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IMPROVING COST AND RESOURCE EFFICIENCY THROUGH OPTIMIZATION OF KPI DATA ANALYSIS PROCESSES IN HIGHER EDUCATION

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Abstract. This paper addresses the problem of excessive computational costs, time overhead, and inefficient utilization of processing resources in the analysis of KPI (Key Performance Indicators) data from the perspective of computer science and systems analysis. The study considers the complete lifecycle of KPI data, including acquisition, storage, preprocessing, and analytical processing, within a formalized systems framework. Mathematical models are proposed to describe cost functions, time complexity, and resource consumption associated with KPI data processing workflows. Based on these models, algorithmic solutions are developed using incremental computation, hierarchical data aggregation, and multi-objective optimization techniques aimed at minimizing computational load, memory usage, and processing latency. The proposed algorithms are analyzed in terms of computational complexity and scalability and are experimentally evaluated in comparison with conventional batch-oriented approaches. Experimental results demonstrate a significant reduction in processing time, computational resource consumption, and overall operational costs. The findings confirm the applicability of the proposed models and algorithms for optimizing KPI-driven decision-support systems in public administration, higher education management, and large-scale corporate information systems.

Keywords. *KPI, computational complexity, data processing algorithms, optimization models, incremental computation, resource-efficient systems, digital management.*

Introduction In recent years, the rapid development of the digital economy and digital governance concepts has been shaping fundamentally new requirements for mechanisms of organizational performance evaluation and management. In particular, data-driven decision making has become a dominant paradigm in decision-making processes, increasing the demand for accurate, reliable, and measurable indicators for assessing organizational effectiveness. From this perspective, KPI (Key Performance Indicators) have emerged as an integral component of modern management systems and have been widely adopted in practice [9, 10].

KPI systems enable the quantitative and qualitative evaluation of the performance of an organization, its structural units, or individual employees, ensure alignment between strategic objectives and day-to-day operations, and provide a foundation for making management decisions on a scientific basis [9]. International studies emphasize that KPI systems serve as an important instrument for enhancing management effectiveness and improving control and monitoring processes [6, 10, 11].

However, practical experience shows that the effectiveness of KPI systems depends not only on the correct selection of indicators, but also directly on how efficiently the processes of collecting, processing, and analyzing KPI data are organized. In many organizations, KPI data are stored in a fragmented manner across different information systems and are processed using manual or semi-automated methods. This, in turn, leads to excessive costs, time losses, and inefficient utilization of computational resources during the analysis process [12].

The continuous growth in the volume of KPI data further increases the relevance of this problem. In particular, in public administration bodies, higher education institutions, the banking and financial sector, and large corporate organizations, the number of KPI indicators is steadily increasing, leading to the necessity of their analysis in real time. Under such conditions, traditional KPI analysis methods based on full recomputation result in high time complexity and excessive computational costs [12, 13].

In the context of Uzbekistan, the implementation and development of KPI systems is considered one of the important directions of state policy. Within the framework of developing the digital economy, digitalizing public administration, and improving the performance efficiency of higher education institutions, KPI-based management mechanisms are being widely applied in the country [12]. The works of the President of the Republic of Uzbekistan and national development strategies place particular emphasis on management principles based on performance, efficiency, and personal accountability [1].

Studies conducted by Uzbek scholars have extensively addressed the organizational and methodological aspects of implementing KPI systems, the role of information systems in managerial decision-making, and issues of digital governance [1,2]. However, the majority of these studies focus primarily on the correct selection of KPI indicators and the transparency of performance evaluation, while the problem of reducing excessive costs, processing time, and computational resource consumption in KPI data analysis has not been sufficiently investigated. From this perspective, KPI data analysis should be considered not merely as a process of calculating outcome indicators, but as a complex system that requires substantial economic and computational resources.

Optimizing KPI data analysis makes it possible to reduce analysis time and operational costs, ensure efficient utilization of computational infrastructure, and accelerate decision-making processes [13]. The present research is specifically aimed at addressing these challenges and proposes optimization models designed to reduce excessive costs, time consumption, and resource usage in KPI data analysis. The study analyzes the lifecycle of KPI data, as well as cost and time complexity, and proposes approaches based on incremental computation, data aggregation, and multi-objective optimization methods [12,15].

Literature review

KPI systems have been widely discussed in the scientific literature as an effective instrument for evaluating and managing organizational performance. Early studies considered KPI as a strategic management tool, with particular emphasis on linking organizational objectives to measurable indicators and monitoring performance outcomes [9,10]. These studies provided a theoretical justification for the role of KPI in managerial decision-making processes.

In classical management theory sources, KPI indicators are primarily focused on measuring performance outcomes, while the time, cost, and computational resources required for KPI data collection and analysis have rarely been examined as independent research objects [11]. This limitation represents a significant research gap, especially in the context of digital governance systems where data volumes are continuously increasing. The development of digital transformation and Big Data concepts has introduced new technological approaches to KPI data analysis. Several studies have proposed the use of data warehouses, distributed computing environments, and cloud-based platforms for processing large volumes of KPI data [12]. However, these works are mainly oriented toward increasing computational capacity, whereas issues related to optimal resource management and efficiency-oriented optimization have not been sufficiently addressed.

From an algorithmic perspective, a number of studies apply statistical methods, regression models, and rule-based algorithms for KPI data analysis. Although the scientific literature notes the simplicity and interpretability of these approaches, it is emphasized that they exhibit high time complexity when processing large-scale datasets [13]. Consequently, optimized approaches based on incremental computation and data aggregation methods have been proposed to address these limitations [15].

Machine learning and artificial intelligence–based approaches are emerging as a distinct research direction in the field of KPI analysis. Several studies employ neural networks and ensemble models to forecast KPI indicators, identify trends, and detect anomalies [17, 14]. At the same time, the high computational costs associated with training and deploying such models further intensify the need to ensure resource efficiency in KPI data analysis.

In studies that consider KPI data analysis as a business process model, integrated architectures comprising data collection, cleansing, transformation, and visualization stages have been proposed [16]. While these approaches enable a systematic organization of KPI analysis, the availability of precise mathematical models aimed at reducing excessive costs at each processing stage remains limited.

Research conducted by Uzbek scholars and national sources primarily addresses KPI system implementation in the context of public administration, higher education, and the digital economy. In particular, national studies extensively discuss the use of information systems in managerial decision-making, digital governance, and the practical deployment of KPI indicators [12, 18, 14]. Although these works highlight the practical significance of KPI systems, the problem of reducing time and resource consumption in KPI data analysis processes has not been sufficiently systematized. Additionally, studies focused on KPI-based performance evaluation in higher education and public administration in Uzbekistan emphasize transparency, fairness of assessment, and reliability of results [1, 2, 6]. However, these studies do not provide an in-depth analysis of computational costs and time complexity in KPI data analysis through formal economic or mathematical models.

The above literature review indicates that despite the availability of substantial theoretical and practical research on KPI data analysis, comprehensive optimization models aimed at reducing excessive costs, processing time, and computational resource consumption remain insufficiently developed [3, 4]. The present study is specifically intended to address this research gap.

Methods

In this study, a comprehensive set of scientific methods was employed to develop and evaluate optimization models aimed at reducing excessive costs, processing time, and computational resource consumption in KPI data analysis. The research methodology includes theoretical analysis, mathematical modeling, algorithmic approaches, and experimental evaluation techniques.

Theoretical analysis and systems approach. At the initial stage of the study, national and international scientific literature related to KPI systems was analyzed. Using theoretical analysis, the lifecycle of KPI data—namely data collection, storage, processing, and analysis stages—was systematically examined. The systems approach made it possible to consider KPI analysis as a unified and integrated process and to identify sources of excessive costs arising at each stage of the data lifecycle.

Method for formalizing KPI data costs. This method serves to evaluate the efficiency of KPI systems and to provide a scientifically grounded approach to cost management in digital transformation processes. The costs associated with KPI data analysis generally consist of the following main components:

1. **Data collection costs (C_1)**
   – manual data entry;
   – integration from automated sensors, LMS, ERP, and information systems;
   – costs related to correcting errors caused by the human factor.

2. **Data transmission costs (C_2)**
   – network traffic;
   – server and cloud infrastructure;
   – costs associated with ensuring data security.
3. **Data storage costs (C_3)**
   – database volume;
   – data archiving;
   – creation of backup copies.
4. **Data processing and analysis costs (C_4)**
   – computational power;
   – algorithmic complexity;
   – use of Big Data and AI-based models.
5. **Data visualization and decision-making costs (C_5)**
   – analytical dashboards;
   – report generation;
   – expert assessments.

To evaluate costs in KPI data analysis, a mathematical formalization method was applied. The total costs associated with KPI data processing were expressed using the following model [11]:

$$C_{KPI} = C_1 + C_2 + C_3 + C_4 + C_5 \quad (1)$$

here:
C_{KPI}— the total cost of KPI data management; C_1–C_5— the functional cost components defined above.
In this model, the cost function is variable and depends on the algorithmic complexity and the system architecture.

Parameterization of KPI Costs. In the formalization process, each cost component is expressed as a function of the following parameters:
n— number of KPI indicators;
t— data update frequency;
v— data volume;
r— computational resources;
h— level of human involvement.
For example, data processing and analysis costs can be represented as:

$$C_4 = f(n, v, r, t) \quad (2)$$

In this expression, the cost function is variable and depends on the algorithmic complexity and the system architecture. This approach enables a detailed analysis of costs across individual components of the KPI data analysis process.

Time Complexity Analysis Method. To evaluate time consumption in KPI data processing workflows, an algorithmic analysis method was applied. In traditional KPI analysis approaches, full data recomputation leads to the following time complexity [13]:

$$T_{\text{trad}}(n) = O(n^2) \quad (3)$$

In contrast, the proposed incremental and aggregation-based approaches reduce the time complexity to the following form [14]:

$$T_{\text{opt}}(n) = O(n \log n)$$

This improvement enables a significant acceleration of computational processes in KPI data analysis.

Resource utilization evaluation method. To assess the utilization of computational resources in KPI data analysis, a resource model was developed. The total resource consumption is defined as follows [12, 16]:

$$R_{\text{total}} = R_{\text{CPU}} + R_{\text{MEM}} + R_{\text{IO}} \quad (4)$$

where:
R_{CPU}— processor (CPU) resources;
R_{MEM}— memory (RAM) consumption;
R_{IO}— input/output operations.

Algorithmic Modeling Method. To reduce redundant computations, an algorithmic modeling method was applied. The KPI calculation process was implemented in an incremental manner as follows [15, 16]:

$$KPI_t = KPI_{t-1} + \Delta KPI \quad (5)$$

here, ΔKPIdenotes the change resulting from newly introduced data.

Experimental evaluation method. To assess the effectiveness of the proposed methods, an experimental comparative analysis was conducted. Performance efficiency was evaluated using the following metric [17]:

$$E = \frac{C_{trad} - C_{opt}}{C_{trad}} \times 100\% \quad (6)$$

here, E denotes the increase in economic efficiency.

In this section, optimal models aimed at reducing excessive costs, processing time, and computational resource consumption in KPI data analysis are proposed. The proposed models are designed to simultaneously optimize costs, time, and resource utilization while taking into account the complete lifecycle of KPI data. The models are based on mathematical formalization, algorithmic approaches, and automated data flow mechanisms [9, 11, 17].

General optimization model of KPI data analysis. Since the KPI data analysis process represents a multi-factor system, its optimization is considered as a multi-objective optimization problem. The general optimization model is expressed by the following objective function [17, 19]:

$$\min Z = \alpha T + \beta R + \gamma C \quad (7)$$

here:

Z— the overall optimization criterion; T— time required for KPI data analysis; R— computational resource consumption; C— total costs associated with KPI analysis; α, β, γ— weighting coefficients representing the relative importance of the corresponding factors ($\alpha + \beta + \gamma = 1$).

This model enables the identification of the most optimal decision for various KPI analysis scenarios.

Incremental KPI Data Analysis Model. In traditional KPI analysis methods, data are fully reprocessed during each computation cycle, which leads to excessive time and resource consumption when dealing with large-scale datasets. Therefore, this study proposes an incremental analysis model to address these limitations [15, 16].

The incremental KPI computation model is expressed as follows:

$$KPI_t = KPI_{t-1} + \Delta KPI \quad (8)$$

here:

KPI_t— the KPI value at the current time;
KPI_{t-1}— the KPI value computed at the previous time step;
ΔKPI— the change resulting from newly introduced data.

This model accelerates the analysis process by reducing redundant computations.

KPI data aggregation and filtering model. In KPI data analysis, excessive computations often arise as a result of processing insignificant or redundant data. To address this issue, a data aggregation and filtering model is proposed [12, 16].

Data aggregation is expressed as follows:

$$A_{KPI} = \sum_{i=1}^{n} w_i \cdot x_i \quad (9)$$

here:

A_{KPI}— the aggregated KPI value;
x_i— individual KPI indicators;
w_i— weighting coefficients representing the importance of KPI indicators;
n— number of KPI indicators.

The filtering model is implemented based on the following condition:

$$x_i = \begin{cases} x_i, & \text{if } x_i \geq \theta \\ 0, & \text{else} \end{cases}$$

here, θ denotes the minimum significance threshold.

Resource-aware KPI analysis model. In situations where computational resources are limited, it is appropriate to apply a resource-aware model for KPI analysis. This model is aimed at optimizing the KPI analysis process within the constraints of available computational resources [12, 19]. The model is defined by the following constraints:

$$\sum_{i=1}^{n} R_i \leq R_{max} \quad (10)$$

here:

R_i— the amount of resources consumed by an individual KPI computation process;
R_{max}— the maximum available resource capacity.

This constraint prevents excessive resource utilization in KPI data analysis.

Automated KPI data flow model. Manual collection and processing of KPI data often lead to time losses and errors. Therefore, an automated data flow (data pipeline) model is proposed to address these issues [16,17].

The model is expressed through the following functional relationship:

$$Pipeline = \{Collect \rightarrow Clean \rightarrow Transform \rightarrow Analyze \rightarrow Store\}$$

his model contributes to reducing time and costs by automating KPI analysis processes.

Advantages of the proposed models. The proposed optimization models have the following advantages:
– reduction of computation time in KPI analysis;
– efficient utilization of computational resources;
– reduction of excessive operational costs;
– capability to perform analysis in real time.

These models are suitable for practical application in public administration, higher education institutions, and corporate information systems [12, 15, 19].

Results

The effectiveness of the optimal models proposed in this paper was evaluated through experimental studies, and the obtained results were analyzed. The experiments were conducted based on a comparative analysis between traditional KPI data analysis approaches and the proposed optimized models [12, 15, 17].

The experimental studies were carried out using a realistic synthetic dataset of KPI data. The dataset includes KPI indicators collected from multiple sources, including time series data and aggregated indicators. The following configuration was applied in the experiments:
– number of KPI records: $n = 10^5$;
– number of analysis periods: $t = 12$;
– traditional full recomputation model;
– proposed incremental and aggregation-based model.

Analysis time, computational resource consumption, and total operational costs were used as evaluation criteria [13, 16].

Comparative results of time consumption. A comparative analysis of the time required for KPI analysis was conducted for the traditional and the proposed models. The experimental results demonstrate that the proposed incremental computation model leads to a significant reduction in analysis time.

Time efficiency was evaluated using the following metric:

$$S_T = \frac{T_{trad} - T_{opt}}{T_{trad}} \times 100\% \qquad (11)$$

here:
– T_{trad}— analysis time using the traditional approach;
– T_{opt}— analysis time using the optimized model.

According to the experimental results, the analysis time was reduced by an average of **55–65%**

Model Type	**Analysis Time (s)**	**Reduction (%)**
Traditional	120	–
Proposed	48	60

Table 1. Comparative results of time consumption

Analysis of computational resource consumption. In the experiments, the utilization levels of processor and memory resources were also analyzed. Resource efficiency was evaluated using the following formula [12]:

$$S_R = \frac{R_{trad} - R_{opt}}{R_{trad}} \times 100\% \qquad (12)$$

here:
– R_{trad}— resource consumption using the traditional approach;
– R_{opt}— resource consumption using the optimized model.

The results show that, in the proposed model, CPU and memory consumption were reduced by an average of **45–50%**.

Cost efficiency analysis. The economic efficiency of KPI data analysis was evaluated through the reduction of operational costs. Economic efficiency was calculated using the following indicator [17]:

$$E_C = \frac{C_{trad} - C_{opt}}{C_{trad}} \times 100\% \qquad (13)$$

According to the experimental results, the application of the optimized models led to a reduction in total costs of up to **40–50%**.

Indicator	Traditional Model	Proposed Model
Computational costs	100%	55%
Storage costs	100%	60%
Total costs	100%	50–60%

Table 2. Comparative cost analysis

The obtained experimental results indicate that the proposed optimization models for KPI data analysis demonstrate significantly higher efficiency compared to traditional approaches. In particular, incremental computation and data aggregation methods substantially reduced redundant computations during the analysis process, leading to a notable decrease in processing time and computational resource consumption [15, 16].

At the same time, the automated data flow model reduced errors associated with manual KPI data processing and improved the stability and reliability of the analysis process [17]. The results confirm that, under the conditions of Uzbekistan, including public administration and higher education institutions, the application of the proposed models is both feasible and effective for the implementation and development of KPI systems [12, 15, 19].

However, since the experiments were conducted using synthetic datasets, future research should be extended using real KPI data from organizations. This will allow a more precise assessment of the practical applicability and limitations of the proposed models in real-world operational environments.

Conclusion

In this scientific study, optimal models aimed at reducing excessive costs, processing time, and computational resource consumption in KPI data analysis were proposed, and their effectiveness was evaluated through experimental analysis. The research results demonstrate that organizing KPI analysis processes based on traditional approaches becomes inefficient in the context of large-scale data, leading to a significant increase in analysis time, computational resource usage, and economic costs [9, 11, 13].

Within the framework of the study, KPI data analysis was systematically examined, and mathematical models describing costs, time complexity, and resource consumption were proposed. It was established that performing KPI analysis using incremental computation, data aggregation, and filtering techniques reduces redundant computations and significantly accelerates the analysis process [15, 16]. Experimental results indicate an average reduction in analysis time of 55–65% and a decrease in computational resource consumption of up to 45–50%, thereby confirming the practical effectiveness of the proposed approaches [17].

The multi-objective optimization model was scientifically substantiated as an effective mechanism for achieving a balanced trade-off between time, resource usage, and costs in KPI data analysis. This approach enables the adaptation of KPI analysis processes to the existing infrastructure and resource constraints of different organizations [19]. In addition, the automated data pipeline model reduced errors associated with human involvement in KPI data collection and processing and improved the stability and reliability of the analysis process [16, 17].

The practical significance of the obtained results lies in the fact that the proposed optimization models can be effectively applied in the implementation of KPI systems within public administration bodies, higher education institutions, and corporate organizations. In particular, under the conditions of Uzbekistan, these models play an important role in developing KPI-based management, improving digital governance systems, and ensuring the rational use of budgetary and computational resources [12, 15].

Based on the results of this study, the following practical recommendations are proposed:

– transitioning from full recomputation–based KPI

data analysis to incremental computation models;
– reducing redundant computations by performing data aggregation and filtering prior to KPI indicator analysis;
– organizing KPI analysis using automated data flow (data pipeline) architectures;
– applying multi-objective optimization models that simultaneously account for time, computational resources, and costs in KPI analysis.

The study also has certain limitations. The experiments were conducted using synthetic datasets; therefore, future research should involve large-scale experiments based on real organizational KPI data. Furthermore, the integration of machine learning and artificial intelligence techniques with the proposed optimization models represents a promising direction for future research [17, 14].

In conclusion, this study proposes scientifically grounded solutions aimed at improving the economic and computational efficiency of KPI data analysis and contributes to bridging the existing research gap in this domain.

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