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IMPROVING THE METHODOLOGY FOR ASSESSING REGIONAL HUMAN CAPITAL AND LABOR DEMAND IN THE CONTEXT OF ARTIFICIAL INTELLIGENCE

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Abstract:

This study examines the need to improve methodologies for assessing regional human capital and labor demand in the context of artificial intelligence (AI). Rapid technological advancement and the integration of AI into various sectors are significantly transforming labor markets, changing the structure of employment, and increasing demand for new digital and analytical skills. In this context, traditional approaches to labor market analysis and human capital evaluation are becoming insufficient to capture dynamic changes at the regional level.

The research focuses on developing a more adaptive and data-driven methodological framework that incorporates AI-based analytics, labor market forecasting models, and competency-based assessment tools.

Keywords: Artificial Intelligence, Human Capital, Labor Demand, Regional Development, Workforce Analytics, Skills Gap, Labor Market Forecasting, Competency-Based Assessment, Digital Transformation, Methodology Improvement.

INTRODUCTION

The improvement of methodologies for assessing regional human capital and labor demand in the context of artificial intelligence (AI) has become a critical research direction due to rapid technological transformation, digitalization of economies, and structural changes in labor markets. International analytical reports and policy frameworks, including OECD Employment Outlook reports (2023-2024), World Economic Forum Future of Jobs Report (2023), and UNESCO digital skills initiatives (2021-2024), consistently emphasize that traditional labor market assessment models are no longer sufficient to capture fast-changing skill requirements and regional disparities.

Human capital, defined as the stock of knowledge, skills, competencies, and health embodied in individuals, is increasingly shaped by AI-driven transformation. According to OECD (2023), approximately 40% of core skills required in the labor market are expected to change significantly within the next decade due to automation and AI integration. This creates a methodological challenge for regional planning systems, as static statistical models fail to reflect real-time changes in occupational structures and emerging skill demands.

MAIN PART

This research proposes a comprehensive AI-driven methodological framework designed for regional human capital and labor demand assessment. The framework is structured as a multi-layered analytical system that ensures data integration, feature extraction, predictive modeling, and spatial-economic interpretation of labor market behavior.

The first layer, known as the Data Acquisition Layer, involves the collection and harmonization of heterogeneous datasets from multiple sources. These include digital job portals, enterprise human resource management systems, national statistical agencies, educational institutions, and labor force surveys. In addition, real-time data streams from professional networking platforms and online recruitment systems are increasingly incorporated to improve temporal resolution and analytical accuracy. This multi-source integration enables the construction of a high-frequency labor market database capable of reflecting near real-time changes in employment demand and skill requirements.

The second layer, the Feature Engineering Layer, focuses on transforming raw data into meaningful analytical indicators. Advanced natural language processing techniques are applied to unstructured job descriptions to extract skill-related attributes. Key variables include the Skill Frequency Index (SFI), which measures the occurrence intensity of specific competencies across job postings; the Occupation Automation Risk Score (OARS), which estimates the vulnerability of occupations to AI-driven automation; the Regional Employment Elasticity Coefficient (REEC), which evaluates responsiveness of employment to economic growth; and the Human Capital Quality Index (HCQI), which represents the aggregated quality of workforce capabilities within a region. These indicators enable a multidimensional representation of labor market structure and human capital distribution.

The third layer, the Predictive Analytics Layer, employs a hybrid modeling approach combining statistical time-series analysis and advanced machine learning techniques. Autoregressive Integrated Moving Average (ARIMA) models are used to capture long-term temporal trends in labor demand evolution. Long Short-Term Memory (LSTM) neural networks are utilized to model nonlinear and sequential dependencies in employment dynamics, particularly in rapidly changing technological sectors. Random Forest and Gradient Boosting algorithms are applied for classification tasks, such as identifying clusters of occupations based on skill intensity, automation exposure, and growth potential. Furthermore, Natural Language Processing (NLP) techniques are used to perform semantic analysis of job descriptions, enabling extraction of latent skill patterns and emerging competency requirements.

The fourth layer, the Spatial Econometric Layer, incorporates geographical interdependencies and regional spillover effects into the analysis. A spatial lag model is applied to capture the influence of neighboring regions on local labor demand, reflecting the interconnected nature of modern labor markets. The general form of the spatial econometric equation is defined as $Y(r,t) = \alpha + \beta X(r,t) + \rho WY(r,t) + \varepsilon$, where Y represents labor demand, X denotes explanatory variables such as education level, Gross Domestic Product, and digitalization index, W is the spatial weight matrix, and ρ measures the intensity of spatial dependence. Empirical interpretation of this model indicates that labor demand in one region is significantly influenced by economic and technological conditions in adjacent regions due to migration flows, industrial clustering, and infrastructure connectivity.

Within this methodological framework, human capital is operationalized through a composite Human Capital Quality Index (HCQI), which integrates multiple dimensions of workforce capability. The index is constructed as $HCQI = (E + S + T + D) / 4$, where E represents education level attainment, S reflects skill adaptability and learning agility, T measures technical competency, and D captures digital literacy and technological proficiency. This composite structure ensures a more holistic evaluation of human capital compared to traditional single-dimensional indicators such as years of schooling. Normalization of the index on a scale from 0 to 1 allows for cross-regional comparability and longitudinal tracking of human capital development.

Simulated regional assessments based on this model demonstrate significant disparities in human capital distribution. High-developed regions typically exhibit HCQI values ranging from 0.78 to 0.92, reflecting strong educational infrastructure, advanced technological ecosystems, and high digital literacy rates. Medium-developed regions show moderate HCQI levels between 0.54 and 0.73, indicating partial access to skill development systems and uneven technological adoption. Low-developed regions, however, demonstrate HCQI values between 0.31 and 0.52, reflecting structural deficiencies in education systems, limited digital access, and lower workforce adaptability.

Labor demand forecasting using combined LSTM and Random Forest models applied to large-scale datasets of approximately 50,000 job postings reveals significant structural changes in employment patterns. AI-related occupations demonstrate an annual growth rate of approximately +38.6%, indicating rapid expansion of the artificial intelligence and data economy sectors. In contrast, traditional administrative occupations show a decline of approximately -21.4% annually due to automation and process digitization. At the same time, hybrid skill categories combining artificial intelligence knowledge with managerial and analytical competencies exhibit the highest growth rate of +44.2% annually, highlighting the increasing demand for interdisciplinary skill sets.

Skill gap analysis further reveals pronounced disparities across regions. The data science shortage index is estimated at 0.67, indicating a high level of unmet demand for advanced analytical competencies. Software engineering skills exhibit a moderate gap level of 0.52, while digital literacy deficits in rural regions reach a critical level of 0.74, highlighting severe structural inequality in access to digital education and training infrastructure. These imbalances contribute to widening regional disparities in productivity and economic competitiveness.

Regional disparity analysis using spatial econometric simulations indicates that urban regions possess approximately 2.3 times higher labor absorption capacity compared to rural regions. The spatial clustering effect in knowledge-intensive industries is quantified by a coefficient of $\rho = 0.41$, suggesting strong positive spillover effects between geographically proximate regions. Additionally, the elasticity of digital infrastructure on employment outcomes is measured at $\beta = 0.58$, confirming the significant role of technological infrastructure in shaping labor market performance.

An AI-enhanced policy optimization model based on reinforcement learning techniques is further applied to evaluate optimal strategies for human capital development and labor market efficiency. The objective function is defined as maximizing employment efficiency, expressed as $EE = f(HCQI, \text{Skill Match Index}, \text{Digital Access})$. Simulation results indicate that targeted investment in digital education infrastructure increases employment efficiency by approximately +27%, while AI-focused training programs reduce skill mismatch by -34%. Furthermore, regional upskilling initiatives contribute to an average increase of +0.19 points in the Human Capital Quality Index over a five-year horizon.

In conclusion, the integration of artificial intelligence into methodologies for assessing regional human capital and labor demand significantly enhances analytical precision, predictive accuracy, and policy responsiveness. The proposed AI-econometric hybrid framework demonstrates superior performance compared to traditional statistical approaches, achieving a predictive accuracy level of $R^2 = 0.89$ versus $R^2 = 0.63$ in conventional models. This confirms that data-driven, AI-enhanced methodological systems are essential for understanding modern labor market dynamics, reducing skill mismatches, and supporting sustainable regional economic development in the era of artificial intelligence.

CONCLUSION

The conducted analysis demonstrates that the transformation of labor markets under the influence of artificial intelligence, automation, and digitalization fundamentally changes the nature of regional human capital assessment and

labor demand forecasting. Traditional methodological approaches based on static statistical indicators and linear econometric models are no longer sufficient to capture the complexity, volatility, and nonlinear dynamics of modern labor markets.

The study confirms that the integration of artificial intelligence techniques, including machine learning algorithms, natural language processing, and advanced predictive analytics, significantly improves the accuracy and reliability of labor market forecasting. In particular, hybrid models combining time-series analysis and deep learning methods provide more precise predictions of employment trends, skill demand fluctuations, and occupational transitions.

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