig. 1 Utilisation of methods among managers (relative frequency)

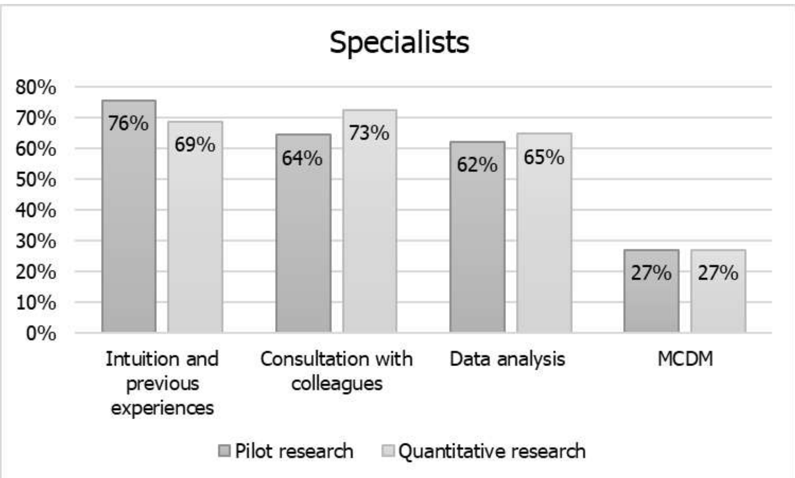


Source: own processing

And it was the largest increase in the relative share within the application of individual methods between the two surveys that was recorded among managers. Specifically in the application of data analysis and MCDM, this share increased by 12% over one year. While during the first survey, even more data analysis users were recorded as specialists (62% to 59%), in the next survey, over 70% of managers included these techniques in their decision-making process and rely on them almost as often as consultations with colleagues (73%).

Minor differences in habits in the decision-making process were found among specialists. The complete data is presented in the graph in Figure 2.

Fig. 2 Utilisation of methods among specialists (relative frequency)



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Source: own processing

As for managers and specialists, it was impossible to rely so significantly on previous experience, and they used consultations with colleagues in decision-making in response to new events and situations far more often. Almost 2/3 of specialists have already used data analysis, but the increase was only marginal (62% → 65%). The involvement of MCDM in the decision-making process remained at the same level, yet only 27% of the respondents applied it in solving decision-making problems.

Although researchers have long (and successfully) explored applications of more complex decision-making tools (Bernroider & Schmöllerl, 2013; Ishizaka & Siraj, 2018; Seddon et al., 2012; Visinescu et al., 2017), applying techniques based on previous knowledge of both their own and closest colleagues still prevails among the respondents addressed. Asadabadi et al. confirm that although the above studies show better results from evaluating the researched problem using MCDM, companies still mainly rely on intuitive approaches. The main reason companies avoid them is their shortcomings (Asadabadi´s article discusses the inability of AHP (Analytic Hierarchy Process) method to provide a good assessment of options). According to Asadabadi, future research should focus on the reasons for the non-usability of the MCDM processes thus far promoted and develop more valuable methods (Asadabadi et al., 2019).

CONCLUSION

The paper aimed to present the evaluation of changes in the decision-making process among employees of Czech companies based on two questionnaire surveys conducted in 2020 and 2021. Due to the timing of both surveys, it was possible to reflect the possible consequences of the Covid-19 pandemic. Methods based on an irrational decision-making model, i.e., intuition, previous experience and consultation with colleagues, and methods used in a rational approach to solving decision-making problems, i.e., data analysis, business intelligence-based techniques and methods based on multicriteria decision-making, were selected for the survey.

Although both surveys have been relatively quickly consecutively conducted, the circumstances surrounding the global Covid-19 pandemic indicate trends that have changed behaviour within the decision-making process. It would previously not have been highly probable to capture significant behavioural changes among decision-makers in the course of one year.

More complex and time-consuming support tools have become more popular among the respondents in the surveyed group. The period between the two surveys when production completely stopped in some sectors gave managers more time to apply otherwise neglected techniques. At the same time the developers of these tools gained more time and feedback from users, which could lead to any necessary adjustments and optimisations for easier and faster applications in future situations.

As in most studies, several limiting facts can be revealed, one of which is the representativeness of both questionnaire surveys. Due to low availability and difficulty obtaining similar types of data, both surveys had to be based on voluntary participation in the research. These types of results cannot be generalised, but the obtained data can still be properly evaluated, outlining possible trends in the examined files. The selected techniques for obtaining the first overview of the researched topic were very generally chosen, and subsequent research can be focused on several directions.

With a one-year interval, it would be possible to repeat the survey, which could be further extended by more detailed research of individual methods and the way or timing of their application. In the next phase, a more extensive literature search can be carried out, focusing

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on studies proposing modifications and updates of the MCDM methods thus far used to ensure their broader application in business practice.

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