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Naiden Kirilov Naidenov

RESEARCH AND MODELING OF BUSINESS PROCESSES SUPPORTING DECISION-MAKING RELATED TO DIGITAL TRANSFORMATION

ABSTRACT

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Author: **Naiden Kirilov Naidenov**

Title: **Research and modeling of business processes supporting decision-making related to digital transformation**

INTRODUCTION

Digital transformation is a phenomenon of extreme importance to the modern business environment, which not only changes the way companies interact with each other and with consumers, but also fundamentally rethinks the goals and strategies of organizations. It encompasses many aspects of business, including technology, processes, culture and customer experience, not only a technological advance, but also a strategic variable that requires a new perspective on the management of companies.

Digital transformation is a multidimensional process that encompasses a number of components, including technological, organizational, and cultural aspects. First, innovation in strategic approaches is essential as companies need to rethink how they create value for their customers in the context of a rapidly changing digital environment. This can include new business models that integrate digital technologies into core operations, as well as adapting the products and services offered to meet consumer needs. Second, the organizational structure also needs to transform to meet new requirements and facilitate innovation. This can include cross-functional teams working on projects, as well as a culture of collaboration and open communication that encourages the exchange of ideas and innovation. Third, the technology infrastructure of companies is a key factor for successful digital transformation. Organizations need to invest in modern technologies that support process automation, data analysis, and the implementation of innovations.

When these aspects are combined, it becomes clear that digital transformation requires a strategic approach that takes into account the interaction between technological, organizational and cultural changes. Companies must develop comprehensive strategies that encompass all levels of the organization and reflect business objectives as well as customer needs.

The dissertation is structured into an introduction, 3 chapters, conclusion, contributions, list of publications, declaration of originality and bibliography.

Chapter 1 provides an overview of the main tasks contributing to the achievement of digital transformation. The main business processes are analyzed, as well as the stages for successful digital transformation. Particular attention is paid to the human factor in this process, including customer relationship management systems. The second part of this chapter analyzes the decision-making support techniques applicable to digital transformation processes. Based on the analysis, conclusions are drawn, on the basis of which the purpose of this dissertation is formulated.

Chapter 2 describes the proposed models that support decision-making in various processes related to digital transformation. An integrated approach is presented for assessing the progress of digital transformation using multiple objective and subjective indicators. Based on the identified indicators, a mathematical model is formulated for assessing the current state of digital transformation. For the 3 main stages of digital transformation (operational readiness, organizational readiness and business value), corresponding groups of indicators are identified and used to formulate a mathematical model for assessing the progress of digital transformation. Mathematical models are described that are applicable and support the work of the chief information manager in the digital transformation process. Taking into account the need for a digital transformation leader, a model for group decision-making for selecting a candidate for the position of chief digital transformation manager is also proposed.

Chapter 3 presents the numerical experiments conducted on the proposed models. The results of testing the proposed integrated approach for assessing the progress of digital transformation using multiple objective and subjective indicators are described. The results of testing the proposed model for assessing digital transformation, based on groups of indicators for operational and organizational readiness and business value, are presented. The applicability of the formulated models supporting the work of the chief information manager in the digital transformation process is described. At the end, the results of numerical testing of the model for group decision-making in assessing and selecting candidates for the position of chief digital transformation manager are also presented.

The conclusion summarizes the results obtained as a result of the proposed and tested mathematical models to support decision-making and directly related to digital transformation.

CHAPTER 1. ANALYSIS OF BUSINESS PROCESSES AND TASKS OF DIGITAL TRANSFORMATION, MATHEMATICAL MODELS TO SUPPORT DECISION MAKING

This chapter presents the tasks and processes that accompany digital transformation. Particular attention is paid to the human factor in this process, as well as to customer relationship management systems. The second part of this chapter analyzes the decision-making support techniques applicable to digital transformation processes. Based on the analysis, the conclusions were determined, on the basis of which the purpose of this dissertation was formulated.

1.1. Analysis of the tasks and processes of digital transformation

Digital transformation accelerates the conversion of R&D into patents and reduces the time between patent application and approval. It fosters innovation by improving the quality of labor and easing financial constraints, with these mediation effects being more pronounced for operational innovations (Qiao et al., 2025). Interdisciplinary knowledge exchange contributes to a better understanding of the strategic imperatives of digital transformation, as it involves multiple functional areas, including marketing, information systems, innovation, strategic and operational management (Henfridsson et al., 2014; Bharadwaj et al., 2013). In today's rapidly evolving digital landscape, terms such as digitization, digitalization, and digital transformation are often used interchangeably. However, each concept has different meanings and implications for businesses and organizations (Brennen & Kreiss, 2016).

1.1.1. Purpose and objectives of digital transformation

The goal of digital transformation is to improve business operations by harnessing the power of digital technologies, creating a more efficient, adaptive, and competitive organization that is able to respond to the ever-changing needs of customers and market dynamics (Westerman, Bonnet & McAfee, 2014). To achieve this goal, it is necessary to implement multiple strategic tasks and initiatives that integrate digital technologies into all aspects of the organization and transform both internal processes and external interactions (Kane et al., 2015). By using digital technologies and innovations, organizations can not only optimize their processes, but also provide better customer service, increase their competitiveness, and adapt quickly to market changes. Some of the main areas subject to improvement as a result of the implementation of digital technologies are shown in Fig. 1.1:

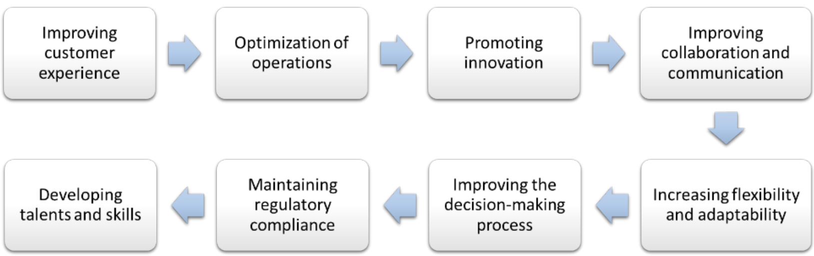


Fig. 1.1. *Processes subject to improvement as a result of the application of digital technologies*

1.1.2. Key areas related to digital transformation

Digital transformation refers to the process of moving from analog to digital systems and technologies, and this involves not only technological change but also a complete rethinking of business processes, organizational culture and customer experience (Bharadwaj et al., 2013). Therefore, digital transformation affects a wide range of industries, including healthcare, education, finance, manufacturing, retail and government (Schwab, 2016). It covers a wide range of business processes, but most often refers to key areas such as: sales and marketing; manufacturing and supply chain; finance and accounting; human resources; project management; customer service; IT management.

1.1.3. Processes involved in digital transformation

The digital transformation process involves several key steps and aspects that help organizations move from traditional, analog methods to digital solutions. Fig. 1.3 shows some of the key processes and elements involved in digital transformation:

Fig. 1.3. *Main processes and elements involved in digital transformation*

1.1.4. Human resources in the context of digital transformation

Implementing technologies to automate administrative tasks, such as processing applications, scheduling interviews, and organizing documents, helps to facilitate HR professionals and allows companies to focus on strategic and creative aspects of talent management (Stone et al., 2015; Parry & Tyson, 2018). Fig. 1.4 shows the main aspects of human resources in the context of digital transformation.

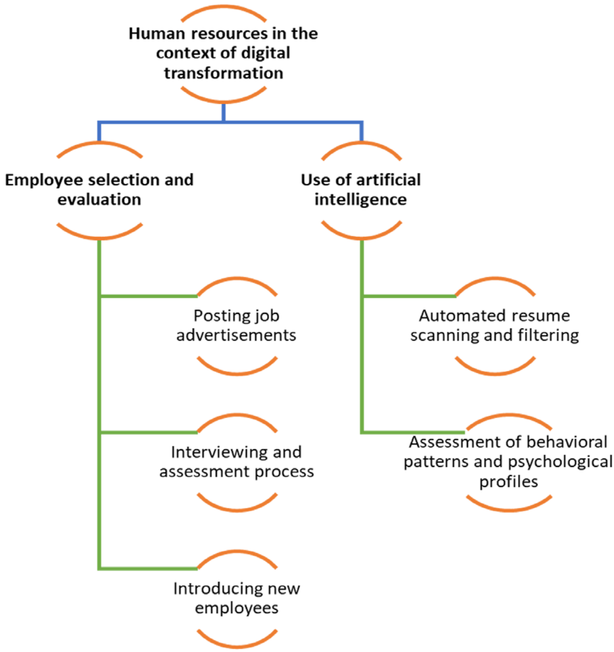


Fig. 1.4. *Main aspects of digital transformation in the field of human resources.*

Studies show that AI reduces application processing time by up to 75%, while also reducing the risk of bias and personal preferences in selection (Cascio & Montealegre, 2016; Bodea et al., 2020). The main approaches to using AI in candidate assessment include:

- *Automated resume scanning and filtering – Using keyword and phrase analysis methods, II systems quickly detect and classify applications that best meet the requirements of the position (Upadhyay & Khandelwal, 2018).*
- *Assessment of behavioral patterns and psychological profiles: Some AI tools use psychometric data and behavioral pattern analysis to assess candidates' personality characteristics, their soft skills, and likelihood of successful adaptation to the corporate culture.*

1.1.5. Customer relationship management systems as a tool for digital transformation

Customer Relationship Management (CRM) systems and their role in the transformation of customer relationship management are fundamental to the successful digitalization of business. Through these software systems, organizations can successfully manage customer relationships by collecting and analyzing data from various communication channels. The main goal of CRM systems is the integration and automation of sales, marketing and customer support, which is achieved by integrating 3 main components: sales automation, marketing automation and service automation. CRM platforms help businesses make informed decisions by providing them with key data about customer behavior and their interactions with the brand.

1.2. Analysis of decision support techniques applicable to digital transformation processes

Multi-criteria decision-making (MCDM) has a variety of tools and methods that can be applied in various fields from finance to engineering design. In this context, this section aims to briefly present the concept of MCDM, main categories and different methods that would be applicable to the considered problem related to digital transformation. MCDM is one of the basic problems in decision-making, which aims to determine the best alternative by considering more than one criterion in the selection process. MCDM includes different elements and concepts based on the nature of the decision-making problem, the main ones being as follows:

- Alternatives are "different possible courses of action"
- An attribute is defined as a "measurable characteristic of an alternative" (Taherdoost & Madanchian, 2023)
- Aggregation refers to "considering the performance of an alternative against specific criteria for making a decision about the alternative"
- Decision variables are defined as "components of the vector of alternatives"
- The decision space is presented as "feasible alternatives"
- Weights are defined as "elements used to quantify the attribute of an alternative by assigning a value"
- Criteria are defined as "tools for evaluating and comparing alternatives in terms of the consequences of their choice"
- Preferences are defined as "how an alternative satisfies the decision maker's needs regarding a given attribute"
- Solutions vary depending on the type of problem, which may include selection, ranking, and sorting problems (Borissova et al., 2020)

1.2.1 General presentation of the problems of multi-criteria analysis

The MCDM process can be viewed as selecting the best (meaning the most preferred) alternative from a predefined set of alternatives. In mathematical form, the MCDM problem is defined by the set of alternatives, the set of evaluation criteria, and the set of weighting factors expressing the importance of the criteria. All this information is usually organized in a matrix form, as shown in Table 1.1.

Table 1.1. Multi-criteria analysis matrix

Alternatives	Criteria/weighting factors			
	C_1	C_2		C_n
	$\boldsymbol{w_1}$	$\boldsymbol{w_2}$		$\boldsymbol{w_n}$
$\boldsymbol{A_1}$	x_{11}	x_{12}		x_{1n}
$\boldsymbol{A_2}$	x_{21}	x_{22}		x_{2n}
			x_{ij}	
$\boldsymbol{A_m}$	x_{m1}	x_{m2}		x_{mn}

In this matrix x_{ij} represents the value of the alternative A_i, the criterion C_j is the criterion, and (W = $\{w_1, w_2, . . . , w_2\}$) is the vector of weight coefficients for the importance of the criteria. These two main parameters characterize the problems of multi-criteria analysis. Multi-criteria analysis provides the opportunity to evaluate the alternatives, which is a prerequisite for these alternatives to be able to be arranged from the best to the worst performance or vice versa. Considering the matrix described in this way, on the basis of which the ranking is implemented, the main steps of this type of problem can also be identified, as shown in Fig. 1.6 (Ceballos et al., 2016).

Fig. 1.6. *Basic steps for solving multi-criteria analysis problems*

There are many methods of multi-criteria decision making and each method has its own definition of the best alternative and it is not certain whether using the same input data in different multi-criteria decision making methods will lead to the same results.

1.2.2 Categories of problems for multi-criteria decision making

The different methods of multi-criteria decision making have characteristics that can be related to many aspects from the quality of the answers to the type of problem that these methods solve. Therefore, for a better understanding of the methodologies of these methods, it is essential to consider the classification of MCDM problems. There are different variants, considering different aspects of the problems, recognized in many studies such as structured or unstructured problems, problems with uncertainty, problems with multiple criteria and objective functions. The different methods of multi-criteria decision making are summarized in Fig. 1.7 (Taherdoost & Madanchian, 2023; Sabaei et al., 2015; Baizyldayeva et al., 2013).

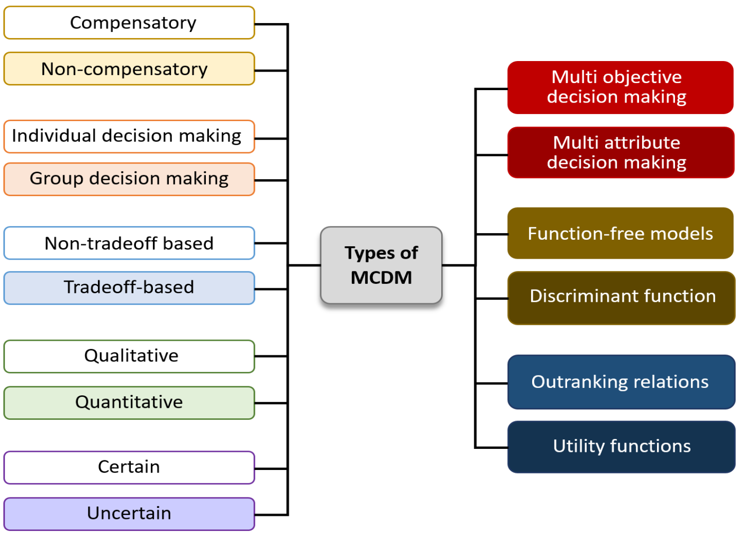


Fig. 1.7. *MCDM Classification*

It has been shown that decision-making support methods based on multi-criteria analysis are significantly more frequently discussed in the scientific literature compared to multi-criteria optimization methods (Taherdoost & Madanchian, 2023).

1.2.3. Some commonly used multi-criteria analysis methods

The Weighted Sum Method (WSM) is probably the most commonly used approach, especially for one-dimensional problems. If there are M alternatives and N criteria, then the best alternative is the one that satisfies (in the case of maximization) the following expression (Triantaphyllou, et al., 1998):

$$A^*_{WSM} = max \sum_{j=1}^{N} q_{ij} w_j, for\ i = 1,2,3, \dots, M \quad (1.4)$$

where: $A^{\ *}_{WSM}$ is the corresponding score for the best alternative, N is the number of criteria based on which a decision is made, q_{ij} is the actual value of the i-th alternative with respect to the j-th criterion, and w_j is the weight for the importance of the j-th *criterion.*

Weighted Product Model (WPM). This method is very similar to the previous method. The difference is that instead of the addition operation, the multiplication operation is used. To compare the alternatives $\mathrm{A_K}$ and $\mathrm{A_L}$, the following equation must be calculated (Triantaphyllou, et al., 1998):

$$R\left(\frac{A_k}{A_L}\right) = \prod_{j=1}^{N} \left(\frac{a_{Kj}}{a_{Lj}}\right)^{w_j} \quad (1.5)$$

where: N is the number of criteria, $a_{\ Kj}$ is the actual value of the i-th alternative with respect to the j-th criterion, and w_j is the importance weight of the j-th criterion.

1.3. Conclusions

As a result of the overview analysis of the business processes, phases and tasks of digital transformation, the following conclusions can be drawn.

- The adoption of digital technologies in various business processes has a significant impact on the efficiency, productivity and competitiveness of organizations. These technologies not only enable faster and more efficient access to customers, but also facilitate internal processes and risk management, thus creating a solid foundation for sustainable development.
- Digital transformation requires new employee skills, and infrastructure, along with employee skills, are among the main factors influencing digital transformation processes. The successful integration of new technologies into organizations is directly proportional to the level of digital maturity of organizations.
- The conditions of complexity and diversity of factors that need to be taken into account predetermine the important role of decision support methods. They provide an effective way to deal with the variety of problems that both organizations and individuals face. With the increasing importance of data analysis and intelligent systems in decision-making processes, MCDM methods continue to play a key role in optimizing decisions at various levels of management and strategic planning.

Based on the analysis of the processes related to digital transformation and the analysis of appropriate techniques for supporting decision-making, this dissertation research aims to propose models leading to the evaluation and improvement of digital transformation processes.

1.4. Purpose and objectives

The aim of the dissertation is to study business processes related to digital transformation, on the basis of which to propose appropriate mathematical models supporting decision-making and leading to improvement of digital transformation processes. To achieve this goal, the following tasks need to be completed:

1) to analyze the main business processes and elements, the presence of which is a prerequisite for successful digital transformation;
2) to identify key indicators for assessing the progress of digital transformation;
3) to propose a model for assessing the progress of digital transformation, taking into account both objective and subjective indicators;
4) to propose a model for supporting the work of the person driving digital transformation;
5) to propose a model for selecting the person driving digital transformation.

CHAPTER 2. DECISION-SUPPORTING MODELS IN VARIOUS PROCESSES RELATED TO DIGITAL TRANSFORMATION

This chapter of the dissertation describes the proposed models that support decision-making in various processes related to digital transformation.

2.1. An integrated approach to assessing the progress of digital transformation using multiple objective and subjective indicators

Regardless of the field of application, the general goal of digital transformation is to improve efficiency, value or innovation. The measures that influence the digital transformation of SMEs can be represented by the four groups (Schuh et al., 2017), referring to: 1) resources, 2) information systems, 3) organizational structure and 4) culture.

Digital transformation can be measured by how an organization uses IT, people, and processes to realize new business models and revenues, motivated by customer expectations for products and services. There are several key positions whose integration is key to the digitalization of the company:

1) Chief Information Officer (CIO),

2) Chief Information Security Officer (CISO),
3) Chief Technology Officer (CTO) and
4) Chief Digital Officer (CDO).

For different companies, some of these roles may be combined or may be considered with different importance due to the company's focus. For example, for a business-oriented company, the most important is the CIO, for a technology-oriented company, the most important is the CTO, for a digitally-oriented company, the most important is the CDO.

2.1.1. Role and hierarchy of the chief information officer, chief information security officer, chief technology officer and chief digital officer

The Chief Information Officer (CIO) is the executive director of the company, responsible for the management, implementation and usability of information and computer technology.

The Chief Technology Officer (CTO) is an executive-level person who focuses on creating and implementing appropriate company policies in accordance with scientific needs to achieve business objectives. The responsibilities of the CTO are focused on the development of procedures and strategies, R&D, and technology utilization. In the past, the roles of the CIO and CTO were performed by the CTO. Empirical results reveal a positive relationship between gender and CTO innovation, and companies with a stronger corporate culture supporting innovation have female CTOs (Wu et al., 2021).

The main responsibilities of the CIO (CISO) relate to information and data security issues by ensuring appropriate prevention and protection against information security attacks, as well as rapid recovery from a security breach (Dhillon et al., 2021).

The role of the Chief Digital Officer (CDO) is related to various activities that enable the transformation of traditional operations into digital processes. Based on a large-scale sample of companies and conducted research, it was found that only about 5% of companies had a CDO by the end of 2018 (Kunisch et al., 2020). Considering the main responsibilities of these managers, the following six combinations and situations can be identified, as shown in Fig. 2.2.

What is common in all these cases shown in Fig. 2.2 is the leading role of the CIO. This means that in a micro-sized or small company situation, the CIO position should be available, even if it is a part-time position

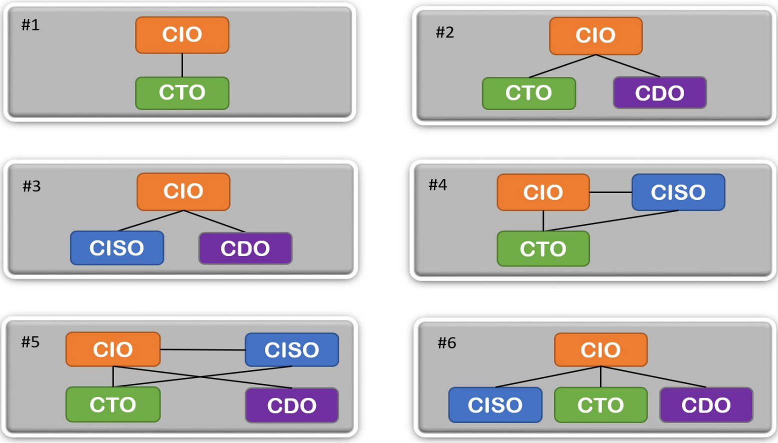


Fig. 2.2. *Relations between CIO, CISO, CTO, and CDO*

2.1.2. Indicators for assessing digital transformation

To assess the success of implementing digital transformation, a set of objective and subjective indicators are proposed to measure the results of digital transformation, as shown in Table 2.1.

Table 2.1. *Evaluation criteria for measuring the effectiveness of business activities in digitalization*

Objective evaluation criteria	Subjective evaluation criteria
IT infrastructure	Strong leadership skills
Successfully implemented market innovations	Strong business communication
Return on investment	Building trust
New Customers	Problem solving
Employee productivity	Time management
	Decision making
	Entrepreneurial mindset
	Strategic thinking

2.1.3. Mathematical model for assessing the state of digital transformation, taking into account objective and subjective indicators

To measure the effectiveness of business activities in digitalization, it is necessary to consider both groups of objective and subjective indicators within a single generalized utility function ($DT^{performance}$) as follows (Borissova et al., 2022):

$$DT^{performance} = \max\{\alpha \sum_{i=1}^{O} w_i e_i + \beta \sum_{j=1}^{S} w_j e_j\} \tag{2.1}$$

$$\alpha + \beta = 1 \tag{2.2}$$

$$\sum_{i=1}^{O} w_i = 1 \tag{2.3}$$

$$\sum_{j=1}^{S} w_j = 1 \tag{2.4}$$

The coefficient α expresses the importance of the objective criteria, and the coefficient β expresses the subjective ones. The coefficients w_i and w_j express the relative importance between objective and subjective indicators, e_i and e_j represent evaluation points for the performance of objective and subjective criteria. The coefficients α and β allow for a more flexible model, taking into account objective and subjective criteria of different importance in the final complex assessment.

2.2. A model for assessing digital transformation based on groups of indicators for operational and organizational readiness and business value

Digital technologies are dramatically reshaping industries, and many companies are undertaking massive change efforts to keep up with competitors. Research shows that digital transformation requires changes in the employee skills that organizations need (Ostmeier & Strobel, 2022). IT infrastructure and employee skill levels are important factors influencing digital transformation processes (Cirillo et al., 2023).

2.2.1. Key indicators for assessing the stages of digital transformation operational readiness, organizational readiness and business value

Key performance indicators play a significant role in determining the progress of digital transformation. There are no universal key performance indicators (KPIs) for measuring progress in digitalization, but it is possible to divide them into groups of indicators related to the stages of (1) operational readiness, (2) organizational readiness, and (3) business value or return (Kimberling, 2022).

2.2.2. Mathematical model for assessing the state of digital transformation, taking into account objective and subjective indicators

This section describes the proposed sequence of steps applicable for the purposes of assessing the progress of the three different stages of digital transformation, as shown in Fig. 2.4.

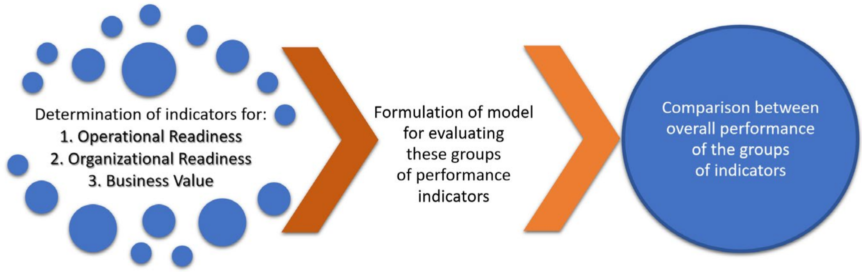


Fig. 2.4. *Stages of digital transformation assessment*

There are no strict indicators for expressing readiness at these stages and therefore the following general indicators for the three groups are proposed, shown in Table 2.2.

Table 2.2. Indicators for measuring the stages of digital transformation

Groups of indicators	Key indicators
Operational readiness	1.1. Number of licenses purchased to the number of users actually using the software 1.2. Number of digital points 1.3. Number of analysis tools used
Organizational readiness	2.1. Number of executives engaged in digital initiatives 2.2. Number of detected cyberattacks 2.3. Number of successfully prevented cyberattacks 2.4. Time to detect and respond to cyber threats
Business value	3.1. Number of successfully implemented innovations 3.2. Number of applications of innovative solutions 3.3. Number of new products or services 3.4. Ratio of funds received due to transformation and spent on it 3.5. Time to market for a new offer

To assess the state of digital transformation (DX), 3 groups of indicators are used, for which maximum productivity is sought (Borissova et al., 2024):

$$DX = \begin{cases} \max OpR \\ \max OrR \\ \max BV \end{cases} \quad (2.5)$$

Subject to

$$OpR = \sum_{i=1}^{I} w_i m_i > 0 \quad (2.6)$$

$$OrR = \sum_{j=1}^{J} w_j m_j > 0 \quad (2.7)$$

$$BV = \sum_{k=1}^{K} w_k m_k > 0 \quad (2.8)$$

$$\sum_{i=1}^{I} w_i = 1 \quad (2.9)$$

$$\sum_{j=1}^{J} w_j = 1 \quad (2.10)$$

$$\sum_{k=1}^{K} w_k = 1 \quad (2.11)$$

The coefficients w_i, w_j and w_k express the relative importance between the indicators in each group, while m_i, m_j and m_k represent the quantity of measurable indicators. Metrics for measurable indicators can be expressed in different units, which requires their normalization.

Over time, the value of measurable indicators for operational readiness should increase, as this is one of the main prerequisites for implementing digital transformation. The same applies to the second group of indicators, which show the extent to which managers are engaged in digitalization activities and how well this digital data is protected. Good performance of indicators from these two groups is a prerequisite for good performance of indicators from the third group, related to business value.

It should be noted that in the model (2.5) – (2.11), all indicators must be measurable. However, it is permissible to use non-measurable indicators, the measure of which can be the assessment given by an authorized person.

2.3. Models supporting the work of the chief information officer in the digital transformation process

Today, the role of the chief information officer (CIO) is changing rapidly. CIOs, together with top managers, must discuss the challenges and requirements for strategic IT innovation and select appropriate and reliable software tools to support IT (Gogan et al., 2020).

2.3.1. A model for group decision-making through rapid evaluation and selection of software tools for collaborative remote work

The mathematical model for evaluating and selecting software tools for collaborative remote work can be expressed similarly to the classical weighted sum (SAW) model and the modified SAW (Korsemov & Borissova, 2018). Instead of using estimates, the proposed mathematical model (M-1) considers the parameters of the software tools as variables (Borissova et al., 2022):

$$max A_i = \sum_{e=1}^{E} \lambda^e \sum_{j=1}^{N} w_j^e p_{ij} \, , \; i = \{1,2,\dots,M\} \quad (2.12)$$

$$\sum_{j=1}^{N} w_j^e = 1 \quad (2.13)$$

$$\sum_{e=1}^{E} \lambda^e = 1 \tag{2.14}$$

where the index $i = 1, \dots, M$ is used to represent the number of alternatives; the evaluation criteria are denoted by the index j = 1,…,N; the performance of the parameters of the i-th alternative with respect to the j-th criterion is expressed by p_{ij}; the coefficients expressing the importance of the j-th criterion with respect to the e-th expert opinion are w_j^e; and the weighted coefficients λ^e express the importance of the e-th expert opinion.

The efficiency of alternatives is the sum of the multiplication of the parameter efficiency, taking into account the opinions of experts in relation to (2.12). The most suitable suitable alternative should have maximum performance.

2.3.2. A group decision-making model using combinatorial optimization for simultaneous evaluation and selection of multiple remote collaboration software tools

The second modeling approach is also based on SAW, but the utility function includes two additional types of coefficients. The first of them represents binary integer variables for selecting the best alternative(s) as the final group decision, while the second type of coefficients expresses the importance of the experts' opinions. Taking into account these additional considerations, the simultaneous evaluation and selection of several remote collaboration software tools can be implemented through the following group decision-making model (M-2), as follows (Borissova et al., 2022):

$$max\left(\sum_i^M x_i \left(\sum_{e=1}^{E} \lambda^e A_i^e\right) + \sum_s^S y_s \left(\sum_{e=1}^{E} \lambda^e A_s^e\right) + \sum_t^T z_t \left(\sum_{e=1}^{E} \lambda^e A_t^e\right)\right) \tag{2.15}$$

Subject to

$$\forall i = 1,2, \dots, M: (\forall e = 1,2, \dots, E: A_i^e = \sum_j^N w_j^e a_{i,j}^e) \tag{2.16}$$

$$\forall s = 1,2, \dots, S: (\forall e = 1,2, \dots, E: A_s^e = \sum_p^P w_p^e a_{s,p}^e) \tag{2.17}$$

$$\forall t = 1,2, \dots, T: (\forall e = 1,2, \dots, E: A_t^e = \sum_q^Q w_q^e a_{t,q}^e) \tag{2.18}$$

$$\sum_{i=1}^{M} x_i = 1, x_i \in \{0,1\} \tag{2.19}$$

$$\sum_{s=1}^{S} y_s = 1, y_s \in \{0,1\} \tag{2.20}$$

$$\sum_{t=1}^{T} z_t = 1, z_t \in \{0,1\} \tag{2.21}$$

$$\sum_{j=1}^{N} w_j^e = 1 \tag{2.22}$$

$$\sum_{p=1}^{P} w_p^e = 1 \tag{2.23}$$

$$\sum_{q=1}^{Q} w_q^e = 1 \tag{2.24}$$

$$\sum_{e=1}^{E} \lambda^e = 1 \tag{2.25}$$

where A_i^e expresses the total evaluation of the *i*-th alternative against all criteria, taking into account the point of view of the e-th expert, and respectively for the next two types of choices A_s^e and A_t^e, while $a_{i,j}^e$ denotes the evaluation result by the e-th expert for the i-th alternative to the j-th criterion and the evaluation scores for the remaining two types of choices are $a_{s,p}^e$ and $a_{t,q}^e$, respectively. Relations (2.19) – (2.21) guarantee only one choice from each type of software and are based on three types of binary integer variables for each type of software. The weighted coefficients representing the importance of the criteria for the different selection groups are expressed by the equalities (2.22) – (2.24). The last expression (2.25) shows that the sum of the weighted coefficients for the importance of the experts' opinions must be exactly equal to 1.

2.4. Model for group assessment and selection of a candidate for the position of Chief Digital Transformation Manager

Developing leadership skills that foster data-driven decision-making, collaborative problem-solving, and adaptive management is crucial (Seppanen et al., 2025). The leadership role of CIO s requires building digital capabilities that contribute to digital acceleration, digital marketing, and digital alignment, related to digital innovation, data analytics, and customer engagement (Tumbas et al., 2017). It should be noted that while CIO s have a stronger focus on technical aspects and IT efficiency, CIO s are more business and strategic oriented (Ulrich & Lehmann, 2023).

2.4.1. Responsibilities, tasks, technical and software skills for the position of Chief Digital Transformation Manager

Several key areas such as IoT, social media, mobile applications, artificial intelligence, augmented and virtual reality, metaverse and corporate digital responsibility are at the core of digital transformation (Fynn-Hendrik et al., 2024). The combination of strong leadership skills and technical expertise can define the ideal CIO candidate. The CIO is also known as a digital director or digital transformation manager and must handle a variety of tasks, summarized in 4 main directions, as shown in Fig. 2.5.

The important positioning of the CDO due to their influence in the organization motivates the need to select the right candidate who can go beyond the scope of their past and current successes. Thus, assessing potential in addition to current performance is crucial for the successful recruitment of digital strategists and CDO.

Fig.2.5. *Responsibilities of the CDO*

2.4.2. Model for selecting the person driving digital transformation - a model for group decision-making when selecting a chief digital transformation manager

The basic formulation of the multi-criteria decision-making problem is usually expressed in the following matrix format (Shih et al., 2007):

$$\begin{array}{c} \\ A_1 \\ \dots \\ A_m \end{array}\begin{array}{c} C_1 \quad \dots\dots \quad C_n \\ \begin{bmatrix} r_{11}^k & \cdots & r_{1n}^{k1} \\ \vdots & \ddots & \vdots \\ r_{m1}^k & \cdots & r_{mn}^k \end{bmatrix} \end{array} \begin{array}{c} \\ \begin{bmatrix} w_1^k \\ \dots \\ w_n^k \end{bmatrix} \end{array} \tag{2.26}$$

where the alternatives (candidates for the GDM) are denoted by $A_1, \dots A_m$, the evaluation criteria are expressed by $C_1, \dots C_n$, the effectiveness of the alternative A_m with respect to the criterion C_n by the k-th expert is represented by r_{mn}^k, and w_n^k are coefficients for the importance of the n-th criterion given by the k-th expert.

In order to make an effective selection of the most preferred candidate according to the opinions of the entire group, the evaluations of each member of the group should be considered with different importance. For this purpose, the following optimization model is proposed:

$$CDO^* = max\left\{\left(\alpha^1 \begin{bmatrix} r_{11}^1 & \cdots & r_{1n}^1 \\ \vdots & \ddots & \vdots \\ r_{m1}^1 & \cdots & r_{mn}^1 \end{bmatrix}\begin{bmatrix} w_1^1 \\ \dots \\ w_n^1 \end{bmatrix}\right) + \cdots + \left(\alpha^k \begin{bmatrix} r_{11}^k & \cdots & r_{1n}^{k1} \\ \vdots & \ddots & \vdots \\ r_{m1}^k & \cdots & r_{mn}^k \end{bmatrix}\begin{bmatrix} w_1^k \\ \dots \\ w_n^k \end{bmatrix}\right)\right\}^i \tag{2.27}$$

Subject to

$$\sum_{k=1}^{K} \alpha^k = 1 \tag{2.28}$$

$$\sum_{j=1}^{N} w_j = 1 \tag{2.29}$$

where α^k denotes a weighting factor that expresses the level of expertise/importance of the k-th expert. Given the ratios (2.28) and (2.29), the range of evaluation points is between 0 and 1 in order to obtain comparable values for the three parameters.

In the proposed model (2.27) – (2.29) all hard and soft skills are considered with equal importance. If it is necessary to distinguish these skills, additional coefficients for technical knowledge and soft skills should be introduced. In order to select the most suitable candidate for the CDO position, the use of two types of groups of evaluation criteria is proposed, relating to hard and soft skills. These two groups of evaluation criteria are shown in Table 2.3.

Table 2.3. Criteria for assessing the technical and soft skills of candidates for the CDO

#	Hard skills	#	Soft skills
t-1	Broad technological awareness	**s-1**	Communication
t-2	Understanding digital structures and products	**s-2**	Leadership
t-3	Diploma in Business/Technology/Engineering	**s-3**	Responsibility and perseverance
t-4	Data analysis and problem-solving ability	**s-4**	Time management
t-5	Leadership of successful digital transformation projects.	**s-5**	Emotional intelligence
t-6	Experience in managing and leading a digital team	**s-6**	Collaboration and teamwork
		s-7	Strategic thinking

CHAPTER 3. NUMERICAL TESTING OF THE PROPOSED DECISION-MAKING MODELS RELATED TO DIGITAL TRANSFORMATION

This chapter describes the results of the numerical experiments conducted with the proposed mathematical models described in Chapter 2.

3.1. Numerical testing of the proposed integrated approach to assess the progress of digital transformation using multiple objective and subjective indicators

To assess the digitalization process, the CEO assigned ratings to the IT director's performance, as the test was conducted in a micro-company with an IT director.

3.1.1. Input data for numerical testing

The predefined and provided ratings for business activities related to digital transformation, along with the importance weights of the criteria, as described in section 2.1, are shown in Table 3.1.

Table 3.1. Evaluation points and corresponding weights for objective and subjective criteria.

Criteria		Importance weights		Rating points	Case-1	Case-2	Case-3
Objective evaluation criteria		w_i (S-1)	w_i (S-2)	e_i	α	α	α
o-1	IT infrastructure	0.25	0.12	0.65	0.50	0.45	0.55
o-2	Successfully implemented market innovations	0.25	0.15	0.45			
o-3	Return on investment	0.25	0.26	0.54			
o-4	New Customers	0.25	0.23	0.58			
o-5	Employee productivity	0.25	0.24	0.55			
Subjective evaluation criteria		w_j	w_j	e_j	β	β	β
s-1	Strong leadership skills	0.125	0.13	0.57	0.50	0.55	0.45
s-2	Strong business communication	0.125	0.15	0.78			
s-3	Building trust	0.125	0.12	0.44			
s-4	Problem solving	0.125	0.14	0.80			
s-5	Time management	0.125	0.11	0.56			
s-6	Decision making	0.125	0.13	0.93			
s-7	Entrepreneurial mindset	0.125	0.09	0.78			
s-8	Strategic thinking	0.125	0.13	0.81			

Two scenarios of importance of sub-criteria (S-1 and S-2) and three cases are presented, which express different preferences regarding objective and subjective evaluation criteria. It should be noted that all evaluations given in Table 3.1 are subjective and reflect the specific point of view of the participating CEO from a specific company. Therefore, these data are valid only for this company. Using these input data from the table above, several optimization problems are solved based on the proposed model (2.1) – (2.4). The obtained results are illustrated and discussed in the next section.

3.1.2. Numerical testing results

The results of scenario S-1, where all objective and subjective sub-criteria are considered with equal importance, are further considered in 3 different cases for importance between objective and subjective indicators, as shown in Fig. 3.1.

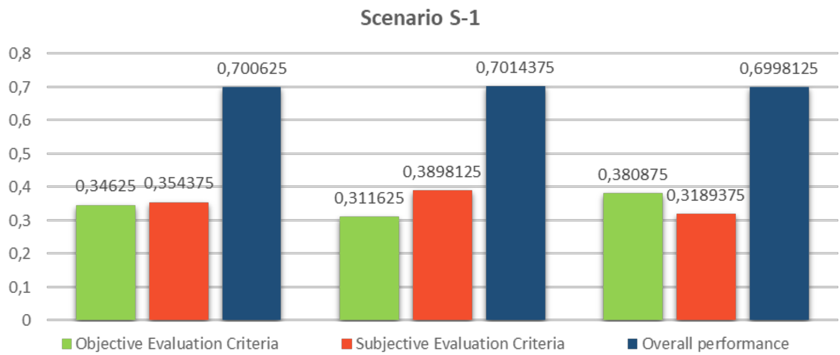


Fig. 3.1. *Comparison of results under scenario S-1*

From Fig. 3.1 it can be seen that the effectiveness of objective criteria in case-1 and case-2 has lower results compared to the effectiveness of subjective criteria for the same cases. The situation expressed by case-3, where more importance is given to objective criteria by using coefficient α=0.55, the results show higher results (0.380875) of objective criteria.

By combining objective and subjective criteria, the overall performance of the company's progress in digital transformation can be assessed. This assessment may vary depending on the given preferences for the importance of objective and subjective criteria. For example, if the objective and subjective criteria are considered with equal importance α=β=0.50 (case-1), the total score is 0.700625, if more importance is given to the subjective criteria α=0.45,β=0.55 (case-2), the score is 0.7014375 and vice versa in case-3 α=0.55,β=0.45 with the total score being 0.6998125. The results of scenario S-2, where the sub-criteria are considered with different importance and the importance of the objective and subjective groups considered in 3 different cases, are shown in Fig. 3.2.

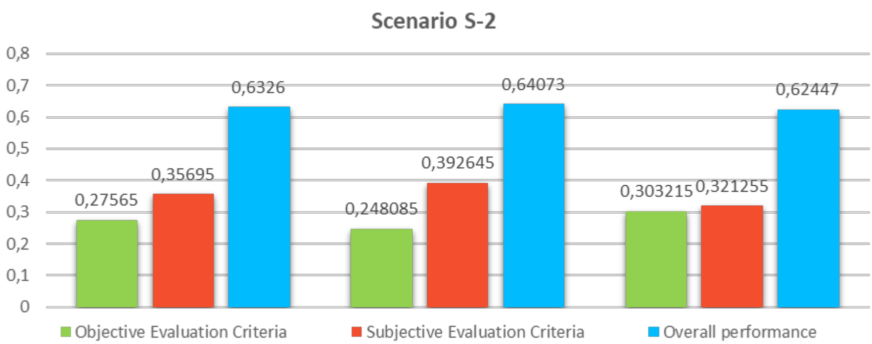


Fig. 3.2*. Comparison of results under scenario S-2*

The effectiveness of objective criteria in all 3 cases (0.27565; 0.248085; 0.303215) has a lower value compared to the effectiveness of subjective criteria (0.35695; 0.392645; 0.321255). The overall performance in case-1 ($\alpha = \beta$ =0.50) is equal to 0.6326, for case-2 (α =0.45,β=0.55) the result is 0.64073, and for case-3 (α =0.55, β = 0.45) the overall result is 0.62447.

For the two different scenarios described above in three different cases for the importance of objective and subjective criteria for the overall presentation of the company's progress, a comparison was made, which is shown in Fig. 3.3.

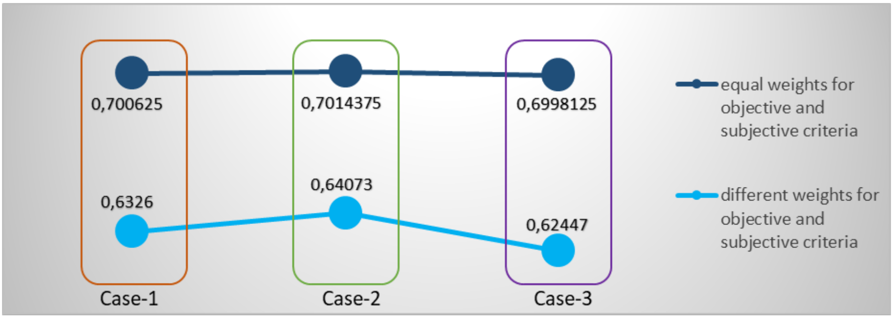


Fig. 3.3. *Comparison of overall performance under 2 different preferences regarding the weights of subjective and objective criteria for 3 cases*

Considering the objective and subjective criteria of equal importance (Case-1) in both scenarios (S-1 & S-2), the results obtained show a difference of 0.068025 for the overall performance of the company. For Case-2, this difference is 0.0607075 and for Case-3, the difference is 0.0753425, respectively.

The results obtained show that digital transformation can be measured using information about the available IT, the managers involved and the new business processes, as well as the revenues from improved products and services. Based on the main responsibilities of the CIO, CISO, CTO and CDO, a set of different objective and subjective criteria is identified that influence the digital transformation process. The results prove the effectiveness of the proposed model, as well as the suitability of the defined two groups of objective and subjective criteria for evaluation.

3.2. Numerical testing of the proposed model for assessing digital transformation, based on groups of indicators for operational and organizational readiness and business value

For the numerical testing of the proposed model (2.5) – (2.11), the CDO has provided information on the performance indicators relevant to a micro-company. To solve the multi-criteria model (2.5) – (2.11), the weighted sum method is used, which requires the transformation of the multi-criteria objective function (2.5) into a single-criteria function, as follows:

$$max\left(w_i\left(\frac{OpR^{max}-OpR}{OpR^{max}-OpR^{min}}\right)+w_j\left(\frac{OrR^{max}-OrR}{OrR^{max}-OrR^{min}}\right)+w_k\left(\frac{BV^{max}-BV}{BV^{max}-BV^{min}}\right)\right) \tag{3.1}$$

The rest of the restrictions remain the same.

3.2.1. Output data for numerical testing

The normalized data for the measurable indicators by groups together with the weighted coefficients for their importance are shown in Table 3.9.

Table 3.9. Normalized metrics for indicators and weights for their importance.

Key indicators	Normalized indicators	Key Indicator Importance Weights (Case-1)			Weights for the importance of key indicators (Case 2)		
	m_i, m_j, m_k	w_i	w_j	w_k	w_i	w_j	w_k
1.1. Number of licenses purchased to the number of users actually using the software	1.00	0.33			0.20		
1.2. Number of digital points	0.00	0.33			0.40		
1.3. Number of analysis tools used	0.067	0.34			0.40		
2.1. Number of executives engaged in digital initiatives	0.001		0.25			0.50	
2.2. Number of detected cyberattacks	0.00		0.25			0.10	
2.3. Number of successful cyberattacks prevented	0.00		0.25			0.15	
2.4. It's time to detect and respond to cyber threats	1.00		0.25			0.25	
3.1. Number of successfully implemented innovations	0.002			0.20			0.15
3.2. Number of applications of innovative solutions	0.005			0.20			0.15
3.3. Number of new products or services	0.007			0.20			0.10
3.4. The ratio of funds received due to transformation and spent on it	0.010			0.20			0.40
3.5. Time to market for a new offer	1.000			0.20			0.20

The normalized input data from Table 3.9 and the proposed model (2.5) – (2.11), respectively the transformed objective function (3.1) subject to the constraints (2.6) – (2.11) are used to formulate an optimization problem.

3.2.2. Analysis of results and discussion

The results of the two tested situations (Case-1 and Case-2) regarding the prioritization of indicators according to different perspectives for the key indicators within 3 groups (respectively 3 stages) are illustrated in Fig. 3.5.

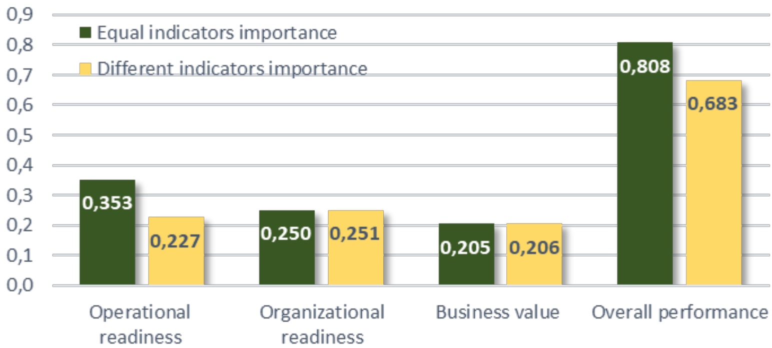


Fig. 3.5. *Comparison of results using different weights for importance indicators*

Fig. 3.5 shows the difference in overall performance when using different weighted coefficients for the indicators – the value of 0.808 with equal importance of all indicators and 0.683, when some indicators are preferred over others. These values do not provide complete information about the progress of the digital transformation, so it is good to pay attention to the individual groups of indicators.

In case 1 (with equal weights for the key indicators) operational readiness has a better performance with the resulting value equal to 0.353 compared to organizational readiness, whose value is 0.250, and the business value is 0.205, despite the missing activities for "Number of digital points" and "Number of detected cyberattacks" and "Number of prevented successful cyberattacks".

When some metrics are preferred over others, as in Case-2, the results show a better performance for organizational readiness (0.251) compared to operational readiness (0.227) and business value (0.206). In this situation, it cannot be expected that the digital transformation will succeed, since the business processes and technologies are not well aligned before their implementation.

Using such models, it is possible to predict the failure or success of the digital transformation, since it focuses not only on the organization's ability to implement new technologies and software, but also on its people, culture, processes, etc.

3.3. Testing the proposed models supporting the work of the chief information officer in the digital transformation process

This section describes the numerical testing of the proposed models supporting the work of the CIO in the digital transformation process, according to item 2.3 (Chapter 2).

3.3.1. Output data

Among the existing videoconferencing platforms, 5 were selected, the main parameters of which used during the evaluation are given in Table 3.2.

Table 3.2. Parameters of videoconferencing tools

Parameters	Video conferencing tools					
	Zoom	Webex	Skype	Google Hangouts	UMeetin	Lifesize
Number of participants	100	100	50	25	25	25
HD video	yes	--	yes	--	--	--
HD audio	yes	--	--	--	--	--
Screen sharing	yes	yes	yes	yes	--	yes
Group chat	yes	--	yes	yes	--	yes
Video meeting recordings	yes	yes	yes	yes	--	--
Meeting time limit	40 min	40 min	unlimited	unlimited	30 min	24 hour

Learning Management Systems (LMS) are applicable in the field of education and business training due to their numerous advantages (Chtouka et al., 2019). The main parameters of some free and popular LMS are shown in Table 3.3.

Table 3.3. Learning Management Systems (LMS) Parameters

Parameters	Learning Management Systems			
	Moodle	Chamilo	ILIAS	Forma LMS
SCORM 1.2	yes	yes	yes	yes
SCORM 2004	yes	--	yes	yes
xAPI	yes	--	--	--
Mobile application	yes	yes	--	--
Self-Hosted Cloud-based	yes	yes	--	--
Self-Hosted System	yes	yes	--	yes
SaaS/Cloud	--	yes	yes	yes
WordPress	--	yes	--	yes
Google Calendar	--	yes	--	yes

The main parameters of a predefined set of project management (PM) software products are given in Table 3.4.

Table 3.4. Project management tool parameters

Parameters	Project management tools			
	Jira	Bitrix24	Infolio	GitHub
Limit on collaborators	Up to 10	Up to 12	Unlimited	Unlimited
Storage limit	2 GB	5 GB	1 GB	0.5 GB
Custom workflow	yes	yes	yes	--
Tracking timeline	yes	yes	--	--
Calendar	yes	yes	yes	--
Chat	yes	yes	yes	yes
Portfolio management	--	yes	--	yes
Gantt chart	--	yes	--	--
Version control	--	--	--	yes

All of the presented PM alternatives can be implemented and implemented as software as a service (SaaS), including a mobile application interface.

3.3.2. Numerical testing results

The software tools are evaluated by a formed group that includes a CIO (E-1), IT (E-2) and an expert from the digital services team (E-3). To make a group decision, each expert has determined the corresponding coefficients expressing the relative importance between the criteria (parameters) for evaluating the videoconferencing tools given in the first 3 rows of Table 3.5, and the remaining rows contain the points for the evaluations of each alternative against the criteria.

For the first modeling approach (2.12) – (2.14) the normalization is in the range between 0 and 1. The supported maximum number of participants is chosen to be equal to 1 and the same applies to the duration of the video conference, expressed as “unlimited”. The other values are normalized proportionally. The weighting coefficients for the importance of the criteria together with the evaluation points of the alternatives against the LMS criteria are shown in Table 3.6.

Table 3.5. Weighting factors for the criteria and evaluations of the alternatives concerning videoconferencing tools, determined by a group of 3 experts

Experts and alternatives	Number of participants	HD video	HD audio	Screen sharing	Group chat	Video meeting recordings	Meeting time limit
	w_1	w_2	w_3	w_4	w_5	w_6	w_7
E-1	0.2	0.08	0.07	0.13	0.05	0.15	0.32
E-2	0.1	0.13	0.18	0.15	0.07	0.15	0.22
E-3	0.13	0.1	0.2	0.19	0.1	0.08	0.2
A-1	0.78	0.91	0.93	0.98	0.79	0.69	0.19
A-2	0.65	0.12	0.15	0.92	0.21	0.70	0.08
A-3	0.50	0.89	0.12	0.95	0.81	0.66	0.97
A-4	0.25	0.11	0.19	0.90	0.73	0.62	0.94
A-5	0.25	0.09	0.07	0.02	0.31	0.11	0.06
A-6	0.25	0.05	0.10	0.89	0.84	0.13	0.81

Table 3.6. Weighting factors for the criteria and evaluations of the alternatives related to LMS, determined by a group of 3 experts

Experts & Alternatives	**Supported specifications**								
	SCORM 1.2	SCORM 2004	xAPI	Mobile application	Self-hosted cloud-based	Self-hosted system	SaaS / Cloud	Word press	Google Calendar
	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9
E-1	0.08	0.15	0.16	0.12	0.09	0.13	0.07	0.10	0.10
E-2	0.07	0.13	0.17	0.11	0.08	0.20	0.10	0.08	0.06
E-3	0.07	0.10	0.05	0.10	0.13	0.15	0.10	0.10	0.20
A-1	0.88	0.94	0.94	0.86	0.95	0.92	0.15	0.72	0.13
A-2	0.84	0.17	0.27	0.90	0.88	0.90	0.92	0.89	0.92
A-3	0.91	0.79	0.25	0.42	0.25	0.21	0.88	0.15	0.09
A-4	0.92	0.88	0.23	0.18	0.31	0.88	0.91	0.75	0.69

The expert-determined weighted coefficients for the relative importance between the criteria together with the evaluation scores of the alternatives regarding the PM criteria are shown in Table 3.7.

Table 3.7. Weighting factors for the criteria and alternative assessments related to PM instruments, determined by a group of 3 experts

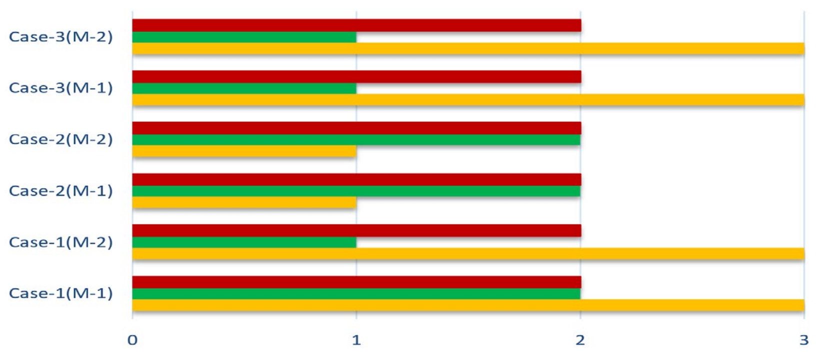
Experts & Alternatives	Employees limit	Storage limit	Custom workflow	Tracking timeline	Calendar	Chat	Portfolio management	Gantt chart	Version control
	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9
E-1	0.09	0.1	0.05	0.18	0.19	0.05	0.1	0.11	0.13
E-2	0.18	0.09	0.07	0.07	0.07	0.1	0.02	0.13	0.27
E-3	0.12	0.1	0.17	0.14	0.17	0.06	0.02	0.11	0.11
A-1	0.1	0.4	0.83	0.93	0.79	0.76	0.2	0.14	0.25
A-2	0.12	0.9	0.92	0.88	0.84	0.86	0.93	0.98	0.12
A-3	0.95	0.2	0.87	0.23	0.91	0.72	0.17	0.11	0.19
A-4	0.98	0.1	0.12	0.21	0.11	0.92	0.88	0.09	0.99

The results obtained for the selected combination of VCT, LMS and PM using both approaches together with the significance coefficients of the experts' opinions under three scenarios are shown in Table 3.8.

Table 3.8. Group decision for the selected combination of VCT, LMS and PM under three scenarios for the importance of experts' opinions

	E-1	E-2	E-3	Model M-1			Model M-2		
				VCT	LMS	PM	VCT	LMS	PM
Case-1	0.33	0.33	0.34	A-3	A-2	A-2	A-3	A-1	A-2
Case-2	0.20	0.35	0.45	A-1	A-2	A-2	A-1	A-2	A-2
Case-3	0.50	0.40	0.10	A-3	A-1	A-2	A-3	A-1	A-2

Case-1 represents the scenario where the opinions of the experts are of equal importance; Case-2 illustrates a scenario with the most important opinion of expert E-3, followed by E-2 and E-1, while Case-3 emphasizes the opinion of expert E-1, followed by E-2 and then E-3. The empirical comparison of the results using model M-1 and M-2 at the same criteria importance coefficients e w_j^e, along with the parameter estimates for VCT, LMS and PM from Table 3.6, Table 3.7 and Table 3.8 are graphically presented in Fig. 3.4.



	Case-1(M-1)	Case-1(M-2)	Case-2(M-1)	Case-2(M-2)	Case-3(M-1)	Case-3(M-2)
PM	2	2	2	2	2	2
LMS	2	1	2	2	1	1
VCT	3	3	1	1	3	3

Fig. 3.4. *Comparison of the results of two group decision-making models*

The first modeling approach (2.12) – (2.14), based on the parameters of the software tools used as variables and expressed by 0 or 1, if the functional characteristics are present or not, is suitable for fast group decision-making.

The second modeling approach (2.15) – (2.25) requires more attention to evaluation in terms of the use of a scale to obtain a result expressing the performance of the alternatives against given criteria. The advantage of this modeling approach is the fact that the optimal choice of the interesting combination of software elements is obtained as a single execution of the optimization task.

Despite the difference between the described approaches, both can be successfully applied to group decision-making. Depending on the chosen strategy, which is the basis of each of the models, it is possible to use one of them at different stages to determine the reasonable group decision.

3.4. Numerical testing of the proposed model for group decision-making in the evaluation and selection of candidates for the position of Chief Digital Transformation Manager

The proposed mathematical model (2.27) – (2.29) for group decision-making in the selection of a CDO, described in Galav 2, item 2.4, is tested numerically, with the formed decision-making group including the following experts: a CEO who formulates business goals and makes strategic decisions (E-1), a human resources expert (E-2) and a chief technology officer (E-3). Unlike soft skills, hard skills can be measured and therefore in this numerical testing they are considered to be already assessed and available and normalized. A degree in business, technology, engineering or project management can be proven through relevant certificates, etc.

3.4.1. Input data for numerical testing

5 candidates have applied for the position of CDO, who must be ranked according to the formed summary assessment according to a group of 3 experts. It should be noted that the specific example concerns the selection of CDO for a small company, the activity of which is related to trade. The pre-determined assessments of hard skills together with the corresponding weights for their importance according to the experts' points of view are presented in Table 3.10.

Table 3.10. Ratings and weights for candidates' hard skills determined by a group of 3 experts

Technical skills	Candidates					Weights for hard skills		
	1	2	3	4	5	E-1	E-2	E-3
t-1	0.8	0.85	0.78	0.79	0.84	0.100	0.080	0.090
t-2	0.77	0.85	0.8	0.85	0.75	0.100	0.085	0.095
t-3	0.87	0.78	0.75	0.68	0.7	0.085	0.050	0.070
t-4	0.8	0.82	0.86	0.76	0.84	0.070	0.090	0.080
t-5	0.78	0.75	0.85	0.69	0.85	0.075	0.070	0.080
t-6	0.76	0.73	0.8	0.84	0.67	0.060	0.100	0.080

The soft skills assessments from the interview conducted along with the coefficients for their importance according to each expert are shown in Table 3.11.

Since the proposed model is based on group decision-making, 3 different scenarios were simulated. These scenarios represent 3 specific cases of different combinations regarding the importance of experts' opinions, as shown in Table 3.12.

Table 3.12. Different cases for combining expert opinions

Cases	Weight for the importance of expert opinion		
	E-1	E-2	E-3
Case -1	0.333	0.333	0.333
Case -2	0.20	0.35	0.45
Case -3	0.45	0.30	0.25

Table 3.11. Scores and weights for candidates' soft skills determined by a group of 3 experts

Soft skills	Candidates					Soft skills weights
	1	2	3	4	5	
			E-1: ratings			
s-1	0.68	0.75	0.67	0.7	0.7	0.085
s-2	0.69	0.78	0.82	0.8	0.8	0.08
s-3	0.75	0.65	0.7	0.8	0.75	0.06
s-4	0.7	0.72	0.73	0.75	0.75	0.07
s-5	0.8	0.67	0.76	0.8	0.78	0.075
s-6	0.8	0.75	0.8	0.82	0.76	0.075
s-7	0.68	0.73	0.82	0.85	0.72	0.065
			E-2: ratings			
s-1	0.72	0.65	0.7	0.85	0.68	0.08
s-2	0.78	0.75	0.73	0.78	0.75	0.07
s-3	0.66	0.8	0.7	0.7	0.65	0.075
s-4	0.85	0.73	0.72	0.65	0.85	0.08
s-5	0.82	0.78	0.67	0.75	0.82	0.065
s-6	0.75	0.72	0.75	0.8	0.75	0.075
s-7	0.78	0.73	0.75	0.67	0.75	0.08
			E-3: ratings			
s-1	0.72	0.74	0.82	0.72	0.78	0.07
s-2	0.68	0.72	0.75	0.67	0.82	0.09
s-3	0.72	0.75	0.7	0.75	0.85	0.065
s-4	0.7	0.72	0.8	0.76	0.72	0.07
s-5	0.8	0.67	0.75	0.85	0.77	0.06
s-6	0.75	0.75	0.75	0.82	0.75	0.07
s-7	0.75	0.68	0.65	0.78	0.82	0.08

3.4.2. Analysis of results and discussion

The results for the simulated 3 cases regarding the importance of experts' opinions on the combination of technical and soft skills are shown in Fig. 3.6.

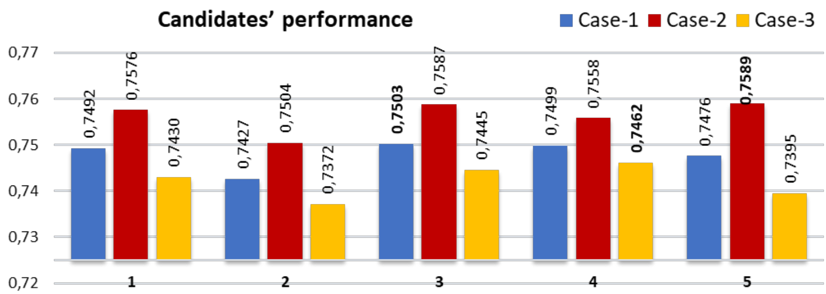


Fig. 3.6. *Comparison of the simulated 3 different cases of group decision making*

Using Case-1, where all experts' opinions are given equal importance, the most suitable candidate for the CDO position is candidate #3. When simulating the situation of Case-2 (Table 3.12), with the predominant importance of E-3, the results show another suitable candidate below #5, considering the aggregated preferences of all experts. In the situation determined by Case -3 of Table 3.12, the results show that the most suitable candidate for the CDO position is #4 with a total value of 0.7462.

It is interesting how each expert rated the candidates and who was the best choice according to their preferences. The answer to this question regarding the best candidate according to the individual preferences of the experts in the group is illustrated in Fig. 3.7.

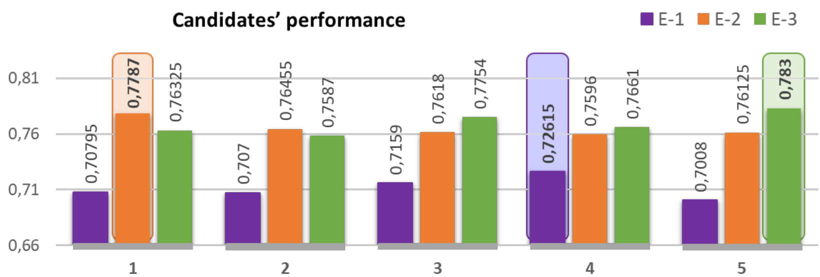


Fig. 3.7. *Comparison between individual choices for the CDO position*

The comparison between the selected candidates in the group decision-making scenarios and the selected candidates according to the individual preferences of the experts in the group is shown in Fig. 3.8.

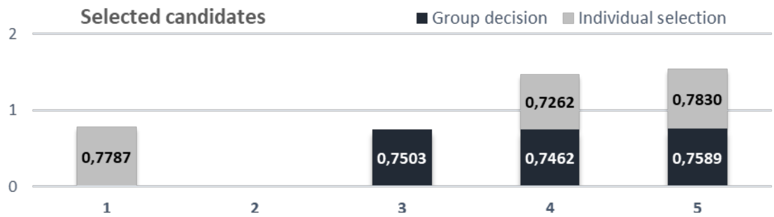


Fig. 3.8. *Comparison between group decisions and individual choices for the CDO position according to different experts*

From Fig. 3.8 it can be seen that there are 2 candidates (#4 and #5) who are the preferred choice of both individual experts and as a result of a formed group decision. Although candidate #1 is not among those selected in the group decision (see Fig. 3.8), he is the preferred choice according to the point of view of expert E-2 for the CDO position. Therefore, by appropriately aggregating the different points of view of multiple experts, it is possible to determine the most suitable candidate for the CDO position. This choice can be considered as sufficiently objective, since it is able to integrate the different views of the experts regarding the ideal candidate for the CDO position.

The proposed model for group decision-making can be easily modified by adding or reducing some of the evaluation criteria. In addition, it is possible to use a different number of experts for group decision-making. By changing some of the technical and/or soft skills, it is possible to select suitable candidates for other or similar positions. In this way, it is possible to improve progress in digitalization, which in turn contributes to better economic sustainability.

CONCLUSION – SUMMARY OF THE RESULTS OBTAINED

Digital transformation with its processes and stages is primarily a management task related to the use of digital technologies to create new or modify existing business processes, culture and customer experience in order to meet changing business and market requirements. This process of transforming business in the digital era expresses the essence of digital transformation. The resulting innovations and modifications of business models have fundamentally changed consumer expectations and behavior, putting enormous pressure on companies. On the one hand, this is due to the continuous progress of information technologies and the infrastructure used. On the other hand, the Covid-19 pandemic has proven to be an additional stimulus for transforming some traditional businesses into fully electronic ones.

All this determined the main goal of this dissertation work, related to the study and modeling of business processes supporting decision-making in the field of digital transformation. To establish the current state of digital transformation, a number of objective and subjective indicators have been determined. Based on the determined indicators, a mathematical model has been formulated to assess the current state of digital transformation. Three main stages of digital transformation have been distinguished (1) operational readiness, (2) organizational readiness and (3) business value, for which corresponding groups of indicators have been identified, used to formulate a mathematical model for assessing the progress of digital transformation. In response to the growing responsibilities of the chief information manager, mathematical models have been proposed that aim to find relevant solutions. The first of them is a variation of the classic SAW model, where instead of criteria estimates, normalized parameter values are used. This model is suitable for decision-making in the absence of sufficient time and the need for timely decision-making. The second model simultaneously determines the best group solution, which is a combination of different software products. This model requires more time and a group of experts authorized to make the choice. Another important aspect of digital transformation is finding the right leader for the specific organization. For this specific task, a group decision-making model has been proposed for evaluating candidates and selecting a person for the position of chief digital transformation manager. Here, the formed group solution takes into account both the knowledge and experience of the candidates, as well as their leadership abilities.

The practical applicability of all formulated models for supporting decision-making has been proven through testing on real problems.

As a future development of the research in the dissertation, it is planned to explore the possibilities of other models, with the aim of modifying them for group decision-making, as well as creating new models and algorithms to support decision-making, taking into account various essential parameters and situations in group decision-making.

CONTRIBUTIONS

The results obtained, described in this dissertation, can be summarized in the following scientific and applied scientific contributions:

1. A model for assessing the progress of digital transformation is proposed, taking into account both objective and subjective indicators. This model can easily be modified, if necessary, to take into account only objective or only subjective evaluation criteria.
2. Three groups of indicators have been identified to measure the progress of the digital transformation stages, namely operational readiness indicators, organizational readiness indicators and business value indicators. These groups of indicators have been used to formulate a corresponding model.
3. Two models have been formulated to support the work of the chief information manager. The first of them is a variation of the classic SAW model, using normalized parameter values instead of criteria scores. The second model simultaneously determines the best group solution, which is a combination of the 3 software products for remote collaborative work.
4. A group decision-making model is proposed that considers the combination of technical and soft skills of candidates when selecting a person for the position of chief digital transformation manager. The formulated model can also be applied in organizations and companies with different fields of activity.

LIST OF PUBLICATIONS ON THE DISSERTATION

1. Borissova, D., **Naidenov, N.**, Yoshinov, R.: Digital transformation assessment model based on indicators for operational and organizational readiness and business value. In: Guarda, T., Portela, F., Diaz-Nafria, J.M. (eds) Advanced Research in Technologies, Information, Innovation and Sustainability. ARTIIS 2023. Communications in Computer and Information Science, vol. 1935, pp. 457–467 (2024), Springer, Cham. https://doi.org/10.1007/978-3-031-48858-0_36 (**SJR=0.2 Q4)**
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3. Borissova, D., Dimitrova, Z., Dimitrov, V., Yoshinov, R., **Naidenov, N.**: Digital transformation and the role of the CIO in decision making: A Comparison of two modelling approaches. In: Saeed, K., Dvorský, J. (eds) Computer Information Systems and Industrial Management. CISIM 2022. Lecture Notes in Computer Science, vol. 13293, pp. 93–106 (2022)., Springer, Cham. https://doi.org/10.1007/978-3-031-10539-5_7. (**SJR=0.32 Q2**)

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    1) Guliashki, V., Marinova G.: Impact of cyberattacks on human's health, In: 2024 IEEE International Workshop on Technologies for Defense and Security (TechDefense), Naples, Italy, 2024, pp. 31-35, https://doi.org/10.1109/TechDefense63521.2024.10863627.
    2) Fynn-Hendrik, P., Henning, B., Nele, K., Mikhail, K., Paula, L., Michael, O., Pascal, W.: Competences for Digital Transformation in Organizations: A Literature Review and Expert Survey. ECIS 2024 Proceedings. 15. (2024). https://aisel.aisnet.org/ecis2024/track12_digtrans/track12_digtrans/15
    3) Psarommatis, F., Konstantinidis, F., Azamfirei, V., May, G.: Identification of the benefits from the use of Digital Product Passport in a value chain and single organizations. IFAC-PapersOnLine, Vol. 58(19), 2024, pp. 301-306, https://doi.org/10.1016/j.ifacol.2024.09.199.
    4) Gospodinov, M.: The role of the concept of trust in trust services in cyberspace to enhance cyber security. Problems of Engineering Cybernetics and Robotics, Vol. 81, 2024, pp. 23-28, https://doi.org/10.7546/PECR.81.24.03.
- **Borissova, D., Dimitrova, Z., Naidenov, N., Yoshinov, R.: Integrated approach to assessing the progress of digital transformation by using multiple objective and subjective indicators. In: Guizzardi, R., Ralyté, J., Franch, X. (eds) Research Challenges in Information Science. RCIS 2022. Lecture Notes in Business Information Processing, vol. 446, 2022, pp. 626–634, Springer, Cham.**

5) Stoyanova, K., Guliashki, V.: Group drop of sustainability: Trade-off solutions between low returns and portfolio stability. Computers and Informatics, vol. 4(1), 2024, pp. 13-19, https://dergipark.org.tr/en/pub/ci/issue/82700/1271141.

- **Borissova, D., Dimitrova, Z., Dimitrov, V., Yoshinov, R., Naidenov, N.: Digital transformation and the role of the CIO in decision making: A comparison of two modelling approaches. In: Saeed, K., Dvorský, J. (eds) Computer Information Systems and Industrial Management. CISIM 2022. Lecture Notes in Computer Science, vol. 13293, pp. 93-106, 2022, Springer, Cham.**

6) Nikitashin, M., Kaluža, M., Werber, B.: Analysis of methodologies and tools for software development in different architectures. In: 2024 47th MIPRO ICT and Electronics Convention (MIPRO), Opatija, Croatia, 2024, pp. 1999-2007, https://doi.org/10.1109/MIPRO60963.2024.10569545.
7) Tomov, P., Mateeva, G., Parvanov, D.: Entropy test degradation after random numbers scaling. Problems of Engineering Cybernetics and Robotics, Vol. 80, 2023, pp. 3-12, https://doi.org/10.7546/PECR.80.23.01.

BIBLIOGRAPHY

1. Seppanen, S., Ukko, J., Saunila, M.: Understanding determinants of digital transformation and digitizing management functions in incumbent SMEs. Digital Business, vol. 5(1), 100106 (2025), https://doi.org/10.1016/j.digbus.2025.100106.
2. Fynn-Hendrik, P., Henning, B., Nele, K., Mikhail, K., Paula, L., Michael, O., Pascal, W.: Competences for Digital Transformation in Organizations: A Literature Review and Expert Survey. ECIS 2024 Proceedings. 15. (2024). https://aisel.aisnet.org/ecis2024/track12_digtrans/track12_digtrans/15.
3. Baizyldayeva, U., Vlasov, O., Kuandykov, A.A., Akhmetov, T.B.: Multi-criteria decision support systems. Comparative analysis. Middle East Journal of Scientific Research, vol. 16, pp. 1725-1730 (2013), http://dx.doi.org/10.5829/idosi.mejsr.2013.16.12.12103.
4. Bharadwaj, A., El Sawy, O.A., Pavlou, P.A., Venkatraman, N.V.: Digital business strategy: Toward a next generation of insights. MIS Quarterly, vol. 37(2) pp. 471-482 (2013), https://ssrn.com/abstract=2742300.
5. Bodea, C., D'Aveni, R., Ashford, S. Human Resources in the Era of AI: A Perspective on the Future of Talent Management. International Journal of HR Technology, vol. 8(2), pp. 129-145 (2020).
6. Borissova, D., Dimitrova, Z., Dimitrov, V., Yoshinov, R., Naidenov, N.: Digital transformation and the role of the CIO in decision making: A comparison of two modelling approaches. In: Saeed, K., Dvorský, J. (eds) Computer Information Systems and Industrial Management. CISIM 2022. Lecture Notes in Computer Science, vol. 13293, pp. 93-106 (2022), https://doi.org/10.1007/978-3-031-10539-5_7.
7. Borissova, D., Dimitrova, Z., Naidenov, N., Yoshinov, R.: Integrated approach to assessing the progress of digital transformation by using multiple objective and subjective indicators. In: Guizzardi, R., Ralyté, J., Franch, X. (eds) Research Challenges in Information Science. RCIS 2022. Lecture Notes in Business Information Processing, vol. 446, pp. 626-634 (2022), https://doi.org/10.1007/978-3-031-05760-1_37.
8. Borissova, D., Korsemov, D., Keremedchieva, N. Generalized Approach to Support Business Group Decision-Making by Using of Different Strategies. In: Saeed, K., Dvorský, J. (eds) Computer Information Systems and Industrial Management. CISIM 2020. Lecture Notes in Computer Science, vol. 12133, pp. 122-133 (2020), https://doi.org/10.1007/978-3-030-47679-3_11.
9. Borissova, D., Naidenov, N., Yoshinov, R.: Digital transformation assessment model based on indicators for operational and organizational readiness and business value. In: Guarda, T., Portela, F., Diaz-Nafria, J.M. (eds) Advanced Research in Technologies, Information, Innovation and Sustainability. ARTIIS 2023. Communications in Computer and Information Science, vol. 1935, pp. 457-467 (2024), https://doi.org/10.1007/978-3-031-48858-0_36
10. Brennen, S., Kreiss, D.: Digitalization and Digitization. Culture Digitally, (2016) http://culturedigitally.org.
11. Cascio, W. F., Montealegre, R.: How technology is changing work and organizations. Annual Review of Organizational Psychology and Organizational Behavior, vol. 3(1), pp. 349-375 (2016), https://doi.org/10.1146/annurev-orgpsych-041015-062352.

12. Ceballos, B., Lamata, M.T., Pelta, D.A.: A comparative analysis of multi-criteria decision-making methods. Progress in Artificial Intelligence, vol. 5, pp. 315-322 (2016), https://doi.org/10.1007/s13748-016-0093-1.
13. Chtouka, E., Guezguez, W., Amor, N.B.: Reinforcement learning for new adaptive gamified LMS. In: Jallouli, R., Bach Tobji, M.A., Bélisle, D., Mellouli, S., Abdallah, F., Osman, I. (eds.) ICDEc 2019. LNBIP, vol. 358, pp. 305-314 (2019), https://doi.org/10.1007/978-3-030-30874-2_24.
14. Cirillo, V., Fanti, L., Mina, A., Ricci, A.: The adoption of digital technologies: investment, skills, work organization. Struct. Chang. Econ. Dyn.Dyn. (2023). https://doi.org/10.1016/j.strueco.2023.04.011
15. Dhillon, G., Smith, K., Dissanayaka, I.: Information systems security research agenda: Exploring the gap between research and practice. The Journal of Strategic Information Systems, vol. 30(4), 101693 (2021), https://doi.org/10.1016/j.jsis.2021.101693.
16. Ghosh, S., Hughes, M., Hodgkinson, I., Hughes, P.: Digital transformation of industrial businesses: a dynamic capability approach. Technovation, 102414 (2021), https://doi.org/10.1016/j.technovation.2021.102414.
17. Gogan, J.L., Conboy, K., Weiss, J.W.: Dangerous champions of IT innovation. In: 53rd Hawaii International Conference on System Sciences, pp. 6144–6153 (2020).
18. Hardwick, J., Anderson, A.R.: Supplier-customer engagement for collaborative innovation using video conferencing: a study of SMEs. Industrial Marketing Management, vol. 80, pp. 43-57 (2019), https://doi.org/10.1016/j.indmarman.2019.02.013.
19. Henfridsson, O., Mathiassen, L., Svahn, F.: Managing technological change in the digital age: The role of architectural frames. Journal of Information Technology, vol. 29(1), pp. 27-43 (2014), https://doi.org/10.1057/jit.2013.30.
20. Julsrud, T.E., Hjorthol, R., Denstadli, J.M.: Business meetings: do new videoconferencing technologies change communication patterns? Journal of Transport Geography, vol. 24, pp. 396-403 (2012).
21. Kane, G.C., Palmer, D., Phillips, A.N., Kiron, D.: Strategy, not technology, drives digital transformation. MIT Sloan Management Review, pp. 14-21 (2015), http://sloanreview.mit.edu/projects/strategy-drives-digital-transformation/.
22. Korsemov, D., Borissova, D.: Modifications of simple additive weighting and weighted product models for group decision making. Advanced Modeling and Optimization, vol. 20(1), pp. 101-112 (2018).
23. Kunisch, S., Menz, M., Langan, R.: Chief digital officers: An exploratory analysis of their emergence, nature, and determinants. Long Range Planning, vol. 55(2), 101999 (2022), https://doi.org/10.1016/j.lrp.2020.101999.
24. Ostmeier, E., Strobel, M.: Building skills in the context of digital transformation: How industry digital maturity drives proactive skill development. Journal of Business Research, vol. 139, pp. 718-730 (2022), https://doi.org/10.1016/j.jbusres.2021.09.020.
25. Parry, E., Tyson, S.: Technology in human resource management: Trends, issues, and challenges. HRM Journal, 28(3), pp. 233-249 (2018).

26. Sabaei, D., Erkoyuncu, J., Roy, R.: A review of multi-criteria decision making methods for enhanced maintenance delivery. Procedia CIRP, vol. 37, pp. 30-35 (2015), https://doi.org/10.1016/j.procir.2015.08.086.
27. Schuh, G., Anderl, R., Gausemeier, J., M. ten Hompel, and Wahlster, W.: Industry 4.0 Maturity Index: Managing the Digital Transformation of Companies. Hacatech STUDY. Munich: Herbert Utz (2017).
28. Schwab, K.: The Fourth Industrial Revolution. Crown Business, (2016).
29. Shih, H-S., Shyur, H.-J., Lee, E.S.: An extension of TOPSIS for group decision making. Mathematical and Computer Modelling, vol. 45(7-8), pp. 801-813 (2007), https://doi.org/10.1016/j.mcm.2006.03.023.
30. Stone, D.L., Deadrick, D.L., Lukaszewski, K.M., Johnson, K.R.: The influence of technology on the future of human resource management. Human Resource Management Review, vol. 25(2), pp. 216-231 (2015).
31. Taherdoost, H.; Madanchian, M. Multi-Criteria Decision Making (MCDM) Methods and Concepts. Encyclopedia, 3, pp. 77–87 (2023), https://doi.org/10.3390/encyclopedia3010006.
32. Triantaphyllou, E., Shu, B., Nieto Sanchez, S., Ray, T.: Multi-criteria decision making: An operations research approach. Encyclopedia of Electrical and Electronics Engineering, (J.G. Webster, Ed.), John Wiley & Sons, New York, NY, 15, pp. 175-186 (1998), https://www.researchgate.net/publication/284107964_Multi-criteria_decision_making_An_operations_research_approach.
33. Triantaphyllou, E.: Multi-criteria decision making Mmethods. In: Multi-criteria Decision Making Methods: A Comparative Study. Applied Optimization, vol. 44, pp. 5-21 (2000). https://doi.org/10.1007/978-1-4757-3157-6_2.
34. Tumbas, S., Berente, N., vom Brocke, J.: Three types of chief digital officers and the reasons organizations adopt the role. MIS Quarterly Executive, vol. 16(2), pp. 121-134, (2017), https://aisel.aisnet.org/misqe/vol16/iss2/5.
35. Ulrich, P., Lehmann, P.: Information is a key: Systematic literature review and empirical results on role configurations of chief information officers and chief digital officers. Corporate & Business Strategy Review, vol. 4(1), pp. 87-98 (2023), https://doi.org/10.22495/cbsrv4i1art8.
36. Upadhyay, A.K., Khandelwal, K.: Applying artificial intelligence: implications for recruitment. Strategic HR Review, vol. 17(5), pp. 255-258 (2018), https://doi.org/10.1108/SHR-07-2018-0051.
37. Westerman, G., Bonnet, D., McAfee, A.: Leading Digital: Turning Technology into Business Transformation. Harvard Business Review Press, 304 pages (2014).
38. Wu, Q., Dbouk, W., Hasan, I., Kobeissi, N., Zheng, L.: Does gender affect innovation? Evidence from female chief technology officers. Research Policy, vol. 50(9), 104327, (2021) https://doi.org/10.1016/j.respol.2021.104327.
39. Qiao, Y., Li, X., Hu, J.: From digital to innovative: How does digital transformation affect corporate innovation? Economics Letters, vol. 247, 112210 (2025), https://doi.org/10.1016/j.econlet.2025.112210.