JEL: O32; O34; M12; M15

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https://doi.org/10.60022/sis.4.(01).1

Received: 21/12/2025
Accepted: 05/03/2026
Published: 19/03/2026

ANALYSIS OF APPROACHES TO THE INTEGRATION OF ARTIFICIAL INTELLIGENCE METHODS INTO INTELLECTUAL CAPITAL MANAGEMENT

Abstract. *The article examines approaches to integrating artificial intelligence methods into intellectual capital management systems of higher education institutions in the context of forced migration and organizational transformation. A comparative analysis of the US market-oriented approach and the EU human-centric approach is conducted, revealing fundamental differences in the philosophical foundations of artificial intelligence implementation in human resources management. The research proposes a hybrid model that combines technological flexibility of American People Analytics with European ethical standards, adapted to the specific challenges faced by Ukrainian higher education institutions. The study analyzes key artificial intelligence technologies: Organizational Network Analysis for diagnosing integration and identifying isolated groups, Natural Language Processing for monitoring psychological well-being and early detection of burnout, and Learning Experience Platforms for personalized professional development. Machine learning models including classification, clustering, regression, and optimization algorithms are proposed for workload redistribution and performance prediction. The developed approach integrates exploratory data analysis, predictive modeling, and optimization techniques (convex optimization and genetic algorithms) with fuzzy logic to ensure transparency and interpretability of managerial decisions. The proposed model enables higher education institutions management to proactively forecast risks, optimize resource allocation, segment staff for targeted support, and fairly evaluate performance considering the forced displacement context.*

Keywords: *artificial intelligence, intellectual capital, human resources management, organizational network analysis, natural language processing, workload optimization, higher education institutions.*

1. Introduction

In the context of the knowledge economy, intellectual capital has become a key strategic asset for any organization, and for higher education institutions (HEIs), it represents the absolute foundation of their competitiveness and existence. However, unprecedented challenges caused by war-related migration processes in Ukraine pose a direct threat to the preservation, development, and effective management of this capital [1]. Traditional approaches to human resources management and productivity assessment prove insufficiently flexible to respond to the physical dispersion of academic staff, destruction of established scientific and communication networks, and extreme psychological stress on collectives.

The full-scale war in Ukraine has caused unprecedented transformations in the higher education system. According to recent data, over 40% of academic staff have been forced to relocate, with approximately 15% leaving the country [2]. This has created a critical situation where traditional human resources management methods based on direct supervision and formal hierarchical structures have lost their effectiveness. The destruction of informal scientific networks, loss of access to laboratory infrastructure, and psychological trauma have fundamentally changed the context in which academic work is performed.

In this context, artificial intelligence (AI) methods open new horizons for analytics, monitoring, and support of intellectual activity. AI's ability to process vast arrays of unstructured data (such as communication flows or textual feedback) enables a transition from delayed fact-finding (e.g., the resignation of a valuable specialist) to proactive management aimed at identifying 'pain points', supporting social cohesion, and preserving staff well-being [3]. However, implementing AI in such a delicate and ethically sensitive area as human capital management during a humanitarian crisis requires not simple copying of foreign practices, but their deep critical analysis.

Recent studies demonstrate the effectiveness of AI methods in human resources management across various sectors. Research by Chowdhury et al. [4] shows that machine learning-based predictive analytics can reduce employee turnover by 25–30% through early identification of risk factors. Raghavan et al. [5] found that organizations using AI-driven people analytics achieve 40% higher employee engagement and 30% better retention rates. However, these studies primarily focus on stable organizational environments and do not address the unique challenges posed by crisis situations and forced migration.

The European approach to AI ethics, codified in the AI Act and GDPR, emphasizes transparency, explainability, and human-centricity [6]. This contrasts with the more market-oriented US approach, which prioritizes efficiency and return on investment. Recent work by Floridi et al. [7] on ethical AI frameworks provides valuable guidance for developing human-centric AI systems that respect individual rights while delivering organizational benefits.

An emerging area of research focuses on optimization of faculty workload allocation using mathematical programming and AI techniques. Studies by Ozdemir and Gasimov [14] demonstrate the application of linear programming for workload balancing, while recent work by Badri et al. [15] explores simplex method approaches for optimal course assignment. However, these methods often lack consideration of individual preferences and contextual factors such as displacement status or psychological well-being.

The purpose of this study is to analyze existing approaches and models of AI used in different sectors (particularly in the USA and EU) for assessing the effectiveness of intellectual activity, and to determine their potential for adaptation to the specific tasks of state management of intellectual capital in Ukrainian HEIs. The research examines fundamental philosophical differences between the market-oriented US approach and the human-centric EU approach, analyzes specific technologies such as Organizational Network Analysis (ONA) and Natural Language Processing (NLP), and proposes a comprehensive framework integrating predictive analytics, optimization algorithms, and decision support systems for practical implementation in crisis-affected educational environments.

2. Materials and Methods

Before comparing specific AI implementation models in human resources management, it is essential to outline the fundamental differences in philosophical approaches characteristic of the United States and the European Union. These distinctions have a direct impact on strategic decisions regarding the development, regulation, and practical use of AI in the human resources context [8].

The American approach to AI implementation in HR is characterized predominantly by a pragmatic, market-oriented paradigm. The primary criteria are process efficiency and return on investment (ROI) maximization. The focus is on increasing productivity, optimizing management procedures, and identifying key performers and employees who may potentially leave the organization [9]. The regulatory field in the US is relatively flexible: although legislative restrictions exist, particularly in the area of non-discrimination (e.g., Equal Employment Opportunity Commission — EEOC provisions), technological innovations often outpace regulatory frameworks.

In contrast, the EU adopts a human-centric approach based on ethical principles, transparency of algorithmic decisions, and prioritization of individual rights protection. Key orientations include ensuring fairness, non-discrimination, AI explainability (XAI), and strict compliance with personal data protection norms codified in the General Data Protection Regulation (GDPR) [10]. The EU's regulatory policy is significantly stricter: the Artificial Intelligence Act establishes clear frameworks for classifying AI systems, specifically designating HR technologies as high-risk, requiring additional safety and transparency

Table 1

Comparison of US and EU Approaches to AI in HR

Criterion	US Approach	EU Approach
Philosophy	Market-oriented, efficiency-focused, ROI maximization	Human-centric, ethics-based, individual rights protection
Regulation	Flexible, innovation-first, EEOC guidelines	Strict, compliance-focused, GDPR and AI Act
Key Metrics	Productivity, performance, attrition prediction	Fairness, transparency, employee well-being
HEI Focus	Research productivity analytics, student success prediction	Ethical AI use, staff well-being, skills development

Source: compiled by authors based on [8, 9, 10] guarantees. Table 1 summarizes the key differences between these approaches.

In the context of educational environment transformation driven by war and the mass migration of academic staff, analytical tools that not only capture individual indicators but also reveal systemic connections shaping the intellectual capital of institutions acquire particular importance. A prominent example is Organizational Network Analysis (ONA), which conceptualizes knowledge not as isolated units but as a dynamic network of interactions through which information circulates, combines, and generates new value [11].

Rather than focusing on formal hierarchies or staffing structures of an organization, ONA visualizes actual flows of information, ideas, and influence. Earlier implementations of ONA relied primarily on surveys, which constrained both accuracy and scalability. Contemporary approaches, widely adopted in the United States and the European Union, employ passive collection of digital interaction traces analyzed through machine learning algorithms. These traces include email metadata (recipients, frequency, excluding content), calendar data (meeting participation), communication records in corporate platforms (Slack, Teams, Zoom), and collaborative document activity (Google Workspace, SharePoint).

On the basis of such data, AI constructs social connection maps that identify critical roles within organizational networks. These include Central Connectors — individuals with extensive ties who often serve as informal leaders, the loss of whom may fragment the network; Brokers — bridges between otherwise disconnected groups and potential sources of innovation; Bottlenecks — overloaded participants who risk obstructing information flows; and Isolates — individuals with limited engagement who face heightened risk of resignation.

In conditions of staff displacement, ONA supports several essential management tasks: diagnosing network gaps by detecting isolation among relocated staff and the emergence of "information bubbles"; identifying and supporting critical intellectual capital by recognizing "hidden leaders" among internally displaced persons (IDPs) who facilitate integration; enabling preventive turnover management by monitoring declines in communication activity; and evaluating the effectiveness of integration measures by comparing network structures before and after interventions.

The mathematical foundation of ONA relies on graph theory and network centrality measures. Let $G = (V, E)$ represent the organizational network where V is the set of employees and E is the set of communication edges. The degree centrality $CD(v)$ of node v is defined as:

$$CD(v) = \frac{deg(v)}{|V| - 1} \tag{1}$$

where $deg(v)$ is the number of connections of node v. Betweenness centrality $CB(v)$, which identifies brokers, is calculated as:

$$CB(v) = \sum_{s \neq t,\, s \neq v,\, t \neq v}^{s,t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}, \tag{2}$$

where σst is the total number of shortest paths from node s to node t, and σst(v) is the number of those paths passing through v.

In the context of deep social transformations caused by war and mass migration of academic staff, tools capable of not only recording the structure of communications (as in ONA) but also interpreting their content, emotional coloring, and hidden signals gain special relevance. In this sense, Natural Language Processing (NLP) technologies play the role of a 'stethoscope' and 'translator' of organizational language — they allow 'hearing' the collective, identifying problems that are not openly articulated, and assessing the moral-psychological state of the academic community [12].

NLP is the ability of computer systems to understand, interpret, and analyze human language (text or voice). In the HEI context, AI models based on NLP not only process text but extract meaning, emotions, and key themes from it. The main technological components are: Sentiment Analysis (automatic determination of text's emotional coloring), Topic Modeling (identification of dominant themes in large text arrays), and Named Entity Recognition (NER, identification of names, locations, organizations in text).

In crisis conditions, when traditional surveys may be ineffective, NLP allows deep diagnostics of the academic community's state. Main application directions include: (1) early diagnosis of IDP problems through anonymous feedback channels and topic modeling; (2) monitoring of psychological state and burnout through sentiment analysis; (3) analysis of skills and knowledge gaps through identification of requests for new competencies; (4) evaluation of management communication effectiveness through analysis of reactions to official messages.

The mathematical foundation of sentiment analysis often employs transformer-based models. For a given text sequence $X = \{x_1, x_2, \ldots, x_n\}$, the sentiment score S is computed as:

$$S = \mathrm{softmax}(W \cdot h + b) \tag{3}$$

where h is the contextualized representation from the final layer of the transformer, W is the weight matrix, and b is the bias vector. The softmax function normalizes the output to produce probability distribution over sentiment classes (positive, negative, neutral).

In the context of educational environment transformation caused by war, digitalization, and migration processes, rethinking approaches to professional development of academic staff gains special relevance. One of the key tools for such transformation is the Learning Experience Platform (LXP) — a learning experience platform representing the evolution of traditional Learning Management Systems (LMS) [13].

Unlike classical LMS that function on the principle of centralized learning process administration (course assignment, completion control), LXP is oriented toward a personalized, flexible, and dynamic approach. It allows forming individual development trajectories, considering both the employee's current role and the organization's strategic needs. In this sense, LXP performs the function not only of content distribution but also of intelligent skills management, automatically identifying and filling 'skill gaps' arising due to environmental changes, technologies, or functional responsibilities.

If ONA and NLP tools allow diagnosing problems and preserving existing intellectual capital, LXP is a means of its growth, adaptation, and preparation for future challenges. In crisis conditions, this gains special weight, as the need for rapid development of new competencies is critical. The platform uses ML models for: (1) recommendation systems based on collaborative filtering and content-based algorithms; (2) skill gap analysis using classification models; (3) learning path optimization through reinforcement learning; (4) impact assessment using regression models to measure the effect of training interventions.

The recommendation system in LXP typically employs collaborative filtering. Let R be an $m \times n$ matrix where R_{ij} represents the interaction (completion, rating) of user i with learning resource j. The predicted rating $\hat{R}_{ij}$ is computed using matrix factorization:

$$\hat{R}_{ij} = p_i^T \cdot q_j \tag{4}$$

where $p_i \in \mathrm{R}^k$ represents user i's latent factors and $q_j \in \mathrm{R}^k$ represents resource j's latent factors, with k being the number of latent dimensions.

The practical implementation of AI methods in intellectual capital management requires a comprehensive analytical framework integrating exploratory data analysis, predictive modeling, and optimization algorithms. This section presents the People Analytics approach adapted to the specific challenges of Ukrainian HEIs, focusing on workload optimization and performance forecasting while maintaining ethical standards and human oversight [14, 15].

The initial stage of faculty workload analysis focuses on identifying fundamental patterns and outliers in the data. This requires application of several complementary methods: descriptive statistics to establish the 'average faculty member' baseline; correlation analysis (Pearson, Spearman, Kendall) between different task categories; statistical analysis across task groups (teaching, research, administrative); clustering by individual tasks and task groups using DBSCAN, Gaussian Mixture Models (GMM), or Spectral Clustering; outlier detection using Isolation Forest or UMAP; temporal trend analysis across years; and other analytical approaches that may prove necessary during the investigation.

This stage enables understanding of data structure, workload distribution across faculty members and years, and observable trends. At this stage, subsequent analysis and modeling methods are determined. The process requires iterative returns to EDA after discovering new patterns for detailed investigation. For clustering analysis, the optimal number of clusters k can be determined using the elbow method by minimizing within-cluster sum of squares:

$$WCSS(k) = \sum_{i=1}^{k} \sum_{x \in C_i} |\, x - \mu_i \,|^2 \tag{5}$$

where C_i represents cluster i, μ_i is the centroid of cluster i, and x represents individual data points (faculty members).

Before proposing changes in faculty workload redistribution, it is necessary to forecast performance indicator changes in the next year assuming continuation of current trends. Given limited historical data, absence of seasonality, and non-stationarity of performance indicators (all verified during EDA), the most suitable forecasting methods are: Exponential Smoothing (ETS), which decomposes data into error, trend, and seasonality components and propagates them to future periods; Bayesian Linear Regression, which builds linear regression with probabilistic intervals, best suited for predictions under stable workload policies; and Polynomial Regression, which finds optimal polynomial functions matching observed trend changes.

Simultaneous use of all three methods with visualization on a common graph is recommended. For Exponential Smoothing, the forecast value y_{t+h} at time $t + h$ can be expressed as:

$$y_{t+h\,|\,t} = \ell_t + h \cdot b_t + s_{t+h-m(k+1)} \tag{6}$$

where ℓ_t is the level component, b_t is the trend component, s_t is the seasonal component, and m is the seasonal period length.

The next stage involves building a model to determine the 'weight' of each task. Since workload from individual tasks has no nonlinear relationships with others, linear regression is the optimal method. This model is key to proper workload redistribution across institutional activity directions. The main challenge is system dimensionality (over 150 parameters), preventing calculations for each faculty member separately due to insufficient data. Therefore, linear regression uses all available data, yielding averaged weights across all faculty. Subsequently, refinement for each faculty member can be performed based on their most recent year.

The linear regression model for workload estimation can be expressed as:

$$W = \sum_{j=1}^{n} \hat{a}_j \cdot x_j + \varepsilon \tag{7}$$

where W represents total workload (FTE), x_j represents hours spent on task j, β_j represents the weight coefficient for task j, and ε represents the error term.

Three redistribution approaches were analyzed for adaptation to Ukrainian HEI context: Manual

Table 2

Comparison of Workload Redistribution Methods

Method	Advantages	Disadvantages
Manual Distribution	Full faculty control; easy interpretability; minimal risk of abrupt changes; accommodates individual preferences; provides clear correction direction	Requires faculty participation; partial automation only; quality depends on conscious faculty choices; may be far from mathematically optimal
Convex Optimization	Mathematically precise and formally optimal; provides unique solution under given constraints; full automation of redistribution	Complex equation system construction; unrealistic results if details omitted; no individual preference accommodation; solution may contain many small changes; transition from continuous to discrete creates errors
Genetic Algorithms	Handles complex rules and constraints including discreteness; supports full or partial automation with flexibility	No guarantee of best or globally optimal solution; strong result dependence on algorithm parameters; requires significant tuning time; faculty cannot influence decisions, only verify post-facto

Source: compiled by authors based on [14, 15]

Distribution, which provides maximum faculty control over workload changes through influence tables showing each faculty member's contribution; Convex Optimization, which formulates redistribution as an optimization problem with constraints; and Genetic Algorithms, which apply evolutionary principles with transition rules based on the weight model. Table 2 compares these approaches.

For convex optimization, the problem can be formulated as minimizing deviation from target performance indicators subject to workload constraints. The objective function minimizes the weighted sum of squared deviations from institutional KPIs:

$$\min \sum_{k=1}^{m} w_k \cdot \left(P_k - T_k\right)^2$$
$$\text{subject to} \quad \sum_{j=1}^{n} x_{ij} \le H_{\max,i} \quad \forall i, \quad x_{ij} \ge 0 \quad (8)$$

where P_k represents predicted performance for KPI k, T_k represents target value for KPI k, w_k represents weight for KPI k, x_{ij} represents hours for faculty i on task j, and $H_{max,\,i}$ represents maximum available hours for faculty i.

As illustrated in Figure 1, the workflow of the predictive analytics and optimization framework integrates multiple layers of analysis and decision-making. The process begins with the data input layer, which aggregates historical workload records, performance ratings, and institutional KPIs. This is followed by exploratory data analysis (EDA), including clustering, correlation analysis, and outlier detection. Predictive modeling is then conducted using ETS, Bayesian regression, and polynomial regression in parallel, while a separate weight model applies linear regression to determine task weights. The optimization stage incorporates three alternative approaches — manual distribution, convex optimization, and genetic algorithms — before results are validated for feasibility. Finally, the framework outputs an interactive dashboard that enables visualization and filtering, with arrows in the diagram indicating data flow and feedback loops.

In modern conditions of educational environment transformation caused by both global technological shifts and local crisis factors, direct borrowing of AI application models developed in the USA or EU is not only inefficient but potentially risky. Ukrainian HEIs require a hybrid model that combines the ethical sensitivity of the European approach with the flexibility and adaptability characteristic of American innovative ecosystems, while integrating the predictive analytics and optimization frameworks described above.

The key principle of such a model should be a shift of focus from assessment to support and preservation of academic potential. The proposed hybrid model integrates four strategic components that must be incorporated into the theoretical framework of AI application in Ukrainian HEIs: (1) data contextualization accounting for IDP status and security situation through the Disruption Factor; (2) priority on 'soft' data using NLP and ONA for psychological state monitoring; (3) predictive analytics framework combining EDA, forecasting models, and workload optimization with human oversight; (4) ethical foundation based on European AI Act principles (transparency, human-in-the-loop, non-discrimination).

The model employs a layered architecture integrating multiple AI techniques. At the data collection layer, the system gathers information from ONA (communication patterns), NLP (sentiment and topic analysis), LMS logs, performance ratings, and institutional KPIs. The processing layer applies exploratory data analysis for pattern identification, predictive models for trend forecasting, and the workload weight model for task valuation. The optimization layer offers three approaches: Manual Distribution for maximum faculty autonomy, Convex Optimization for mathematical precision, and Genetic Algorithms for handling complex constraints. All outputs pass through a fuzzy logic interpretation layer that translates numerical results into linguistic terms and management recommendations.

Critical to this model is the introduction of a Disruption Factor (*DF*), which adjusts performance expectations based on contextual constraints. For an individual i, the adjusted performance P_{adj} is calculated as:

$$P_{adj,i} = \frac{P_{actual,i}}{DF_i} \quad (9)$$

where

$$DF_i = w_1 \cdot IDPstatus + w_2 \cdot InfrastructureAccess +$$
$$+ w_3 \cdot PsychologicalLoad,$$

with weights w_1, w_2, w_3 determined through expert elicitation and validated against historical data.

3. Results and Discussion

The proposed hybrid model requires systematic implementation across multiple stages. The technical architecture consists of five key layers: (1) Data Collection Infrastructure utilizing existing systems (email metadata, LMS logs, anonymous feedback channels, performance databases) while ensuring GDPR compliance through data anonymization and aggregation; (2) AI Processing Layer implementing ONA algorithms, NLP pipelines, and ML models for EDA, prediction, and clustering; (3) Optimization Engine offering three alternative approaches (Manual Distribution, Convex Optimization, Genetic Algorithms) with constraint validation; (4) Fuzzy Logic Interpretation Layer translating numerical outputs into linguistic terms and management recommendations; (5) Dashboard Interface providing interactive visualization with filtering, what-if scenario analysis, and explainable AI outputs.

A critical component of the implementation is the Dashboard Development phase, where effective visualization methods identified during EDA are transformed into a web application. This interface provides HEI administrators with graphical access to data and analysis results, enabling filtering by faculty members, departments, years, and task categories. The dashboard includes: real-time performance metric tracking against institutional KPIs; workload distribution

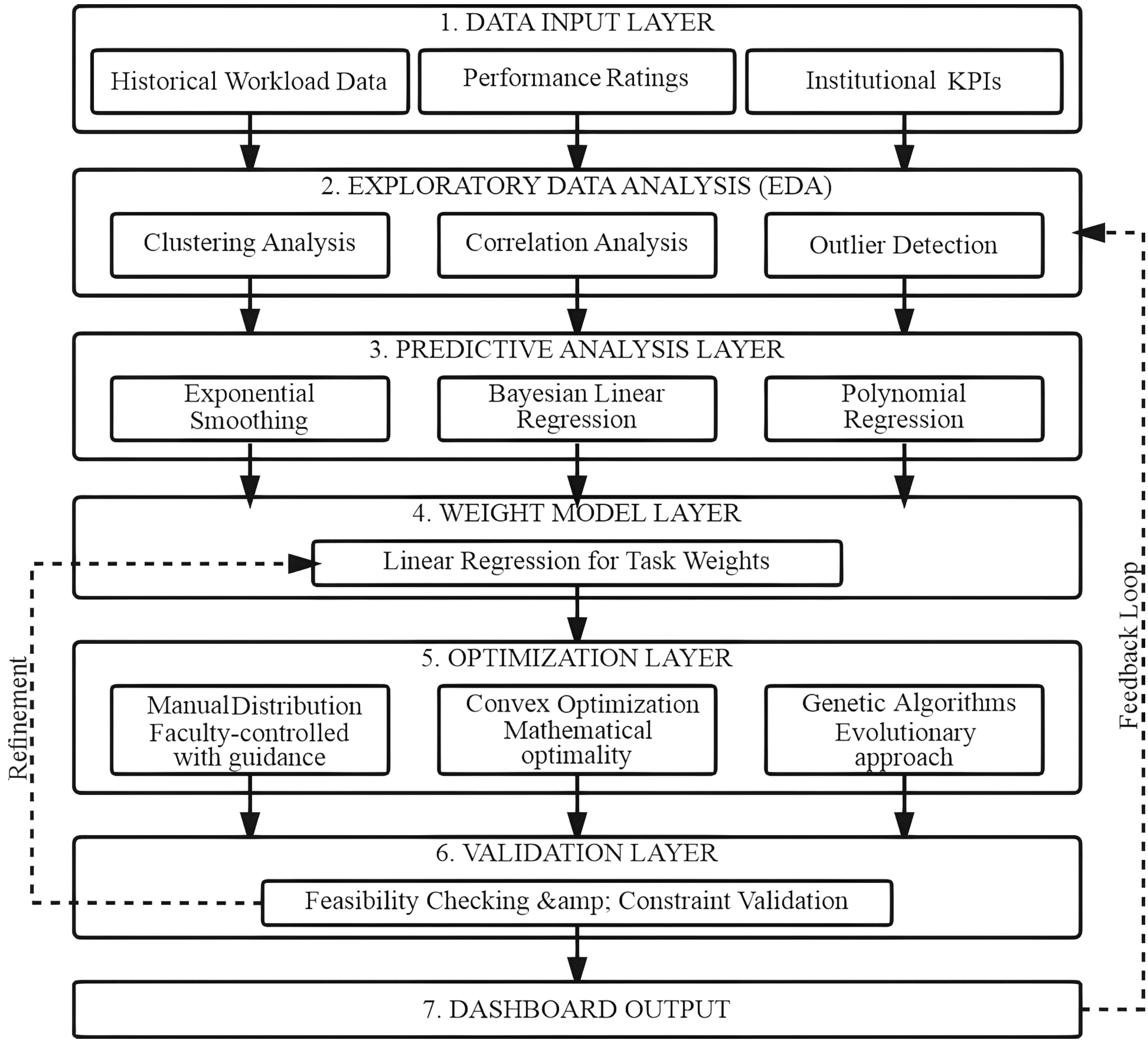

Figure 1. Workflow Diagram of Predictive Analytics and Optimization Framework

Source: proposed by the authors

visualizations with comparative benchmarks; predictive forecast displays with confidence intervals; optimization scenario comparisons; and alert notifications for faculty at risk of burnout or resignation.

Validation of the model involves multiple approaches: (1) Expert validation through consultations with HEI administrators, HR specialists, and AI ethics experts to ensure practical relevance and ethical soundness; (2) Pilot implementation in select departments to test technical feasibility and gather user feedback, particularly regarding the Manual Distribution approach; (3) Performance metrics evaluation comparing traditional assessment methods with AI-augmented approaches, measuring improvements in early risk detection, staff retention, workload balance, and achievement of institutional KPIs; (4) Ethical auditing ensuring compliance with GDPR and AI Act requirements, with particular attention to transparency, non-discrimination, data protection, and proper application of the Disruption Factor; (5) Iterative refinement based on stakeholder feedback, with regular returns to EDA for validation of model assumptions and identification of emerging patterns.

The conducted analysis demonstrates that the intellectual capital of higher education institutions faces critical threats due to unprecedented challenges caused by war-related migration and psychological stress. Traditional management approaches prove inadequate as they cannot adequately respond to physical dispersion and destruction of informal connections among academic staff. In this context, implementing artificial intelligence methods becomes not a technological whim but a strategic necessity, enabling transition from delayed loss acknowledgment to proactive management and support.

Critically important is the development not of copies of foreign practices but of a Hybrid AI Model. This model should organically combine the technical flexibility of the American approach (using highly developed People Analytics, ONA, and LXP technologies for effective monitoring and forecasting) with the human-centric ethics of the European Union. This requires strict adherence to principles of Transparency, Non-discrimination, and Human-in-the-loop, where HR-AI technologies in the Ukrainian context perform the role of a support tool rather than control or punitive scoring. The key innovation of this model is the inclusion of a Disruption Factor that adapts performance assessment considering the IDP context and security situation, combined with a comprehensive predictive analytics framework integrating exploratory data analysis, multiple forecasting methods, and flexible optimization approaches.

The technological framework of such a model is based on the integration of multiple complementary AI approaches creating a closed management cycle: (1) Organizational Network Analysis (ONA) for integration diagnostics, identifying isolated groups and network gaps, enabling stitching of torn academic community and preventive turnover management; (2) Natural Language Processing (NLP) as a well-being diagnostics tool, providing anonymous monitoring of psychological state and burnout, enabling early detection of ‘pain points’; (3) Learning Experience Platform (LXP) as a strategic development tool, personalizing professional development and filling crisis skill gaps; (4) Predictive Analytics framework combining Exponential Smoothing, Bayesian Linear Regression, and Polynomial Regression for performance forecasting; (5) Workload Optimization engine offering three alternative approaches (Manual Distribution, Convex Optimization, Genetic Algorithms) with different tradeoffs between faculty autonomy and mathematical optimality.

To ensure humanitarian sensitivity and management transparency, the system employs Fuzzy Logic as an interpretation layer, creating transparent and interpretable rules. This allows translating numerical ML model results (Classification, Clustering, Regression, Optimization) into management decision language (e.g., ‘IF Mood Very Poor AND Integration Low THEN Intervention Critical’). The fuzzy inference system enables non-technical stakeholders to understand and trust AI recommendations while maintaining the precision of underlying mathematical models.

The practical implementation through a web-based dashboard transforms these analytical capabilities into actionable management tools. By providing interactive visualizations, what-if scenario analysis, and real-time monitoring of key performance indicators, the system enables HEI leadership to make data-driven decisions while preserving human oversight and accommodating faculty preferences. The Manual Distribution approach, in particular, empowers faculty members to participate actively in workload planning, fostering buy-in and reducing resistance to technological change.

Thus, the integration of AI methods into intellectual capital management represents a conceptual transformation enabling HEI management to proactively forecast risks, optimize resource allocation, segment staff for targeted support, and fairly assess activity. The proposed Hybrid AI Model ensures not only technical efficiency but also resilience, competitiveness, and human-centricity of Ukrainian higher education institutions under the most challenging conditions.

4. Conclusions

This study is primarily conceptual, and the proposed model requires empirical validation through pilot implementations in Ukrainian HEIs. Future research should focus on: (1) developing and calibrating specific algorithms for the Disruption Factor calculation based on empirical data from displaced faculty; (2) conducting longitudinal studies to evaluate the model’s effectiveness in reducing staff turnover, improving well-being, and achieving institutional KPIs; (3) exploring the integration of additional data sources such as social media analytics (with appropriate ethical safeguards); (4) investigating the scalability of the model to different organizational contexts beyond higher education; (5) refining the fuzzy logic rule base through systematic expert elicitation and machine learning from historical decisions; (6) developing more sophisticated genetic algorithm configurations for the optimization engine; (7) comparing the three optimization approaches empirically to determine optimal selection criteria for different institutional contexts.

The proposed hybrid model provides HEI administrators with a roadmap for implementing AI-driven intellectual capital management systems. Key recommendations include: (1) starting with low-risk, high-value applications such as EDA and anonymous feedback analysis before implementing optimization algorithms; (2) prioritizing the Manual Distribution approach for initial deployment to build trust and demonstrate value before introducing more automated methods; (3) establishing ethical oversight committees to ensure compliance with GDPR and AI Act requirements; (4) investing in staff training to build AI literacy and reduce resistance to technological change; (5) adopting an iterative approach with continuous monitoring and refinement based on stakeholder feedback; (6) ensuring proper dashboard design with intuitive interfaces and explainable AI outputs; (7) maintaining transparent communication about data usage, privacy protection, and the role of AI as a support tool rather than replacement for human judgment.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All authors have contributed equally.

FUNDING

The Authors received no funding for this research.

CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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https://doi.org/10.60022/sis.4.(01).1

АНАЛІЗ ПІДХОДІВ ДО ІНТЕГРАЦІЇ МЕТОДІВ ШТУЧНОГО ІНТЕЛЕКТУВ УПРАВЛІННЯ ІНТЕЛЕКТУАЛЬНИМ КАПІТАЛОМ

Анотація. *У статті розглянуто підходи до інтеграції методів штучного інтелекту в системи управління інтелектуальним капіталом закладів вищої освіти в умовах вимушеної міграції та організаційної трансформації. Проведено порівняльний аналіз ринково-орієнтованого підходу США та людиноцентричного підходу ЄС, що дозволило виявити фундаментальні відмінності у філософських засадах впровадження штучного інтелекту в управління людськими ресурсами. У дослідженні запропоновано гібридну модель, яка поєднує технологічну гнучкість американської концепції People Analytics з європейськими етичними стандартами, адаптованими до специфічних викликів, що постали перед українськими закладами вищої освіти.*

У роботі проаналізовано ключові технології штучного інтелекту: аналіз організаційних мереж для діагностики інтеграції та виявлення ізольованих груп; обробка природної мови для моніторингу психологічного стану та раннього виявлення професійного вигорання; платформи для створення персоналізованого досвіду навчання для персоналізованого професійного розвитку. Запропоновано використання моделей машинного навчання, включаючи класифікацію, кластеризацію, регресію та алгоритми оптимізації, для перерозподілу навантаження та прогнозування результативності.

Розроблений підхід інтегрує методи дослідницького аналізу даних, прогнозного моделювання та оптимізації (зокрема, методи опуклої оптимізації та генетичні алгоритми) з використанням шару нечіткої логіки, що забезпечує прозорість та інтерпретованість управлінських рішень. Запропонована модель дозволяє керівництву закладів вищої освіти проактивно прогнозувати ризики, оптимізувати розподіл ресурсів, сегментувати персонал для цільової підтримки та справедливо оцінювати результативність з урахуванням контексту вимушеного переміщення.

Ключові слова: *штучний інтелект, інтелектуальний капітал, управління людськими ресурсами, аналіз організаційних мереж, обробка природної мови, оптимізація навантаження, заклади вищої освіти.*