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Modelling and Forecasting Enterprise Transformation in a Digitalising Economy

Ivan BULEEV, Natalya BRYUKHOVETSKAYA, Tetyana KORYTKO, Iryna BRYL, Oleksandra PRYKHODKO

Department of Economic Problems, National academy of sciences of Ukraine, Ukraine

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Abstract

Today, the development of a scientific and methodological approach to modelling the impact of digital transformation on enterprise management is highly relevant. This approach should be based on the rules of fuzzy logic and be adaptable to environmental changes. Consequently, the purpose of this study is to develop an optimal tool for modelling the decision-making process in enterprise management under the influence of digital transformation. The study's outcome is a model for presenting fuzzy knowledge, demonstrated through examples of models designed to assess the impact of digital transformation on enterprise management, based on input from expert assessments. The developed model interprets the scored expert points for a loosely structured or unstructured task, thereby revealing the subjectivity of experts and providing a quantitative assessment for non-formalised tasks.

Keywords

digital transformation; fuzzy knowledge; fuzzy sets; management; enterprise.

Introduction

The main feature of the digital economy is its global nature and its reliance on intangible goods: ideas, information, and relationships, alongside the network principles of market and societal coordination. This necessitates the development of a scientific and methodological approach to modelling the impact of digital transformation on enterprise management.

Under the influence of ICT, artificial intelligence technologies, large-scale data processing, and other factors, the methods and mechanisms of management and functioning, as well as the value orientations of enterprises, undergo drastic changes (Buleev, 2023).

The management of an industrial enterprise is characterised by multicriteria decision-making, a multitude of heterogeneous elements, and a hierarchical structure (Korytko, 2023).

***Corresponding author**: Tetyana Korytko – Department of Economic Problems, National academy of sciences of Ukraine,Postal Address St. Maria Kapnist, 2, Kyiv, 03057, phone: +38 050 929, e-mail: taniakorytko@gmail.com*

To assess the impact of digital transformations on enterprise management by combining two elements – namely, the efficiency of enterprise management and the level of digital transformation – into a single methodological approach, it is necessary to formalise the data obtained from assessing each of these components.

Literature review

In tasks investigating economic and managerial processes, information about the objects of study is typically vague and fuzzy in nature. The Analytical Hierarchy Process (AHP) is used as a multi-criteria method to determine the proportion of criteria and priority of alternatives based on pairwise comparison, which relies on the subjective judgement of experts (Liu et al., 2020; Badri-Kouhi et al., 2019).

It should be noted that the scarcity of extensive statistical data complicated the analysis, as many factors are qualitative or vague. Consequently, econometric models based on such indicators are unsuitable for determining a factor's dependence on other parameters. Various mathematical methods are employed to work with qualitative or fuzzy indicators. One such method is that of fuzzy inference systems, proposed by Zadeh (as cited in Zanon et al., 2020). Simultaneously, in game theory problems (Larbani, 2009), a situation may arise where uncertainties are defined by fuzzy sets, and the value of the objective function is a fuzzy number dependent on both the chosen solution and the realised uncertainty. This leads to the problem of operating with fuzzy numbers (Dutta, 2011; Bansal, 2011) and comparing them. To date, a considerable number of methods for comparing fuzzy numbers have been proposed (Korzhov, 2016; Chen, 2006). However, none of these is universal.

Given the lack of reliable quantitative indicators, the optimal approach to formalising data when assessing the impact of digital transformation on enterprise management is to use fuzzy set theory. This theory offers several advantages: firstly, it allows for the objective demonstration of assessments from both large and small numbers of respondents; secondly, it ensures high reliability of the obtained results. Thirdly, the use of the mathematical apparatus of fuzzy set theory helps to resolve the contradiction between the convenience of using ordinal verbal scales and the difficulty of interpreting the responses in both qualitative and quantitative aspects, thereby enhancing the reliability of the analytical potential.

The complexity of problem-solving in the enterprise management process is constantly increasing, which creates a need for more sophisticated methodological provisions, methods, and recommendations to justify decisions.

Thus, the purpose of this study is to develop an optimal tool for modelling the decision-making process in enterprise management under the influence of digital transformation. Considering the definition of the main problematic aspects and topical issues, as well as the primary objective, the study's tasks include the following:

- Identification of the main directions through which digitalisation impacts enterprise management in established high-tech production at three levels: the macroeconomic level (across the entire national economy), the enterprise level, and the level of human capital development within the enterprise.
- Formalisation of a multi-criteria decision-making model for enterprise management in high-tech production, incorporating indicators that characterise these levels: 1) the digital transformation of the economy; 2) the enterprise's practical use of digital tools; and 3) the development of the enterprise's human capital in the context of digitalisation, to assess the impact of digital transformation on management effectiveness.

The Fuzzy Assessment Model

To solve this task, a scientific and methodological approach to modelling the impact of digital transformation on enterprise management is proposed, based on the use of fuzzy logic (Fig. 1).

In the first stage of this approach, a system of indicators for assessing the impact of digital transformation on enterprise management is formed.

When forming this system of indicators, the following method is proposed to determine the impact. At the first and highest level, there is an integral indicator that comprehensively characterises the impact level. The system of indicators (Fig. 2) is a holistic structure comprising four hierarchical levels, with internal relationships between individual indicators at different levels.

The state of enterprise management is described by a set of indicators that act as influencing factors of digital transformation. When classifying these indicators, it is often difficult to assign them to a specific category (for example, to distinguish between "very low" and "low"). To perform this classification using a fuzzy-set approach, it is proposed to introduce a linguistic variable, G, with its own term set of values. Thus, the variable "level of indicator E" can have a value from the set {"very low", "low", "medium", "high", "very high"}.

Next, a membership function is assigned to each term of the linguistic variable G_i. These terms are defined as fuzzy subsets of the interval $[0, 1]$. The most common type is the trapezoidal membership function.

The membership function for each indicator is determined by the formula:

$$\mu_A(x) \begin{cases} 1 - \dfrac{b-x}{b-a} & a \le x \le b; \\ 1, & b \le x \le c; \\ 1 - \dfrac{x-c}{d-c} & c \le x \le d; \\ 0 & d \le x \end{cases}, \tag{1}$$

The parameters a and d define the lower base of the trapezoid, while the parameters b and c define the upper base. In this case, the membership function is – x a convex fuzzy set with a carrier – the interval (a, d) – and a kernel $[b, c]$. Its boundaries are defined by the intervals (a, b) and (c, d).

To describe the subsets of the term set, a system of corresponding trapezoidal membership functions, $\mu_i(u)$, is proposed. The upper base of the trapezoid corresponds to the expert's full confidence in the correctness of the classification, while the lower base corresponds to the certainty that no other values from the interval $[0, 1]$ belong to the selected fuzzy subset.

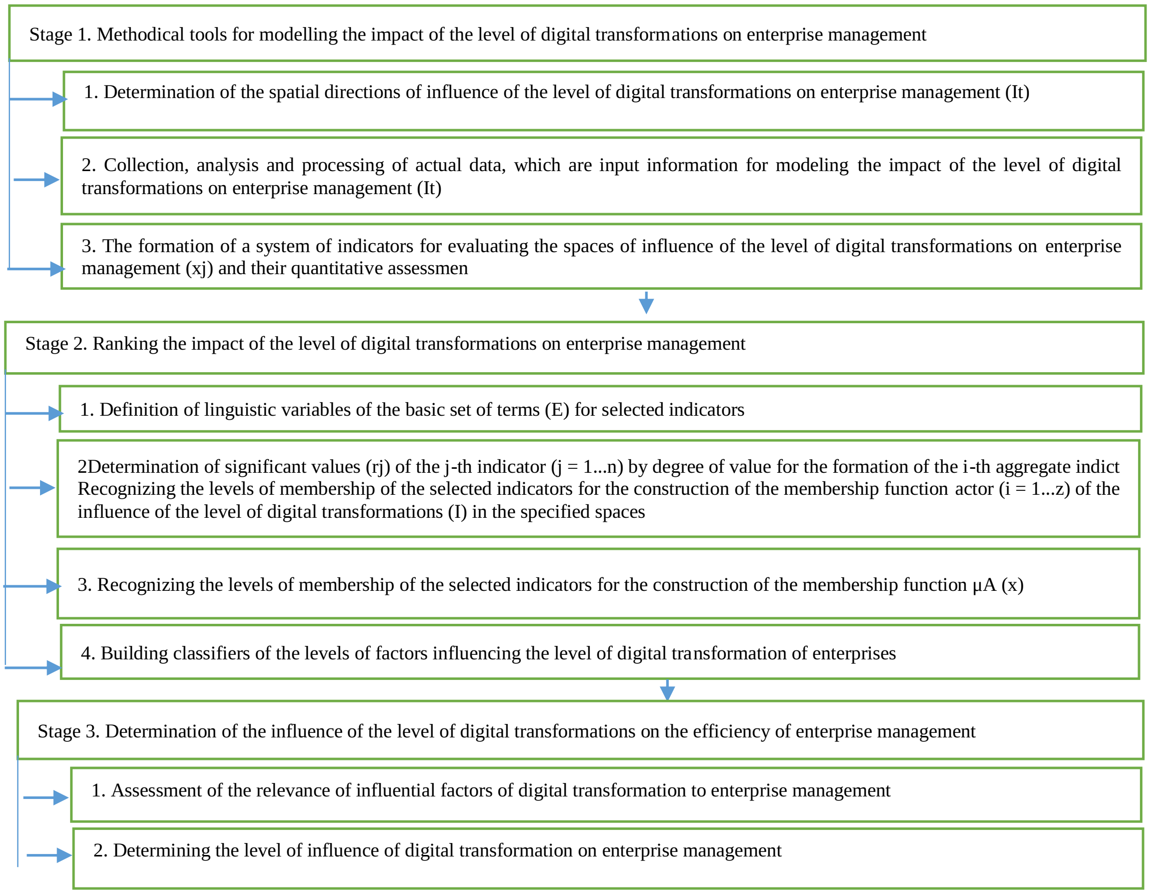

Fig. 1. A scientific and methodological approach to modelling the impact of digital transformation on enterprise management using fuzzy logic (Korytko, 2021)

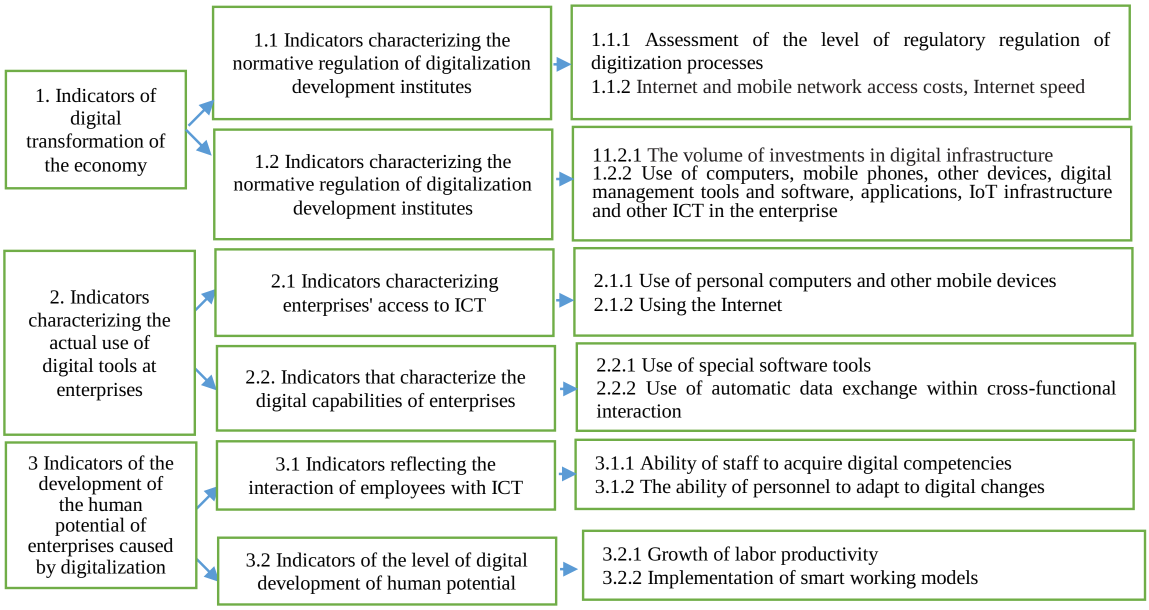

Fig. 2. A framework for ranking the impact of digital transformation on enterprise management (Borissova, 2024; Schönfeld, 2018; Jun, 2020)

In the simplest case, a standard five-level fuzzy classifier can be used to classify the indicators. This classifier is characterised by a set of nodal points: $\alpha_j = (0.1, 0.3, 0.5, 0.7, 0.9)$.

The weighting coefficients of the indicators, used to assess the impact level of digital transformation on enterprise management, are determined using Fishburne's rule (Petrenko, 2010).

$$r_i = \frac{2(N-i+1)}{(N+1)^N}, \quad i = \overline{1, N} \tag{2}$$

where: r_i – is the value of the calculated rank of the i-th indicator; N – is the total number of groups of indicators for which the ranks are calculated; i – is the serial number of the indicator (in order of importance).

The sum of the weights is equal to one. If the indicators are of equal significance, the weight r_i for each indicator is calculated as follows:

$$r_i = \frac{1}{N} \tag{3}$$

Determining the impact of the digital transformation level on enterprise management efficiency. We will construct a classification of the current value of the risk degree indicator, $^*g^*$, as a criterion for dividing the set G into fuzzy subsets.

Following the definition of the linguistic variables for the indicators, it is also necessary to define linguistic variables to determine the impact of the digital transformation level on enterprise management. These linguistic variables are also divided into five states (Table 1).

The levels of indicators for the period are determined by assigning the current indicator values to fuzzy subsets, the boundaries of which are established using the expert method (Ostankova, 2011).

Deputy Directors General and heads of departments within the institute, as well as leading specialists of the enterprise, were selected as experts to classify the indicator values. The selection of these specialists as potential experts was based on their extensive production experience, relevant education, and the specific nature of their duties. Consequently, ten specialists were engaged to classify the indicator values.

The expert selection procedure comprises the following stages: compiling a list of potential candidates for conducting an examination of objects R and evaluating them to select the most competent specialists h (where $n > h$) who have achieved the highest competence coefficients W.

To determine the professional competence of the experts, factors influencing their competence were identified based on an analysis of existing methods for

Table 1
A model for assessing the impact of the digital transformation level on enterprise management

Identifying linguistic variables to assess the impact of the level of digital transformation on enterprise management		
Efficiency of enterprise management		**Level of digital transformation**
E_1 – meets the strategic guidelines		G_1 – very high (VH)
E_2 – almost full compliance with strategic guidelines		G_2 – high (H)
E_3 – partially meets the strategic guidelines		G_3 – average (A)
E_4 – insignificant compliance with strategic guidelines		G_4 – low (L)
E_5 – does not meet the strategic guidelines		G_5 – minor (M)
Interval of g	Level of digital transformation	Degree of estimated certainty (ownership function)
$0 < g < 0.1$	G_5 – minor	1
$0.1 < g < 0.2$	G_5 – minor	$\mu_5 = 10 \times (0.2 - g)$
	G_4 – low	$\mu_4 = 1 - \mu_5$
$0.2 < g < 0.3$	G_4 – low	1
$0.3 < g < 0.4$	G_4 – low	$\mu_4 = 10 \times (0.4 - g)$
	G_3 – average	$\mu_3 = 1 - \mu_4$
$0.4 < g < 0.5$	G_3 – average	1
$0.5 < g < 0.6$	G_3 – average	$\mu_3 = 10 \times (0.6 - g)$
	G_2 – high	$\mu_2 = 1 - \mu_3$
$0.6 < g < 0.7$	G_2 – high	1
$0.7 < g < 0.8$	G_2 – high	$\mu_2 = 10 \times (0.8 - g)$
	G_1 – very high	$\mu_1 = 1 - \mu_2$
$0.8 < g < 1.0$	G_1 – very high	1

forming expert groups. These factors were presented to a group of independent experts, who were asked to select the four most influential ones. Following a mathematical processing of all responses, the following five factors were identified:

1. Length of service. The expert's total professional experience is considered.
2. Relevant work experience.
3. Risk perception. This factor determines an expert's willingness to take risks and their understanding of its necessity and feasibility.
4. Analytical cognitive style.

This specific set of factors, characteristic of fuel and energy enterprises, is proposed here for the first time.

The results of the assessment of the consistency of the respondents' opinions are presented in Table 2.

$$B = \frac{\sum_{i=1}^{3} B_i}{3}, \tag{4}$$

The average sum of ranks is 23.76.

To assess the average degree of consistency of respondents' opinions, the concordance coefficient was used:

$$W = \frac{12 \cdot S}{m^2(n^3 - n)}, \tag{5}$$

where: m is the number of factors; n is the number of observations; S is the deviation of the sum of squares of ranks from the mean of squares of ranks.

$$W = \frac{12 \cdot 164.0}{100 \cdot (125 - 5)} = 0.1649$$

$$S = \sum_{i=1}^{n} \left[\sum_{j=1}^{m} x_{ij} - \frac{1}{2} m(n+1) \right]^2 \tag{6}$$

$S = 59.91 + 25.60 + 1.02 + 60.0 + 14.36 = 164.90$

The concordance coefficient can vary between 0 and 1:

0 – there is no connection between the assessments of different experts;

1 – all experts gave the same ratings.

The obtained value indicates that the experts' opinions are statistically significant.

To ensure that the calculated concordance coefficient – which characterizes the average degree of consensus among the experts – is not random and that the results are reliable, its significance is tested. This assessment is necessary because the study employs a sample of specialists, meaning the findings could arise by chance. For this purpose, Pearson's chi-square test (χ^2) for agreement is used.

Table 2
Ranks proposed by experts

Expert	Level of competence	Parameter*				
		a_1	a_2	a_3	a_4	a_5
1	0.79	2	3	5	4	1
2	1.00	1	3	2	5	4
3	0.76	1	2	3	4	5
4	0.79	2	1	3	5	4
5	0.84	2	3	5	4	1
6	0.92	2	1	3	5	4
7	0.44	2	1	3	5	4
8	0.68	2	3	5	1	4
9	0.79	1	3	2	5	4
10	0.91	5	3	1	2	4
The sum of ranks weighted by the level of competence of experts, B_1		16.02	18.70	24.77	31.76	27.55
Average score		1.60	1.87	2.48	3.18	2.76
Deviation from the average sum of ranks		–7.74	–5.06	1.01	8.00	3.79
Squared deviations		59.91	25.60	1.02	64.00	14.36

* Note. Parameter – weight of coefficients:
a_1 – the impact of the level of digital transformation on enterprise management is very high – $Z_1 = 0.1$;
a_2 – the impact of the level of digital transformation on enterprise management is high – $Z_2 = 0.1$;
a_3 – the impact of the level of digital transformation on enterprise management is medium – $Z_3 = 0.1$;
a_4 – the impact of the level of digital transformation on enterprise management is low – $Z_4 = 0.35$;
a_5 – the impact of the level of digital transformation on enterprise management is insignificant – $Z_5 = 0.35$.

To assess the degree of consistency in the expert opinions, we will use the chi-square (χ^2) test for agreement

$$\chi^2 = \frac{S}{\frac{1}{2} \cdot m \cdot n(n-1)}, \tag{7}$$

If $\chi^2_{\text{calculation}} > \chi^2_{\text{table}}$, then at a given level of significance, the calculated coefficient is considered significant. Otherwise, it can be concluded that there is no association between the studied traits.

By comparing the calculated value ($\chi^2_{\text{calculation}} = 9.894$) with the critical value from the table ($\chi^2_{\text{table}} = 9.5$) for the corresponding number of degrees of freedom ($k = n - 1$) and at a given significance level ($\alpha = 0.05$), it is determined that the concordance coefficient is non-random. This confirms that there is a statistically significant degree of consensus among the expert opinions, and thus the results can be considered reliable.

The classification of indicator values is given in Table 3.

The results of the expert survey conducted as part of this study, along with the subsequent calculations, are presented in Table 4.

The membership levels, λ_{ij}, of the fuzzy subsets from the term set of the input variables will now be calculated. These levels represent the values of the corresponding membership functions for the given input parameters that were computed earlier.

The calculation of the aggregate indicator is the fourth stage of the proposed method for assessing the financial stability of a consolidated group of enterprises.

Based on the works cited above, the aggregate indicator, $g(\mathrm{FS})$, can be calculated using the following formula:

$$g(\mathrm{FS}) = \sum_{j=1}^{5} g_i \sum_{i=1}^{N} r_i \lambda_{ij}, \tag{8}$$

where g_i – nodal points of the standard five-level classifier on the 01 carrier; $g_i = 0.9 - 0.2(j-1)$; r_i – level of significance of the indicator; λ_{ij} – is the value of the level of belonging to the j-th qualitative level relative to the current value of the i-th indicator; $g(\mathrm{FS})$ – is the level of influence of digital transformation on enterprise management.

The final step involves ranking the enterprises according to the level of impact that digital transformation has on governance, thereby creating a comparative ranking. The outcome of this classification is a linguistic description of digital transformation's impact on enterprise management, alongside the expert's degree of confidence in the classification's correctness. The extent to which an enterprise meets the criteria is determined using the Harrington verbal-numerical scale. This scale provides meaningful descriptions for each gradation name alongside its corresponding range of numerical values (Table 5).

These calculations are based on a matrix (Ruzakova, 2019), in which the five qualitative levels – Very Low, Low, Medium, High, and Very High – form the matrix columns. The analysed indicators constitute the rows, and their intersections define the membership level, λ_{ij}, of the quantitative factor levels to a given qualitative class.

The level of digital transformation of an industrial enterprise is characterised by the following indicators (Table 6).

Let's classify the current values of x according to the criterion of Table 7. The result of the classification is shown in Table 6.

Here, we assume $\lambda_{ij} = 1$, if $\beta_{ij} - 1 < x_i < \beta_{ij}$, then $\lambda_i = 0$ otherwise.

Table 3
Classification of indicator values

Indicator	Fuzzy terms				
	minor	low	average	high	very high
X1	$X \le 0.15$	$0.15 < X \le 0.27$	$0.27 < X \le 0.39$	$0.39 < X \le 0.51$	$0.65 < X$
X2	$X \le 0.20$	$0.2 < X \le 0.4$	$0.4 < X \le 0.6$	$0.6 < X \le 0.8$	$0.8 < X \le 1$
X3	$X \le 0.025$	$0.022 < X \le 0.15$	$0.15 < X \le 0.28$	$0.28 < X \le 0.41$	$0.41 \le X \le 0.55$
X4	$X \le 0.2$	$0.2 < X \le 0.4$	$0.4 < X \le 0.6$	$0.6 < X \le 0.8$	$0.8 < X \le 1$
X5	$X \le 0.55$	$0.55 < X \le 0.66$	$0.66 < X \le 0.77$	$0.77 < X \le 0.88$	$0.88 \le X \le 1$
X6	$X \le 0.55$	$0.55 < X \le 0.66$	$0.66 < X \le 0.77$	$0.77 < X \le 0.88$	$0.88 \le X \le 1$
X7	$X \le 0.1$	$0.1 < X \le 0.24$	$0.24 < X \le 0.38$	$0.36 < X \le 0.52$	$0.52 \le X \le 0.65$
X8	$X \le 0.0$	$0 < X \le 0.01$	$0.01 < X \le 0.11$	$0.11 < X \le 0.21$	$0.3 < X$
X9	$X \le 0.15$	$0.15 < X \le 0.25$	$0.25 < X \le 0.45$	$0.45 < X \le 0.65$	$0.65 < X$
X10	$X \le 0.55$	$0.55 < X \le 0.66$	$0.66 < X \le 0.77$	$0.77 < X \le 0.88$	$0.88 \le X \le 1$
X11	$X \le 0$	$0 < X \le 0.01$	$0.01 < X \le 0.11$	$0.11 < X \le 0.21$	$0.3 < X$
X12	$X \le 0$	$0 < X \le 0.01$	$0.01 < X \le 0.11$	$0.11 < X \le 0.21$	$0.3 < X$

Table 4
Parameters (vertices) of the trapezoidal functions of the accessories for the analysed indicators

	Indicator		minor	low	average	high	very high
X1	Assessment of the level of regulatory regulation of digitalisation processes	a	0	0.15	0.25	0.45	0.65
		b	0.05	0.18	0.32	0.52	0.58
		c	0.1	0.21	0.39	0.59	0.51
		d	0.15	0.25	0.45	0.65	0.45
X2	Expenditures on Internet access and mobile communications, Internet speed	a	0	0.2	0.4	0.6	0.8
		b	0.06	0.26	0.46	0.66	0.86
		c	0.12	0.32	0.52	0.72	0.92
		d	0.2	0.4	0.6	0.8	1
X3	Investment in digital infrastructure	a	0	0.025	0.15	0.28	0.41
		b	0.008	0.066	0.19	0.33	0.45
		c	0.016	0.11	0.23	0.37	0.49
		d	0.025	0.15	0.28	0.41	0.55
X4	The use of computers, mobile phones, other devices, digital management tools and software, applications, IoT infrastructure and other ICT in the enterprise	a	0	0.2	0.4	0.6	0.8
		b	0.06	0.26	0.46	0.66	0.86
		c	0.12	0.32	0.52	0.72	0.92
		d	0.2	0.4	0.6	0.8	1
X5	Use of personal computers and other mobile devices, %	a	0	0.55	0.66	0.77	0.88
		b	0.18	0.59	0.70	0.1	0.92
		c	0.36	0.63	0.74	0.85	0.96
		d	0.55	0.66	0.77	0,88	1
X6	Use of the Internet	a	0	0.55	0.66	0.77	0.88
		b	0.18	0.59	0.70	0.1	0.92
		c	0.36	0.63	0.74	0.85	0.96
		d	0.55	0.66	0.77	0.88	1
X7	Use of special software tools	a	0	0.1	0.24	0.38	0.52
		b	0.03	0.15	0.29	0.42	0.56
		c	0.06	0.19	0.33	0.46	0.61
		d	0.1	0.24	0.38	0.52	0.65
X8	Use of automatic data exchange within cross-functional collaboration	a	0	0	0.01	0.11	0.21
		b	0	0.003	0.04	0.14	0.24
		c	0	0.006	0.07	0.17	0.27
		d	0	0.01	0.11	0.21	0.3
X9	Ability of staff to acquire digital competences	a	0	0.15	0.25	0.45	0.65
		b	0.05	0.18	0.32	0.52	0.58
		c	0.1	0,21	0.39	0.59	0.51
		d	0.15	0.25	0.45	0.65	0.45
X10	Ability to adapt staff to digital change	a	0	0.55	0.66	0.77	0.88
		b	0.18	0.59	0.70	0.1	0.92
		c	0.36	0.63	0.74	0.85	0.96
		d	0.55	0.66	0.77	0.88	1
X11	Increase in labour productivity	a	0	0	0.01	0.11	0.21
		b	0	0.003	0.04	0.14	0.24
		c	0	0.006	0.07	0.17	0.27
		d	0	0.01	0.11	0.21	0.3
X12	Implementation of smart working models	a	0	0	0.01	0.11	0.21
		b	0	0.003	0.04	0.14	0.24
		c	0	0.006	0.07	0.17	0.27
		d	0	0.01	0.11	0.21	0.3

Table 5
Ranking of enterprises by the level of impact of digital transformation on management

The level of digital transformation		**Efficiency of enterprise management**	**Characteristics of digital change**
0–0.2	Minor	does not meet the strategic guidelines	No digital transformation is taking place at the enterprise. Very low level of digital technology adoption in the work of employees.
0.2–0.4	Low	insignificant compliance with strategic guidelines	The rapidly growing complexity of the information space leads to a rapid increase in the scale and complexity of the knowledge that employees must possess, so corporate knowledge management is becoming an important characteristic of an enterprise in the context of digital transformation
0.4–0.6	Medium	partially meets the strategic guidelines	The management system should adequately respond to changes in the internal and external environment; hence, management should be carried out in accordance with established standard regulations and procedures. Otherwise, a transition to crisis management is required.
0.6–0.8	High	almost full compliance with strategic guidelines	Technologies such as big data, neural networks, block chain, cloud computing, and virtual reality are being introduced. Such changes significantly increase the efficiency of operations, create opportunities for staff reduction and process automation.
0.8–1	Very high	meets the strategic guidelines	Digital tools are actively used in the process of enterprise management. The introduction of digital technologies blurs the boundaries between internal communication and other departments. Digital technologies, together with various HR methods, including the bottom-up approach, create an employee lifecycle.

Table 6
The level of digital transformation of an industrial enterprise

Designation of the indicator	**Name of the indicator**	**Normalised value of the indicator**		
		2021	**2022**	**2023**
X1	Assessment of the level of regulatory regulation of digitalisation processes	0.27	0.30	0.35
X2	Expenditures on Internet access and mobile communications, Internet speed	0.4	0.5	0.55
X3	Investment in digital infrastructure	0.15	0,.20	0.21
X4	The use of computers, mobile phones, other devices, digital management tools and software, applications, IoT infrastructure and other ICT in the enterprise	0.6	0.7	0.75
X5	Use of personal computers and other mobile devices, %.	0.0	0.75	0.80
X6	Use of the Internet, %.	0.65	0.76	0.82
X7	Use of special software tools, %.	0.19	0.22	0.38
X8	Use of automatic data exchange within cross-functional collaboration	0.1	0.19	0.21
X9	Ability of staff to acquire digital competences	0.20	0.32	0.35
X10	Ability to adapt staff to digital change	0.55	0.65	0.77
X11	Increase in labour productivity	0.01	0.06	0.11
X12	Implementation of smart working models	0	0.09	0.12

Table 7
Assessment of the current values of the analysed indicators

Indicators	**2021**					**2022**					**2023**				
	λ_{1j}	λ_{2j}	λ_{3j}	λ_{4j}	λ_{5j}	λ_{1j}	λ_{2j}	λ_{3j}	λ_{4j}	λ_{5j}	λ_{1j}	λ_{2j}	λ_{3j}	λ_{4j}	λ_{5j}
X1	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0
X2	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0
X3	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0
X4	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0
X5	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0
X6	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0
X7	0	1	0	0	0	0	1	0	0	0	0	0	1	0	0
X8	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0
X9	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0
X10	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0
X11	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0
X12	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0

Results

The values for the significance assessment (r_i) of the i-th indicator will be calculated using Fishburne's rule. The results of this calculation are presented in Table 8.

We will draw a conclusion on the impact of the level of digital transformation on enterprise management (Table 9).

Based on the data in Table 8, it can be concluded that the state of the enterprise from 2021 to 2023 was characterised by an overall average level of impact from digital transformation on management efficiency. The management system adequately respond to changes in the internal and external environment to ensure that management decisions lead to the achievement of strategic objectives.

A comprehensive indicator for assessing the impact of digital transformation on enterprise management will be forecast (Fig. 3).

Thus, the forecast value obtained for 2024 shows an increase in the composite indicator for assessing the impact of digital transformation on management. This suggests that the enterprise's management is effective. Furthermore, the introduction of digital technologies – such as big data, neural networks, blockchain, cloud computing, and virtual reality – will lead to increased management efficiency.

Table 8
Assessment of the level of significance of the indicators

Indicators	**Calculation**	**Significance level r_i**
X1	$(2 \times (12 - 1 + 1)/(12 + 1) \times 6$	0.154
X2	$(2 \times (12 - 2 + 1)/(12 + 1) \times 6$	0.141
X3	$(2 \times (12 - 3 + 1)/(12 + 1) \times 6$	0.128
X4	$(2 \times (12 - 4 + 1)/(12 + 1) \times 6$	0.115
X5	$(2 \times (12 - 5 + 1)/(12 + 1) \times 6$	0.103
X6	$(2 \times (12 - 6 + 1)/(12 + 1) \times 6$	0.090
X7	$(2 \times (12 - 7 + 1)/(12 + 1) \times 6$	0.077
X8	$(2 \times (12 - 8 + 1)/(12 + 1) \times 6$	0.064
X9	$(2 \times (12 - 9 + 1)/(12 + 1) \times 6$	0.051
X10	$(2 \times (12 - 10 + 1)/(12 + 1) \times 6$	0.038
X11	$(2 \times (12 - 11 + 1)/(12 + 1) \times 6$	0.026
X12	$(2 \times (12 - 12 + 1)/(12 + 1) \times 6$	0.013

Table 9
Assessment of the impact of the level of digital transformation on enterprise management

Indicators	**2021**					**2022**					**2023**					**Significance level r_i**
	H3	**H**	**C**	**B**	**DB**	**H3**	**H**	**C**	**B**	**DB**	**H3**	**H**	**C**	**B**	**DB**	
X1	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0.154
X2	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0.141
X3	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0.128
X4	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0.115
X5	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0.103
X6	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0.090
X7	0	1	0	0	0	0	1	0	0	0	0	0	1	0	0	0.077
X8	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0.064
X9	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0.051
X10	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0.038
X11	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0.026
X12	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0.013
q_i	0.1	0.3	0.5	0.7	0.9	0.1	0.3	0.5	0.7	0.9	0.1	0,3	0.5	0.7	0.9	–
Comprehensive indicator for assessing the impact of digital transformation on enterprise management G	0.5293					0.5204					0.5322					–
Classification of the level of digital transformation	Average level of impact of digital transformation on management efficiency															–

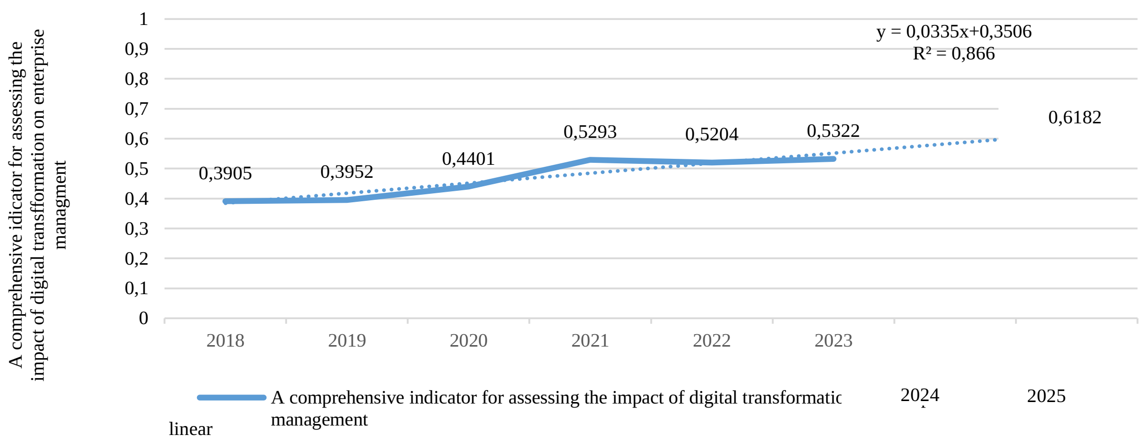

Fig. 3. Trend line of the complex indicator for assessing the impact of the level of digital transformation on enterprise management

The application of this tool in the practical activities of enterprises will:

1. Bridge the gap between, on the one hand, the goals and priorities set by the enterprise and the actual measures to achieve them and, on the other hand, the communication distance between participants in the management process.
2. Form an objective view of the enterprise's level of digital transformation.
3. Identify shortcomings and improve the enterprise's management mechanisms.
4. Determine the guidelines for the further development of digitalisation within the enterprise.

Discussion and Conclusions

For modern complex production systems, organising management within the context of digital transformations – based on data that accounts for production dynamics – reveals the limitations of current formal models of production processes. The authors posit that managing the production of high-tech products should be understood as a decision-making process. This process involves selecting equipment, planning its allocation, managing schedules and working time, and controlling materials, workpieces, units, and assemblies. A key part of this management process is addressing this study's primary task: to assess the impact of digitalisation on enterprise management in product manufacturing. This task involves identifying the optimal solution for implementing the production programme, which may have several variants.

The study of digitalisation processes is currently receiving significant attention. Publications on this topic most frequently consider different approaches to assessing the level of a company's digitalisation (Kysh, 2021; Fernandez-Vidal et al., 2022; Roša, 2022). The work by Duan (2018) addresses the transformation of traditional enterprise management models in the context of digitalisation, focusing on innovative models based on big data. To a lesser extent, research is concerned with analysing the impact of digitalisation on an enterprise's economic and production performance (Grab, 2019). Långstedt (2021) researches the requirements for employee qualifications in a digital economy. To assess the level of digitalisation in enterprises, Bai(2021) developed an assessment mechanism based on terms found in enterprise registration information; this approach quantifies the degree of digitalisation in firms. Liu (2021) considered investments in ERP, MES/DCS, and PLM systems as key methods for implementing digital management. Finally, Niu (2024) measured the level of digital outcomes in conglomerate firms by analysing the number of digital-related software copyrights held by their digital subsidiaries.

This article also highlights the limitations of current research on methods for assessing the impact of digitalisation on management. These include issues such as discrepancies in data sources, difficulties in tracking dynamic changes, and insufficient consideration of industry-specific factors. Given the rapid development of digital technologies, there is a growing need for new measurement methods and indicators that can adapt to these ever-changing technologies.

Developing an effective approach to managing an enterprise with new technologies is a complex task. To ensure the sustainable development of an industrial enterprise, it is necessary to apply innovative management theories and methodologies. As part of the study's second objective, a model for assessing the impact of digital transformation on enterprise management is proposed. This model is based on an algorithm from fuzzy set theory, which aggregates the following heterogeneous set of indicators:

- Digital transformation of the economy: level of regulatory oversight for digitalisation processes; costs of internet access and mobile communications; internet speed; volume of investments in digital infrastructure; use of computers, mobile phones, other devices, and digital management tools and software.
- Actual use of digital tools in enterprises: use of personal computers and other mobile devices; use of the internet; use of specialised software tools; use of automatic data exchange for cross-functional interaction.
- Development of human capital due to digitalisation: the workforce's ability to acquire digital competencies; employee adaptation to digital changes; growth in labour productivity; introduction of smart working models.

This model determines the aggregate level of impact of digital transformations.

The practical significance of the obtained results lies in the ability to set and solve tasks for assessing the impact of digital transformation on enterprise management using a unified methodological basis. The developed mathematical model can be used to facilitate optimal enterprise management in the context of digitalisation.

Furthermore, it is possible to identify limitations in current research on methods for assessing the impact of digitalisation on management. These include issues such as discrepancies in data sources, challenges in tracking dynamic changes, and insufficient consideration of industry factors. Given the rapid progress of digitalisation, there is a pressing need for new measurement methods and adaptable indicators. Future research should prioritise the development of more accurate and universally applicable tools for measuring the impact of digital transformation on production processes. These tools must be better suited to the constantly evolving technological and business environment.

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