This study investigates a system that provides educational institutions with material resources within a multi-level governance structure.

The task addressed relates to the lack of a hierarchical, risk-based model for assessing how educational institutions are provided with material resources that would allow for the aggregation of indicators at various management levels. Such a model should account for the standard equipment requirements, equipment operational risks, as well as the hierarchical aggregation of indicators at the educational institution, municipal, and regional levels.

The result of this work is the devised integrated resource provision indicator that takes into account the standard resource sufficiency, equipment depreciation, failure probability, as well as exceedance of the standard service life. A mechanism for aggregating indicators at the educational institution, municipal, and regional levels has been designed.

The model was tested using synthetic data. At the educational institution level, a significant differentiation in the resource provision index was observed, ranging from 0.492 to 0.782. At the municipal level, the lowest value was 0.580 due to the influence of the school with the lowest resource provision index. The regional index value was obtained at 0.663. Its decline was influenced by the uneven distribution of pupils across schools in the region and the significant risk of infrastructure degradation at one school.

The results have confirmed the model's sensitivity to risk components and the capability to identify regional imbalances in provision. The model built can be used to monitor the state of educational infrastructure and support management decision-making

Keywords: decision support system, multi-level management, educational infrastructure, resource planning

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CONSTRUCTION OF A MODEL FOR THE SYSTEM THAT CONTROLS HOW EDUCATIONAL INSTITUTIONS ARE PROVIDED WITH MATERIAL RESOURCES IN A MULTI-LEVEL MANAGEMENT STRUCTURE

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1. Introduction

Education in a modern school is impossible without computers, laboratory equipment, interactive whiteboards, etc. The availability and use of modern technology directly impacts learning outcomes and children's engagement in learning. For example, studies [1, 2] have proven that a well-equipped classroom increases interest in learning and improves its results. Good material and technical support, comfortable furniture, comfortable classrooms, as well as adequate equipment, are important factors in educational infrastructure.

To make management decisions on the organization, modernization, and regulation of educational infrastructure, it is important to understand its status at both the individual school and regional levels. When devising school infrastructure development plans or procurement plans, it is essential to have up-to-date information on its material condition, understand problem areas, the state of equipment, and understand the risks and volumes of material depletion.

The evolution of information technology and big data processing and analysis methods has facilitated the introduction of information and analytical systems into the education system, capable of storing and analyzing data on pupils, schedules, and academic achievements. Currently, two information and analytical systems, "Kundelik" [3] and "BILIMLand" [4], are operational in the Republic of Kazakhstan. These systems can analyze academic achievements, track homework completion, school attendance, and so on. However, neither system generates reports on school material resources, their adequacy, or equipment depreciation.

At both the school and regional levels, reports on school and regional material resources are generated manually and do not allow for prompt monitoring of infrastructure conditions or management decisions for improvement. It is important to note the lack of an information and analytical system capable of collecting and analyzing data on material resources at the educational institution, municipality, and regional levels. This renders relevance to research in this area.

2. Literature review and problem statement

A risk-based approach for assessing an enterprise's financial risk is described in [5]. The proposed approach takes into account equipment degradation processes and predicts the need for infrastructure upgrades. However, applying such approaches to educational infrastructure requires adaptation to the specific characteristics of the social sector.

Study [6] proposes an integrated decision support architecture for inventory management, combining fuzzy logic, genetic algorithms, as well as neural networks. Such approaches account for environmental uncertainty, as well as the dynamic nature of resource flows and inventory management processes. However, the study does not consider physical deterioration of equipment, the risk of failure, exceeding the standard service life, or the hierarchical structure of system management.

Paper [7] examines the explainability of artificial intelligence models in decision support systems. The authors propose an approach to feature selection, supplemented by expert supervision, which improves the interpretability of analytical models and ensures greater transparency of analysis results for management decision-making. However, the study is based on the analysis of textual rather than numerical data.

Study [8] demonstrates that adaptive information processing mechanisms can significantly improve the quality of management decisions and confirms the importance of integrating analytical data processing tools into modern decision support systems. It is important to note that the study focuses on decision making in a marketing environment and does not consider the specific operating conditions of an educational institution.

Paper [9] reports a multi-tier architecture based on the principles of microservices, cloud technologies, and the Zero Trust concept. The proposed approach enables the construction of flexible and scalable educational ecosystems, forming the technological foundation for the implementation of learning analytics and personalization based on artificial intelligence. However, the study does not address the impact of the adequacy of material resources and infrastructure on academic achievement. Papers [10, 11] consider methods of information analysis and big data. They propose decision-making methods in economics and education but do not address the issue of infrastructure risk.

The authors of [12] propose a new operational approach to risk-based predictive maintenance. The authors of [13] provide an overview of a number of problems and challenges faced by researchers and practitioners in the field of reliability when analyzing modern complex systems. However, those studies do not consider issues of regulatory resource sufficiency, multi-tiered system management structures, and the aggregation of indicators at the organizational, municipal, and regional levels.

Work [14] proposed an information and analytical system based on an ontological approach for analyzing student questionnaires. This approach made it possible to more accurately identify hidden relationships between variables. The use of ontologies allows one to formalize the relationships between indicators and increase the efficiency of data processing in information and analytical systems. Study [15] considers the development of decision-making methods for indicative planning at higher education institutions. In the context of globalization and digital transformation, the ability to make informed management decisions is extremely important for the success of universities but the study does not address the specificity of planning at secondary education organizations. Prospects for the design of information and analytical systems are expressed in the construction of an integrated information analysis system [16]. Such a solution will make it possible to design cloud-based data processing and visualization systems by integrating data into a corporate information system [17].

Our review of the literature show that available papers mainly consider the development of information systems, decision support systems, data processing methods, and knowledge representation. However, those studies do not address issues of mathematical modeling of material resource availability, accounting for equipment operational risks, or hierarchical aggregation of indicators at the educational institution, municipality, and regional levels. This confirms the need to build mathematical models for assessing the availability of material resources for educational institutions, taking into account the technical condition of equipment and the multi-level governance structure of the educational system.

Thus, an unresolved task is the lack of a hierarchical risk-oriented model for assessing how educational organizations are provided with material resources, enabling the aggregation of indicators at various levels of management and allowing for identification of territorial imbalances in educational infrastructure.

3. The aim and objectives of the study

The objective of our study is to build a model for managing how educational institutions are provided with material resources within a multi-level governance structure. The results will enable us to assess the material condition of the education system and make management decisions to improve it at both the municipal and regional levels.

To achieve this goal, the following tasks were resolved:

– a sequence of computational steps for generating an integrated resource index was devised;

– a structure for a regional resource management system was constructed;

– the proposed model was tested on a synthetic dataset.

4. The study materials and methods

The object of our study is a system for managing how educational institutions are provided with material resources within a multi-level management structure.

The principal hypothesis assumes that a risk-based approach and hierarchical aggregation of indicators allow for a more objective assessment of how educational institutions are provided with material resources compared to the conventional normative approach.

Before commencing the study, the following assumptions were adopted:

1. The regional educational system was considered a hierarchical structure consisting of three levels of governance: the educational institution, the municipality, and the region.

2. The standard requirement for material resources was assumed to be proportional to the number of pupils and determined based on the provision standards per 100 pupils.

3. The technical condition of equipment was assumed to be described by an integrated risk indicator, including the depreciation rate, the probability of failure, and the proportion of equipment exceeding its standard service life.

4. The integrated index of an educational institution's provision was assumed to be represented as a function of the standard resource sufficiency and the operational risks of the equipment.

5. It was assumed that aggregation of indicators at the municipal and regional levels could be accomplished using weighted summation, with the number of pupils serving as weights.

6. It was assumed that the synthetic data used to test the model adequately reflect the typical structure of the regional education system and could be used to demonstrate the model's performance.

7. It was assumed that resource categories were independent and their contribution to the integral indicator could be aggregated additively.

The following assumptions were accepted during the study:

– standard values for material resource availability were specified and constant;

– risk components (wear and tear, probability of failure, exceeding service life) were standardized and took values ranging from 0 to 1;

– weighting coefficients for resource categories were considered constant in the experimental calculations;

– educational institution indicators were aggregated proportionally to the number of pupils.

The study's simplifications were as follows:

– the model was tested on synthetic data, which allowed us to verify the correctness of the mathematical apparatus; however, real data may have a more complex distribution;

– the study considered a limited number of material resource categories;

– the model does not take into account financial constraints and investment opportunities in the region;

– the model does not consider strategic plans for the development of the educational system or demographic changes in the student population.

A number of approaches were used in designing the information and analytical system:

1. A systems approach allowed us to formalize the data structure and define mechanisms for aggregating provision indicators.

2. An architectural approach enabled us to design the system based on a three-tier architecture (logical, physical, and software layers), enabling the separation of data and business logic, system scalability, as well as the ability to integrate with existing information resources.

3. Norm-based approach – the assessment of material resource availability is based on a comparison of the actual quantity of material resources with established availability standards, enabling the objectivity and comparability of indicators.

4. Risk-based approach – the system's development takes into account the wear and tear and degradation of equipment, enabling a transition from a static assessment of availability to dynamic monitoring of the state of the material base.

5. Index method – an integrated availability index based on a weighted aggregation of indicators by resource category – is used for a comprehensive assessment.

The choice of mathematical framework for the study was determined by the specificity of the problem under consideration. Unlike multicriteria analysis methods (AHP, TOPSIS) used for ranking alternatives, our study required the construction of a model that would enable a quantitative assessment of material resource availability, taking into account regulatory requirements and operational risks.

Calculations for the proposed model were performed using Microsoft Excel and the Python programming language. Visualization of results and design of an analytical dashboard employed Microsoft Power BI.

PostgreSQL can be used as a database management system when designing an information and analytical system.

Computational experiments were conducted on a personal computer with the following specifications: Intel Core i5 processor, 16 GB of RAM.

The following data were used as input:

– Number of pupils at educational institutions;

– Actual number of units of equipment by resource category;

– Standard resource availability ratios;

– Equipment technical condition indicators, including depreciation rate, failure probability, as well as the proportion of equipment exceeding its standard service life.

To test the model, a synthetic dataset was used, built to simulate various levels of availability and technical condition of educational institution infrastructure.

5. Results of constructing a model for managing how educational institutions are provided with material resources

5. 1. Devising a sequence of computational steps for generating an integrated sufficiency index

The basic element of the management system is the educational institution (school). At the school level, an initial assessment of material and technical support is performed, and an integrated sufficiency index is calculated. The resulting integrated sufficiency index is used to calculate indices at the municipal and regional levels.

For educational institution s, a set of resource categories $C=\{c_1, c_2, \ldots, c_k\}$ was considered. Each category includes homogeneous types of material resources, such as computer equipment, interactive panels, laboratory equipment, etc.

For each category, the actual quantity of equipment $A_{s,ci}$, the standard requirement $R_{s,ci}$, and risk components associated with operation are determined.

The standard requirement is determined based on the established standard sufficiency coefficient v_c, which indicates the required number of resource units. In this study, the calculation was performed for 100 pupils.

If the number of pupils in an organization is N_s, then the standard requirement is determined as

$$R_{s,c}=v_c * \frac{N_s}{100}, \tag{1}$$

where $R_{s,ci}$ is the standard requirement $R_{s,ci}$; v_c is the established standard provision coefficient; N_s is the number of pupils enrolled in the organization.

This indicator reflects the minimum required level of material support for resource category c. To assess the compliance of actual provision with standard requirements, the sufficiency coefficient $K_{s,c}$ (2) is introduced

$$K_{s,c}=\min\left(1, \frac{A_{s,c}}{R_{s,c}}\right). \tag{2}$$

The sufficiency coefficient values lie within the range $0 \le K_{s,c} \le 1$, where: $K_{s,c} = 1$ – the standard is fully met; $K_{s,c} < 1$ – resource shortage.

Using the *min* function prevents artificially inflating the index in the presence of excess equipment.

The actual condition of equipment is determined not only by its quantity but also by its operational characteristics. To account for equipment wear and tear or infrastructure degradation, a composite risk function $p_{s,c}$ (3) is introduced

$$p_{s,c} = \min\left(1, \lambda_u u_{s,c} + \lambda_f f_{s,c} + \lambda_t t_{s,c}\right), \tag{3}$$

where λ_u, λ_f, λ_t are weighting factors reflecting the relative importance of the corresponding risk factors; $u_{s,c}$ is the equipment wear factor; $f_{s,c}$ is the failure probability; $t_{s,c}$ is the proportion of equipment exceeding its standard service life.

The parameters $\lambda_u + \lambda_f + \lambda_t = 1$.

To account for the operational condition of the equipment, the sufficiency factor is adjusted for the risk value $\tilde{K}_{s,c}$ (4)

$$\tilde{K}_{s,c} = K_{s,c}\left(1 - p_{s,c}\right). \tag{4}$$

Thus, even with formal compliance with standards, high levels of wear and tear or failures lead to a decrease $\tilde{K}_{s,c} = K_{s,c}\left(1 - p_{s,c}\right)$ in effective provision.

To obtain a final assessment of the educational institution's provision, the educational institution's provision index I_s (5) is calculated

$$I_s = \sum_{c=1}^{k} w_c \tilde{K}_{s,c}, \tag{5}$$

where w_c is the resource category weight, $\Sigma w_c = 1$.

The weighting coefficients w_c used in calculating the integrated provision index reflect the relative importance of different equipment categories for the educational process. In the experimental calculations reported in this study, the weight values were used only to demonstrate the model's functionality. Subsequently, when implementing the proposed management system, expert methods for multicriteria decision making, such as the analytic hierarchy process, can be used to determine the weights. These methods will allow for the consideration of the relative importance of infrastructure elements. The I_s index takes values from $0 \le I_s \le 1$. Table 1 gives the range of the I_s index.

Table 1

Interpretation and range of index I_s

No.	Range of I_s	Interpretation of I_s
1	$I_s > 0.8$	High level of provision
2	$0.6 < I_s \le 0.8$	Satisfactory level of provision
3	$0.4 < I_s \le 0.6$	Insufficient level of provision
4	$I_s \le 0.4$	Critical level of provision

The algorithm for calculating the I_s index includes the following steps:

1. Collecting initial data $A_{s,c}$, N_s.
2. Calculating the standard requirement $R_{s,ci}$.
3. Determining the sufficiency coefficient $K_{s,c}$.
4. Assessing the risk components $u_{s,c}$, $f_{s,c}$, $t_{s,c}$.
5. Calculating the composite risk $p_{s,c}$.
6. Calculating the risk-adjusted sufficiency $\tilde{K}_{s,c}$.
7. Aggregating the indicators into the integrated I_s index.

The computational process flow diagram for calculating the index assessment of how an educational institution is provided with material resources is shown in Fig. 1.

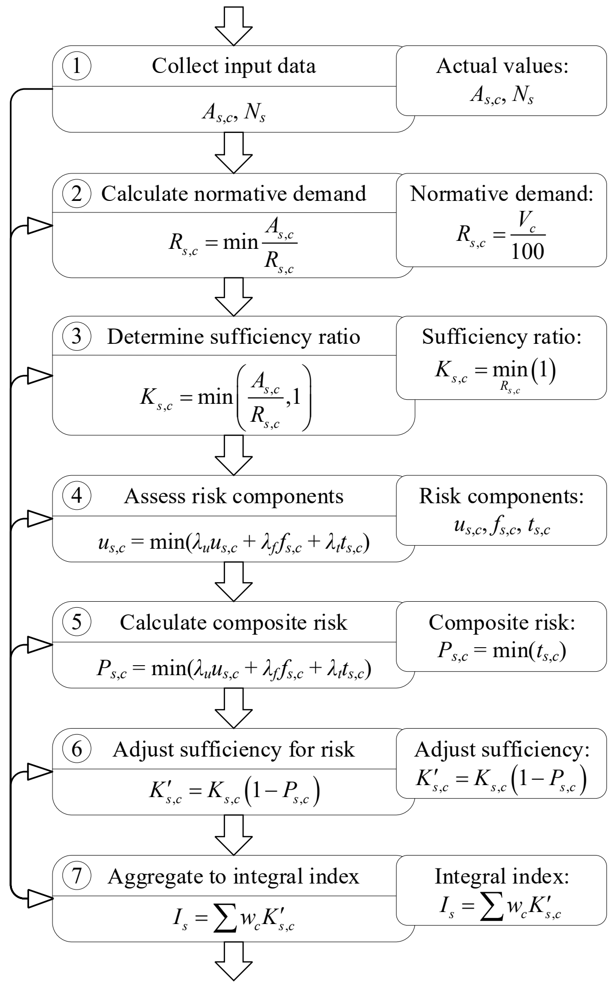

Fig. 1. Flow diagram of the computational process of index assessment of how an educational institution is provided with material resources

Fig. 1 shows the sequence of computational stages for forming the integrated index of sufficiency. At the first stage, initial data on the actual quantity of resources and the number of pupils ($A_{s,c}$, N_s) are collected. At stage 2, the standard requirement indicator $R_{s,ci}$ is calculated. At stages 3–7, the standard sufficiency coefficients $K_{s,c}$ are sequentially determined, the operational risk components $u_{s,c}$, $f_{s,c}$, $t_{s,c}$ are assessed, the composite risk $p_{s,c}$ is calculated, and the risk-adjusted sufficiency $\tilde{K}_{s,c}$. is obtained. At the final stage, the indicators are aggregated by resource categories, taking into account the weighting coefficients w_c, and the integrated index of sufficiency of the educational organization I_s is formed.

5. 2. Building the structure of a regional-level supply management system model

The I_s index obtained in the first stage is the basic element of the hierarchical supply assessment model. At the municipal level, the supply index I_m is calculated as follows (6)

$$I_m = \Sigma a_s I_s. \tag{6}$$

At the regional level, the provision index I_r is calculated as follows (7)

$$I_r = \sum \beta_m I_m. \tag{7}$$

Thus, educational institution-level indicators formed the basis for assessing the provision of the entire educational system.

Fig. 2 shows the structure of the model for managing how educational institutions are provided with material resources within a multi-level governance structure at the regional level.

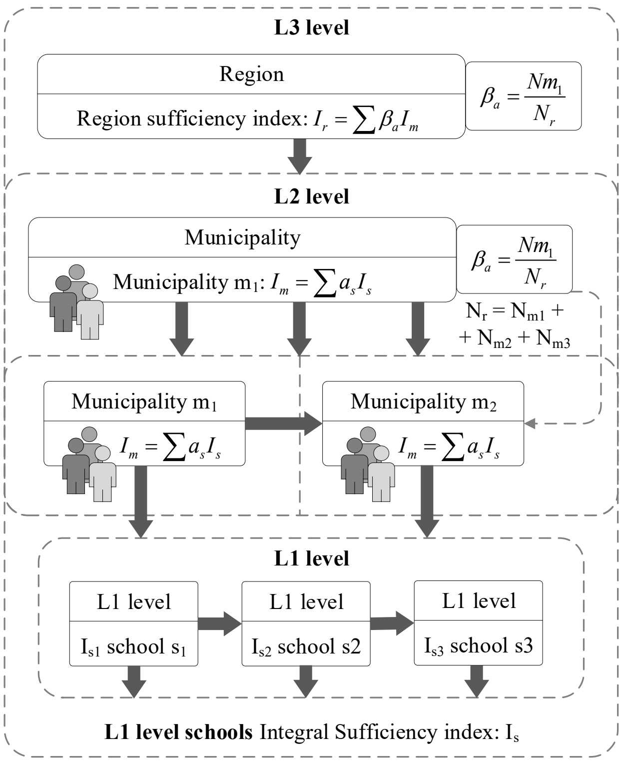

Fig. 2. Model structure of the system to manage how educational organizations are provided with material resources in the context of a multi-level management structure at the regional level

The model's structure is hierarchical and includes three levels:

– L1 – educational organization (school);
– L2 – municipality;
– L3 – region.

Fig. 2 shows the full computational framework of the model, including the stages of generating initial data, calculating the standard requirement, determining the standard sufficiency coefficient, assessing operational risks, and calculating the risk-adjusted provision. Based on the obtained values, an integrated provision index for the educational organization, I_s, is formed, which is then used in hierarchical aggregation procedures when moving to the municipal I_m and regional I_r assessment levels.

At the municipal level, the integrated provision index is formed by aggregating the indices of educational organizations included in the corresponding municipality: $S_m = \{s_1, s_2, ..., s_n\}$.

The municipal provision index was defined as the weighted sum of the organization indices, I_m (8)

$$I_m = \sum_{s \ni S_m} a_s I_s, \tag{8}$$

where a_s is the weight of the educational organization, proportional to the number of pupils. a_s is found using formula (9)

$$a_s = \frac{N_s}{\sum_{s \ni S_m} N_s}. \tag{9}$$

The use of weights allowed us to account for differences in the size of educational institutions and ensure an accurate representation of their contribution to the overall level of provision in a municipality.

The regional provision index is formed by aggregating municipal indices $M = \{m_1, m_2, ..., m_k\}$. $m_1, m_2, ..., m_k$ is the set of municipalities in the region. The regional index is determined using formula (10)

$$I_r = \sum_{m \ni M} \beta_m I_m, \tag{10}$$

where β_m is the weight of the municipality, determined by the number of pupils. β_m is calculated using formula (11)

$$a_s = \frac{N_m}{\sum_{m \ni M} N_m}, \tag{11}$$

where N_m is the number of pupils at municipal schools (12)

$$N_m = \sum_{s \ni S_m} N_s. \tag{12}$$

Thus, the regional index represented a weighted assessment of the regional educational system's provision.

The expanded form of the regional index was obtained as follows (13)

$$I_r = \sum_{m \ni M} \beta_m \left(\sum_{s \ni S_m} a_s I_s \right). \tag{13}$$

Substituting the expression for the index of the educational organization, we obtained the final form of the regional model (14)

$$I_r = \sum_{m \ni M} \beta_m \sum_{s \ni S_m} a_s \sum_{A} w_c \tilde{K}_{s,c}. \tag{14}$$

Thus, the regional index was formed as an aggregate function, taking into account resource availability, operational risks, as well as the structure of the education system.

To analyze the impact of regional differences, an indicator of the municipality's contribution to the regional index was introduced (15)

$$Contribution_m = \beta_m I_m. \tag{15}$$

This indicator allowed us to identify the territorial units that had the greatest impact on the overall level of provision in the education system. A graphical representation of municipal contributions is shown in Fig. 3.

The I_r index takes values $0 \le I_r \le 1$ and characterizes the overall level of material resources available to educational institutions in the region. Table 2 gives the range of the I_r index.

Integrated indices of educational organization and municipal provision allow us to take into account differences in the scale of the organization, municipality, and region, as well as identify existing infrastructure imbalances.

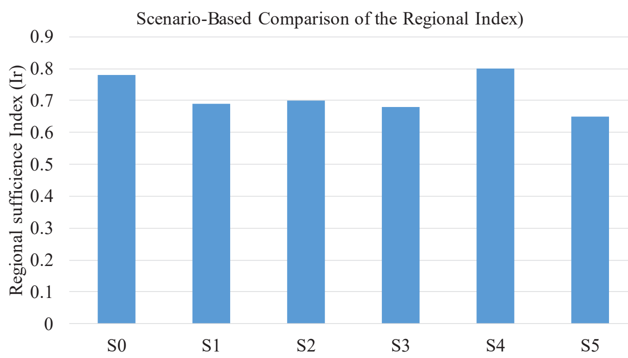

Fig. 3. Graphical interpretation of municipalities' contributions to the regional index

Table 2

Interpretation and range of index I_r

No.	Range of I_r	Interpretation of I_r
1	$I_r > 0.8$	High level of provision
2	$0.6 < I_r \leq 0.8$	Satisfactory level of provision
3	$0.4 < I_r \leq 0.6$	Insufficient level of provision
4	$I_r \leq 0.4$	Critical level of provision

5. 3. Validating the educational institution resource management system model on synthetic data

The model was validated on a synthetic data set to verify the accuracy of the computational procedures and identify modeling errors. Validation of the model allowed us to analyze the sensitivity of the integrated index to changes in risk components and demonstrated data aggregation at various levels of the system.

The following data set was used to validate the model:

– 3 municipalities m_1, m_2, m_3;

– 2 schools s_1 and s_2 in each municipality;

– 3 resource categories were selected: c_1 – computer equipment; c_2 – interactive panels; c_3 – laboratory equipment.

Total number of schools $s = 6$. Student enrollment N at each school: $N_{s_1} = 500$, $N_2 = 450$, $N_3 = 600$, $N_{s_4} = 550$, $N_{s_5} = 400$, $N_{s_6} = 500$.

Synthetic values for the actual number of resources A_{ci} are given in Table 3.

Table 3

Synthetic values of the actual amount of resources A_{ci}

No.	Organization	A_{c1}	A_{c2}	A_{c3}
1	S_1	23	9	14
2	S_2	20	8	13
3	S_3	32	11	18
4	S_4	28	10	15
5	S_5	18	6	10
6	S_6	24	9	13

Using school s_1 as an example, the standard requirement and other indicators of material security were calculated according to formulas (1) to (5). The standard of provision v_c per 100 pupils is as follows: $v_{c1} = 5$, $v_{c2} = 2$, $v_{c3} = 3$. To calculate the risk component, we introduce the weighting coefficients: $\lambda_u = 0.4$; $\lambda_f = 0.3$; $\lambda_t = 0.3$. Synthetic values for s_1: $u_{s1,c1} = 0.30$; $f_{s1,c1} = 0.20$; $t_{s1,c1} = 0.25$, category weights: $w_{c1} = 0.4$; $w_{c2} = 0.3$; $w_{c3} = 0.3$. The calculation results are given in Table 4.

Table 4

Calculation of indicators for how an organization is provided with material resources s_1

C	$R_{s1,c}$	$K_{s1,c}$	$p_{s1,c}$	$\tilde{K}_{s1,c}$
c_1	25	0.92	0.255	0.685
c_2	10	0.9	0.247	0.678
c_3	15	0.933	0.284	0.668
$I_{s1,c}$		0.684		

Fig. 4 shows the calculation of the provision index I_s for each school.

The municipality provision indices I_m were calculated using formula (8), and I_r was calculated using formula (14). The resulting values are given in Table 5.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Municipalit	School	Students	Category	ctual_A_s	rmative_R	K_s,c	u_s,c	f_s,c	t_s,c	rho_s,c	K_tilde_s,c	w_c	
2	m1	s1	500	c1	23	25	0,92	0,3	0,2	0,25	0,255	0,685	0,4	
3	m1	s1	500	c2	9	10	0,9	0,28	0,18	0,27	0,247	0,678	0,3	
4	m1	s1	500	c3	14	15	0,933	0,32	0,22	0,3	0,284	0,668	0,3	
5	m1	s2	450	c1	20	22,5	0,889	0,35	0,24	0,28	0,296	0,626	0,4	
6	m1	s2	450	c2	8	9	0,889	0,33	0,26	0,25	0,285	0,636	0,3	
7	m1	s2	450	c3	13	13,5	0,963	0,3	0,2	0,26	0,258	0,715	0,3	
8	m2	s3	600	c1	32	30	1	0,22	0,12	0,18	0,178	0,822	0,4	
9	m2	s3	600	c2	11	12	0,917	0,25	0,15	0,2	0,205	0,729	0,3	
10	m2	s3	600	c3	18	18	1	0,24	0,14	0,19	0,195	0,805	0,3	
11	m2	s4	550	c1	28	27,5	1	0,26	0,18	0,22	0,224	0,776	0,4	
12	m2	s4	550	c2	10	11	0,909	0,3	0,2	0,24	0,252	0,68	0,3	
13	m2	s4	550	c3	15	16,5	0,909	0,28	0,19	0,23	0,238	0,693	0,3	
14	m3	s5	400	c1	18	20	0,9	0,42	0,35	0,5	0,423	0,519	0,4	
15	m3	s5	400	c2	6	8	0,75	0,48	0,4	0,55	0,477	0,392	0,3	
16	m3	s5	400	c3	10	12	0,833	0,4	0,33	0,48	0,403	0,497	0,3	
17	m3	s6	500	c1	24	25	0,96	0,31	0,21	0,29	0,274	0,697	0,4	
18	m3	s6	500	c2	9	10	0,9	0,29	0,19	0,31	0,266	0,661	0,3	
19	m3	s6	500	c3	13	15	0,867	0,34	0,23	0,33	0,304	0,603	0,3	
20	m1	s1	500	TOTAL_INDEX (I_s)								0,678		
21	m1	s2	450	TOTAL_INDEX (I_s)								0,655		
22	m2	s3	600	TOTAL_INDEX (I_s)								0,789		
23	m2	s4	550	TOTAL_INDEX (I_s)								0,722		
24	m3	s5	400	TOTAL_INDEX (I_s)								0,475		
25	m3	s6	500	TOTAL_INDEX (I_s)								0,658		
26														

Fig. 4. Calculation of the provision index I_s for schools s_1–s_6

Table 5

Values of the indices for provision of municipalities and the region

m	Number of pupils	I_m
m_1	950	0.667
m_2	1150	0.757
m_3	900	0.577
I_r	3000	0.675

To form a complete picture of the region's school supply, a sustainability analysis was conducted taking into account equipment depreciation. With an increase in $\Delta u = 0.1$, the composite risk $p_{s,c}^{new}$ increases by 0.04, and the regional index I_r^{new} decreases to 0.670. The relative change in the regional supply index is –5.6%.

Testing the model on synthetic data showed that it meets the following requirements:

1. Mathematical correctness of aggregation.
2. Sensitivity of the index to risk components.
3. Stability of the hierarchical transmission of indicators.
4. Interpretability of the model.

The final values of the sufficiency index I_s, I_m, I_r obtained from testing the model on a synthetic data set are given in Table 6. The municipal and regional indices were calculated using a weighted aggregation method, taking into account student cohorts.

Table 6

Integrated indices of sufficiency by management levels

Municipality	School	Cohort N_s	School index I_s
m_1	s_1	500	0.648
m_1	s_2	450	0.623
m_1	–	950	0.636 (I_{m1})
m_2	s_3	600	0.782
m_2	s_4	550	0.741
m_2	–	1150	0.762 (I_{m2})
m_3	s_5	400	0.492
m_3	s_6	500	0.651
m_3	–	900	0.580 (I_{m3})
Region	–	3000	0.663 (I_r)

Testing the model on synthetic data revealed that at the level of individual schools (level L1), there is a pronounced differentiation in the sufficiency index $I_s \in [0{,}492;\ 0{,}782]$. School s_5 is the most vulnerable ($I_s = 0.492$). Analysis of the components reveals that the decrease in the index is due to:

– high depreciation ($u_{s,c}$);

– a significant proportion of excess of the standard service life ($t_{s,c}$);

– relatively low provision for category c_2.

It is the combination of these factors that generates an increased value of the composite risk: $p_{s5,c} \to 0.45$–0.50, which leads to a significant decrease in risk-adjusted sufficiency $\tilde{K}_{s,c}$. In contrast to s_5, school s_3 ($I_s = 0.782$) demonstrates:

– standard or excess provision;

– low values of all risk components;

– minimal index degradation upon adjustment.

Our calculations confirm the sensitivity of the model to operating parameters.

At the municipal level (level L2), municipality m_3 demonstrates the lowest index value. This is due to the influence of school s_5, which has a high enrollment (400 pupils) and a low index. Thus, the model accurately translates local problems to the regional government level.

At the regional level (level L3), the overall index decreases due to the high enrollment rate in m_3 and the significant risk of infrastructure degradation at s_5. This demonstrates two key properties of the model:

1. Scale validity – the contribution of municipalities is proportional to the enrollment.
2. Sensitivity to risk accumulation – degradation at level L1 leads to a measurable decrease at level L3.

Fig. 5 shows a chart of the influence of municipal indices on the regional index.

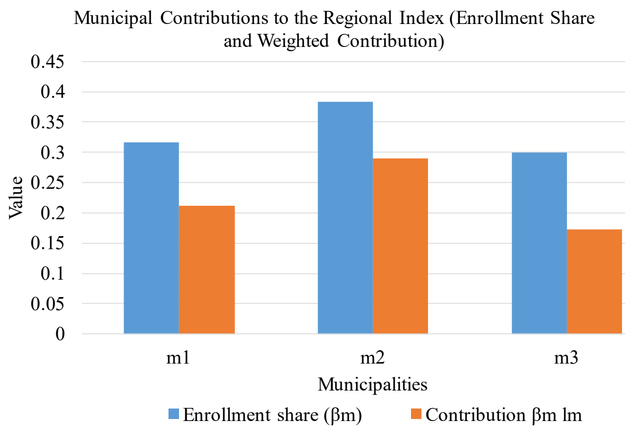

Fig. 5. Chart of the influence of municipal indices on the regional index

β_m is the municipality's share of the regional population, and $\beta_m I_m$ is the municipality's contribution to the regional index.

Fig. 5 shows that m_2 has the largest contribution, high I_m, and a large cohort. m_3, with a comparable cohort share, makes a significantly smaller contribution – it is this contribution that "pulls down" the regional index.

Based on the results of testing the model on synthetic data, the following conclusions were drawn:

1. The model accurately reflected the impact of risk components on the final index.
2. Hierarchical aggregation did not smooth out local imbalances.
3. The most significant factor in the decline in the integrated index was the combination of high equipment wear and tear and exceeding the standard service life.
4. The model identified priority areas for management intervention (in this case, municipality m_3 and school s_5).

The proposed model supports management decision-making in a multi-level governance structure. In this regard, it seems appropriate to conduct a comparative analysis of the proposed model (Table 7) with the most common models used to assess resources and support management decisions.

Our comparison showed that, unlike existing models, the proposed model allows for the simultaneous consideration of the regulatory sufficiency of material resources, operational risks, as well as the hierarchical structure of the management system.

Table 7

Comparison of the proposed model with existing resource assessment models

Model	Scope of application	Advantages	Restrictions
DEA (Data Envelopment Analysis)	Resource efficiency assessment	Allows one to evaluate the relative effectiveness of organizations	Doesn't take into account the technical condition of equipment and the risk of infrastructure degradation
AHP (Analytic Hierarchy Process)	Multi-criteria evaluation and decision making	Allows one to take into account multiple criteria and expert assessments	Expert assessments are highly subjective; equipment depreciation is not taken into account
TOPSIS	Ranking alternatives based on multiple criteria	Ease of implementation and interpretation of results	Doesn't take into account the dynamics of infrastructure degradation and the multi-level governance structure
Risk-based asset management	Risk-based asset management	Considers the likelihood of failures and equipment wear	Doesn't take into account the regulatory sufficiency of resources and the hierarchy of the education system
The proposed model	Assessment of how educational institutions are provided with material resources	Takes into account regulatory resource sufficiency, operational risks, and a multi-level management structure	Requires initial data on the condition of equipment and standards of provision

6. Discussion of results based on constructing a model of the system for how educational organizations are provided with material resources

The basic element of the system is the educational institution. At the school level, the integrated sufficiency index I_s is calculated according to formulas (1) to (5), which is then aggregated to the municipal and regional levels. Table 1 gives the interpretation and range of the I_s index. A high level of sufficiency corresponds to an I_s value greater than 0.8. A critical sufficiency level corresponds to an I_s value less than 0.4.

Fig. 1 shows the computational process flow diagram for the model for index-based assessment of the educational institution's material and technical provision, showing the sequence of calculations for the sufficiency coefficients and the integrated sufficiency index I_s. Using this computational process allowed us to formalize the procedure for assessing how educational institutions are provided with material resources and move from disparate equipment inventory indicators to an integrated assessment of sufficiency. A distinctive feature of the proposed approach is that a single computational process takes into account the standard resource requirement, actual sufficiency, as well as operational risks of the equipment. That has made it possible to obtain an integrated indicator of resource availability, reflecting not only the quantitative sufficiency of resources but also their technical condition.

Formulas (6) and (7) provide the overall calculation of the municipal resource availability index I_m and the regional resource availability index I_r. Thus, educational institution-level indicators form the basis for assessing the resource availability of the entire educational system.

Fig. 2 shows the structure of the hierarchical model for assessing the resource availability for educational institutions at the school-region level. A distinctive feature of the proposed hierarchical model is the ability to assess the contribution of individual educational institutions and municipalities to the formation of the integrated regional indicator. This allows the model to be used not only to assess the current state of resource availability but also to identify territorial zones with increased infrastructure risk and to justify management decisions on resource redistribution.

The municipal resource availability index I_m is defined as the weighted sum of the organization indices I_s, taking into account the educational institution's weight, and is calculated using formulas (8) and (9).

The use of weights allows for differences in the size of educational institutions to be taken into account and ensures an accurate representation of their contribution to the overall resource availability of the municipality.

The regional index of provision I_r, taking into account the weight of the municipality and the number of pupils in the municipality's schools, is calculated using formulas (10) to (14).

To analyze the impact of regional differences, a municipal contribution indicator (I_r) was introduced to the regional index of enrollment at municipal schools and calculated using formula (15).

Table 2 gives the range of the I_r index, where a high level of provision corresponds to an I_r value ≥ 0.8, and a critical level of provision corresponds to an I_r value of ≤ 0.4. The proposed distribution allowed us to rank regions by their level of material resource provision.

A graphical interpretation of municipal contributions is shown in Fig. 3. This graphical interpretation allowed us to assess the degree of influence of each municipality on the formation of the integrated regional resource provision indicator. A distinctive feature of our results is that a municipal contribution to the regional integrated indicator is determined not only by the level of provision of educational institutions but also by the number of pupils and the level of operational risks of the infrastructure within the municipality. That has made it possible to identify municipalities that have the greatest impact on the integrated indicator of regional provision, and to determine the territories in which the modernization of the material and technical base could have the greatest impact on the overall level of provision of the educational system.

Our results showed that municipalities with large student cohorts have the greatest impact on the regional integrated indicator, even with an average level of provision. At the same time, municipalities with high infrastructure risks can significantly reduce the regional integrated indicator, even if their share of the total student cohort is relatively small.

The model was tested using synthetic data. For testing, a condition was proposed: one region with three municipalities (m_1–m_3), with two schools in each municipality (s_1–s_6). For each school, the number of pupils and resource categories (c_1–c_3) were determined. Synthetic values of the actual amount of resources (A_{ci}) are used in Table 3. Based on the proposed synthetic data, the sufficiency coefficient $K_{s,c}$, the integrated risk value $p_{s1,c1}$ (risk – adjusted sufficiency $\tilde{K}_{s1,c1}$), and the integrated organizational index (I_{s1}) were calculated.

I_{s1} was calculated for schools s_1–s_6; the calculations are shown in Fig. 4 and Tables 4, 5. Our calculations showed that the integrated security index is sensitive to equipment operational risks. Even with similar values of the standard sufficiency coefficient, high levels of wear and tear and exceeding the service life lead to a decrease in the risk-adjusted security index and the resulting integrated index.

To calculate the municipal index I_m, the school weights a_s were determined. Next, the regional index I_r was calculated. To form a complete picture of the regional school provision, a sustainability analysis was conducted taking into account equipment depreciation. The integrated sufficiency indices by management levels are given in Tables 5, 6. The chart of the influence of municipal indices on the regional index is shown in Fig. 5. The calculation of the municipal and regional indices of provision made it possible to establish that the value of the integrated indicator at the regional level depends both on the level of provision of individual educational institutions and on the distribution of the student body between municipalities. It was found that municipalities with a large number of pupils have the greatest influence on the regional index. At the same time, the presence of an educational institution with a low level of provision and a large contingent leads to a decrease in the municipal and regional indices. This indicates that the hierarchical aggregation of indicators ensures the transfer of local infrastructure problems to a higher management level. The analysis of municipal contributions made it possible to quantitatively assess the influence of each territorial unit on the integrated indicator of the region and to identify municipalities whose infrastructure modernization would have the greatest impact on the overall level of provision of the educational system. Our stability analysis reveals that an increase in the level of equipment depreciation leads to a decrease in the regional index, which confirms the sensitivity of the model to operational risks and the possibility of using the model to analyze infrastructure degradation scenarios.

The final values of the sufficiency index I_s, I_m, I_r obtained by testing the model on a synthetic data set confirmed that the model accurately reflects the impact of risk components on the final index. The model also enabled the identification of priority areas for management intervention (in this case, municipality m_3 and school s_5) to implement timely measures to improve material support.

Table 7 gives a comparison of the proposed model with existing resource assessment and decision support models. The comparison revealed that existing models address specific resource management tasks but do not provide a comprehensive assessment of the material resource availability of educational institutions within a multi-level management structure. This allowed for consideration not only of resource sufficiency but also the risks of infrastructure degradation and the impact of the educational system structure on integrated resource availability indicators.

The limitations of our study include the use of synthetic data, the limited range of resource categories considered, and the lack of consideration of financial constraints and the dynamics of equipment condition changes over time. These limitations define areas for further development of the model, including the use of real data, expansion of the list of indicators, and the construction of predictive models for infrastructure degradation. First and foremost, it seems appropriate to use real statistical data from educational institutions to validate the model's adequacy and assess its applicability to real-world educational infrastructure management conditions. A promising direction is to advance the model to predict the degradation of physical infrastructure based on an analysis of equipment wear and tear dynamics and the probability of failure. This will allow for a transition from assessing the current state of provision to forecasting changes in future provision levels.

Furthermore, further development of the model could involve incorporating financial indicators, equipment upgrade costs, as well as budget constraints, which would allow the model to be used to optimize the allocation of financial resources among educational institutions.

Another promising direction is the integration of the model built into information and analytical systems for monitoring educational infrastructure and decision support systems for education authorities. The model could be further expanded by using machine learning methods to predict equipment failures, assess the rate of infrastructure degradation, as well as generate development scenarios for the region's educational infrastructure.

7. Conclusions

1. An educational institution was adopted as the basic element in the management system when developing the sequence of computational stages for forming the integrated index of material resources. To assess material resources, formulas were proposed for calculating the standard requirement $R_{s,ci}$, the sufficiency coefficient $K_{s,ci}$, the $u_{s,c}$, $f_{s,c}$, $t_{s,c}$ risk component assessment, the composite risk $p_{s,c}$, and the risk-adjusted sufficiency $\tilde{K}_{s,c}$, of the integrated index I_s. The I_s index takes values $0 \le I_s \le 1$, with $I_s \ge 0.8$ indicating a high level of material resources and $I_s \le 0.4$ indicating a critical level.

2. As a result of constructing the structure of the regional material resources management system model, the calculation of the municipal material resources index I_m and the regional material resources index I_r was proposed for assessing material resources at the regional level. When calculating the material resources indices, the weight of the educational institution, proportional to the number of pupils, and the weight of the municipality, determined by the number of pupils, were taken into account. To analyze the impact of territorial differences, an indicator of the municipality's contribution to the regional index was introduced. The I_r index takes values of $0 \le I_r \le 1$, with $I_r \ge 0.8$ indicating a high level of provision, and $I_r \le 0.4$ indicating a critical level.

3. Testing the model allowed us to analyze the sensitivity of the integrated index to changes in risk components and demonstrate data aggregation at various levels of the system. During the experiment, the material security index was calculated for 6 educational institutions and 3 municipalities using one region as an example.

At the educational institution level, a pronounced differentiation in the adequacy index $I_s \in [0.492;\ 0.782]$ was observed. School s_5 was found to be the most vulnerable ($I_s = 0.492$).

At the municipal level, m_3 exhibits the lowest index value. This is due to the influence of school s_5, which has a high enrollment (400 pupils) and a low index. Thus, the model accurately translates local problems to the regional government level.

Regional index $I_r = 0.663$. Despite the presence of a municipality with a high level of material security, m_2, the overall index is reduced due to the high proportion of pupils in m_3 and the significant risk of infrastructure degradation at s_5.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study and the results reported in this paper.

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Data availability

All data are available, either in numerical or graphical form, in the main text of the manuscript.

Use of artificial intelligence

The artificial intelligence tool ChatGPT (OpenAI, GPT-5.3-series model) was used to support language editing, improve the readability and academic style of the manuscript. The artificial intelligence tool did not contribute to the scientific content, data analysis, interpretation of results or formulation of conclusions. All methodological decisions, analyses, and final interpretations were made by the authors who bear full responsibility for the content of the manuscript.

Authors' contributions

Yelnar Utyubayev: Investigation, Data Curation, Writing – review & editing; **Anna Shaporeva**: Conceptualization, Methodology, Formal analysis, Writing – original draft, Visualization.

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