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Architecture of an AI-based university KPI system: React.js, ASP.NET Core, and PostgreSQL

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Abstract: This article describes a layered architecture of a system designed to calculate university employees' KPIs, detect anomalies, and provide recommendations. The technology stack includes React.js, ASP.NET Core, PostgreSQL, and a separate Python-based machine learning service. The ETL quality index (q_t), Isolation Forest ($F1 = 0.81$), and SHAP-based templates technically support the system's decision support system (DSS) constraints. During load testing with 400 concurrent users, the system achieved a p95 response time of 198 ms.

Keywords: DSS, RBAC, ETL, Isolation Forest, HEMIS, JWT, layered architecture

1. Introduction

Artificial intelligence technologies are widely used in HR analytics [1], but faculty KPI systems in higher education institutions still largely remain at the level of report generators [2]. Modern systems must provide integration with HEMIS, compliance with the requirements of Law No. O'RQ-547, and a mechanism for final human approval [3]. Accordingly, this study adopts a modular monolith with a separate machine learning (ML) process in place of a complex microservice architecture [4].

The central problem extends beyond selecting a suitable algorithm. KPI data are scattered across multiple sources, calculations are delayed, and AI outputs are presented as a black box, adversely affecting system reliability and auditability. This article therefore describes a layered architecture, an ETL quality index, an adaptive anomaly detection method, SHAP-based explanation templates, and system load performance as a unified technical solution.

The proposed approach treats the personnel management system as an auditable decision support system (DSS), rather than a simple research demonstration. Every AI output is stored together with its model version, checksum, and human approval status. In production, XGBoost provides fast forecasts and explanations, LSTM supplies the trajectory of KPI changes, and Isolation Forest generates signals for potential anomalies. All AI outputs appear in the user interface as advice rather than final decisions.

2. Research methodology

ARCHITECTURE

The layered architecture follows this sequence: a React-based RBAC user interface → an ASP.NET Core API with CQRS → a domain layer containing KPI, AHP, and workflow business logic → an ML adapter → a PostgreSQL database → connectors to external systems. Core functions include data ingestion, calculation of the integrated KPI indicator I , generation of the forecast $\hat{y}$, anomaly detection, explanations, handling of objections, and maintenance of an audit history.

The React layer only visualizes data and does not execute business logic for KPI calculations. All calculation rules are centralized at the ASP.NET Core API level.

PostgreSQL uses a star schema based on fact_indicator, partitions large datasets by period, and applies Row-Level Security to restrict database access by department and organizational unit. The ML service exposes /predict and /explain endpoints through FastAPI, while model files are stored with version control.

ETL quality is controlled through the index q_t . If $q_t < 0.90$, the evening KPI calculation process stops automatically, preventing results from being generated from poor-quality data. Anomaly detection uses the condition $A_i = 1[s_i \geq \tau_c \vee I_i < I_{\min} - \kappa \sigma_c]$, combining statistical thresholds with the Isolation Forest model [5]. This combination identifies unusual individual KPI values and routes them for subsequent human review.

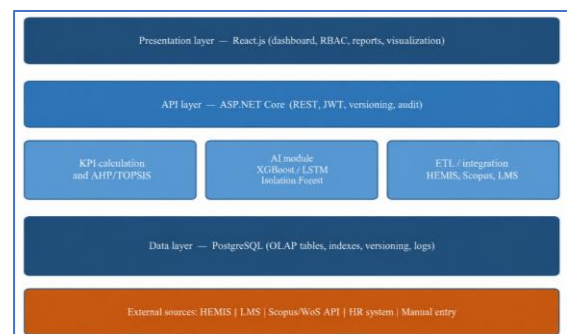


Fig. 1. Layered architecture diagram

$$q_t = 1 - (|null| + |rule_fail| + |dup|) / |expected_cells|_t \quad (1)$$

If $q_t < 0.90$, the evening calculation stops. Anomaly detection: $A_i = 1[s_i \geq \tau_c \vee I_i < I_{\min} - \kappa \sigma_c]$, using Isolation Forest [5].

3. Results and discussion

To evaluate the prototype, technical tests examined system responsiveness, anomaly detection accuracy, recalculation time, and API capabilities. The tests used loads approximating real operating conditions, focusing on stable operation with many simultaneous users and the outputs of the AI module.

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The results indicate that the selected architectural solutions are adequate for practical use. Under a load of 400 users, the p95 response time was 198 ms, and the Isolation Forest model achieved $F1 = 0.81$. Full recalculation took 6.4 minutes, and 28 core API endpoints were operational. These indicators are summarized in Table 1.

Table 1

Technical performance of the prototype	
Indicator	Value
p95 (400 users), ms	198
Isolation Forest F1	0.81
Full recalculation, min	6.4
API endpoints	28

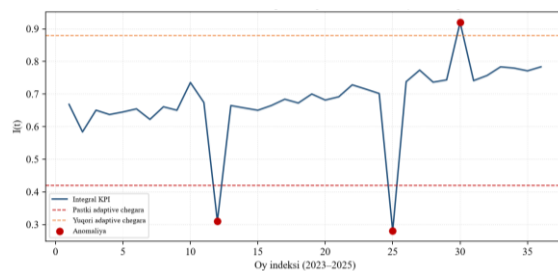


Fig. 2. Anomaly signals with adaptive thresholds.
Legend: Integrated KPI; Lower adaptive threshold;
Upper adaptive threshold; Anomaly. Horizontal axis:
Month index (2023–2025)

In Figure 2, three points fall outside the adaptive thresholds: two below the lower threshold (declines) and one above the upper threshold (an unusual jump). Upward jumps often result from data errors, such as duplicate DOIs, so ETL rules must run before anomaly detection. In the pilot, F1 increased from 0.73 without ETL to 0.81 with ETL. The p95 curve stays within the target up to 400 users and reaches 340 ms at 800 users; since the rector's office load is 100–150 users, spare capacity remains. A full recalculation time of 6.4 minutes is acceptable for an overnight batch; on-demand recalculation covers only changed person_key values. RBAC permissions are separated into `kpi.read.self / .dept / weights.edit`. Bulk export is restricted to HR and is audited. These figures establish the architecture as a measurable prototype rather than merely a diagram.

Discussion

The finding that ETL, rather than ML, is the bottleneck has practical implications: connectors and `q_t` should be addressed before network depth. A modular monolith has lower operating costs than microservices for a small university IT team [4]. A recommendation catalog limits LLM hallucinations by preventing unrestricted text generation. The two layers of authorization, RLS and RBAC, recognize that simply hiding data in the UI is insufficient. The limitation is a prototype at one university. Multitenancy is a later stage, requiring a renewed assessment of data minimization under Law No. O'RQ-547. The C# KPI engine, covered by 46 unit tests, matches the reference Excel calculations to a tolerance of 10^{-6} , addressing the hidden-formula problem. Alert deduplication by employee, type, and week reduces noise; a department head's resolution may provide a label for subsequent training. As a fallback, if the ML timeout exceeds 3 s, Holt–Winters is used and a flag is displayed in the UI, avoiding an unexplained $\hat{y}$. Data are stored within the country, with raw personally identifiable

information (PII) and the training dataset kept in separate schemas. Exports also provide mappings to national rankings, preserving the ministry reporting function. In UX testing, terms such as SHAP and contamination were replaced with Uzbek explanations, addressing the low-scoring satisfaction item on terminology.

4. Conclusion

The proposed architecture turns a hierarchical KPI calculation pipeline into a practical, responsive, and auditable system. Prototype testing recorded $p95 = 198$ ms under a load of 400 users, and the Isolation Forest model achieved $F1 = 0.81$. AI outputs are presented as advice rather than final judgments. Functional requirements FT-1...FT-10 and the main nonfunctional indicators were measured at the prototype level, confirming the architecture's suitability for practical application.

The next stage will compare the system with the conventional Excel-based ranking approach through a 90-day quasi-experiment, evaluating calculation time, the number of errors, and user satisfaction. Deployment should proceed through the following stages: establishing regulations and data owners, ensuring ETL quality, launching shadow calculations without decision making, introducing a dashboard and an objection mechanism, and cautiously linking results to the reward system. The system may later be extended to a multitenant architecture while retaining data minimization: aggregate distribution indicators, rather than individual KPI values, are sufficient for higher-level management.

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