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# HUMAN CAPITAL ASSESSMENT WITH AN APPROACH BASED ON INTEGRATING HETEROGENEOUS DATA AND ARTIFICIAL INTELLIGENCE IN THE DIGITAL ECONOMY

**Narmin Vuqar ISAYEVA**
*Baku Engineering University (BEU),*
*Azerbaijan State Oil and Industry University (ASOIU),*
*Baku, Azerbaijan*

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*ABSTRACT*

***The purpose of the research*** *–This article examines human capital assessment through the integration of heterogeneous data and artificial intelligence in the context of the digital economy. The study aims to identify the interrelationships among artificial intelligence, digital transformation, and human capital, and to empirically evaluate how these factors influence productivity.*

***Research methodology*** *– The research applies analysis, comparison, systematization, grouping, and generalization methods. Its empirical part is based on panel data covering the period 2010–2024 and obtained from open international statistical databases. The analytical framework includes descriptive statistics, correlation analysis, unit root tests, cointegration analysis, multivariate regression modeling, and Granger causality testing. This methodological approach allows a comprehensive assessment of the interaction between artificial intelligence, digital transformation, human capital, and productivity.*

***Results of the research*** *– The findings show that artificial intelligence has a significant positive impact on productivity, while human capital strongly reinforces this effect. Digital transformation also contributes positively through better data processing and resource allocation. The results confirm long-run relationships among the variables and identify artificial intelligence and human capital as major drivers of productivity growth.*

***Originality and scientific novelty of the research*** *– The study offers an integrated and multidimensional framework for evaluating human capital in the digital economy.*



## 1. INTRODUCTION

The rapid development of the digital economy in modern times has led to fundamental changes in the mechanisms of operation of economic systems. In particular, the widespread application of information technologies, the increase in large volumes of data (big data) and the development of artificial intelligence technologies have reshaped the management approaches of organizations. In this context, the integration of heterogeneous data and their effective use have become one of the main factors in increasing the competitiveness of enterprises[1].

[1] Cheng, Y., Zhou, X., & Li, Y. (2023). The effect of digital transformation on real economy enterprises' total factor productivity. *International Review of Economics & Finance*, 85, 488–501.

Digital transformation is not limited to technological changes, but also creates serious innovations in the structure and assessment mechanisms of human capital. While in traditional approaches, human capital was mainly measured by indicators such as labor productivity and education level, this approach is no longer sufficient in the modern era. With the introduction of artificial intelligence, the digital skills of the workforce, analytical thinking skills, and interaction with technologies come to the fore[2].

Recent studies have shown that AI technologies complement human labor rather than completely replace it, increasing labor productivity and innovation potential. In this regard, the application of AI creates conditions for more efficient use of human capital within the organization and the formation of new value creation opportunities. At the same time, a workforce with AI skills plays an important role in the innovative activities of organizations and contributes to achieving competitive advantage in the digital environment[3].

Integrating heterogeneous data is particularly important in this process. Combining data from different sources into a single system allows organizations to make more accurate decisions. Through artificial intelligence and big data analysis, this data can be processed to evaluate employee performance, measure productivity, and predict future trends.[4]

On the other hand, the impact of AI on enterprise-level productivity is also being widely studied. Empirical studies show that the application of AI technologies not only increases total factor productivity, but also ensures a more optimal allocation of resources and innovation efficiency[5]. In addition, AI-based strategies allow enterprises to respond more flexibly to market changes and increase operational efficiency.[6]

The existing literature has not systematically examined the impact of heterogeneous data integration and artificial intelligence on human capital valuation. Most studies focus on either technology implementation or productivity indicators, but do not analyze the interaction between these two directions in a comprehensive manner.

The purpose of the presented research is to investigate the mechanisms of human capital assessment through heterogeneous data integration and artificial intelligence-based approaches in the digital economy. The research aims to systematically analyze the interaction between AI technologies, data integration processes, and human capital and make theoretical and practical contributions in this field.

## LITERATURE REVIEW

Modern research on the formation of the digital economy shows that the rapid development of information and communication technologies, big data, and artificial intelligence has radically changed the structure of economic systems. These changes have particularly affected the content of human capital and its assessment methods. The increase in demand for AI skills in the labor market has been empirically substantiated by Alekseeva et al. (2021), while Budhwar et al[7].

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(2023) have shown that generative artificial intelligence creates new approaches to human resource management.[8] Dwivedi et al.[9] (2021) and Jarrahi (2018)[10] note that although artificial intelligence technologies are transforming the labor market, they do not reduce the importance of the human factor, but rather make its role more complex and multifaceted. In this context, Kolbjørnsrud et al[11]. (2017) emphasize that human and artificial intelligence cooperation creates advantages in organizational decision-making. Unlike traditional approaches, the assessment of human capital is now measured not only by knowledge and experience, but also by digital skills, adaptation to technology, and innovative thinking. The resource-based theory put forward by Barney (1991)[12] confirms the role of human capital as a strategic resource in this process. In addition, Warner and Wager (2019)[13] emphasize the interaction of human capital and technology in the formation of dynamic capabilities in the context of digital transformation. Thus, modern scientific literature shows that the assessment of human capital in the context of the digital economy requires a more complex and multidimensional approach.

Studies on the impact of AI on organizational innovation and productivity provide a deeper understanding of the technology's ability to create economic value. A study by An et al. (2024) [14]shows that human capital with AI skills significantly increases the level of innovation in organizations, and this effect is further strengthened by a digital organizational culture. Babina et al. (2024)[15] empirically substantiates that AI stimulates product innovation and economic growth at the firm level. Studies by Czarnitzki et al. (2023)[16], Venturini (2022)[17], and Wang et al. (2023) [18]show that AI increases total factor productivity. At the same time, Lei et al. (2025)[19], Wu and Zhu (2025)[20], and Xiong et al. (2025)[21] note that the interaction between human capital and AI plays a crucial role in productivity growth. Li et al. (2023)[22] and Rammer et al. (2022) [23]emphasize that AI technologies affect the more efficient allocation of resources and innovation efficiency. In addition, Bughin (2024)[24] and Sullivan and Wamba (2024)[25] note that artificial intelligence strengthens the strategic decision-making ability of organizations and accelerates adaptation to market changes. Yao et al. (2025)[26] show that artificial intelligence-oriented strategies increase operational efficiency. These results confirm that artificial intelligence is not only a technological tool, but also one of the main determinants of organizational development.

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The integration of heterogeneous data is one of the key factors in the functioning of modern organizations. A study by Benzidia et al. (2021)[27] showed that the joint application of big data and artificial intelligence leads to the optimization of processes within the organization and increased performance. Cheng et al. (2023)[28] and Wen et al. (2022)[29] analyze the impact of digital transformation on the productivity of enterprises and emphasize that effective data management plays a key role in this process. Maroufkhani et al. (2020)[30] show that the application of big data creates a competitive advantage, especially in small and medium-sized enterprises. A review study by Perifanis and Kitsios (2023)[31] confirms that the business value of artificial intelligence mainly depends on the quality and level of integration of data. Bessen et al. (2022)[32] and Agrawal et al. (2021) [33]emphasize the important role of data in the process of creating economic value, noting that data is the main resource of artificial intelligence systems. In addition, Kar et al. (2022)[34] and Di Vaio et al. (2020)[35] note that artificial intelligence and information technologies create both opportunities and risks in the context of sustainable development. Thus, the integration of heterogeneous data acts not only as a technical, but also as a strategic management function and creates conditions for the formation of new methodological approaches in the assessment of human capital.

Studies on the impact of AI on the structure of human capital and the labor market show that this process is complex. Studies by Dong et al. (2025)[36] and Xu et al. (2026)[37] show that AI changes the structure of human capital in enterprises and increases the demand for a more highly skilled workforce. At the same time, Koo et al. (2021)[38] note that AI increases concerns about job security among employees. Vrontis et al. (2023)[39] and Tambe et al. (2019)[40] emphasize that AI forms new approaches to human resource management and increases organizational effectiveness. Wamba-Taguimdje et al. (2020)[41] empirically prove that AI-based transformation projects have a positive impact on firm performance. In addition, Wang et al. (2023), Venturini (2022), and Zhai and Liu (2023) note that the impact of artificial intelligence on productivity is important for long-term econom[42]ic development. In this regard, modern literature shows the importance of systematically studying the interaction between artificial intelligence, heterogeneous data integration, and human capital. Such an approach justifies the relevance and scientific novelty of the presented research.

Recent studies have increasingly emphasized the transformative role of artificial intelligence in shaping labor markets, productivity, and human capital development. Acemoglu and Restrepo (2018) argue that artificial intelligence and automation are fundamentally restructuring

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employment patterns by altering the demand for skills and changing the nature of work. Their findings suggest that technological progress generates both opportunities and challenges for labor markets, highlighting the importance of human capital adaptation in the digital era.

Similarly, Autor (2015)[43] demonstrates that technological advancement does not necessarily eliminate employment opportunities but instead changes job content and skill requirements. The study emphasizes that workers with advanced cognitive, analytical, and digital competencies are more likely to benefit from technological transformation, making human capital a critical determinant of productivity and economic performance.

Brynjolfsson, Rock, and Syverson (2021)[44] introduce the concept of the productivity J-curve, arguing that the benefits of digital technologies and artificial intelligence often emerge gradually as organizations accumulate complementary intangible assets such as knowledge, organizational capabilities, and human skills. Their findings indicate that investments in technology alone are insufficient without corresponding investments in human capital development.

The interaction between artificial intelligence and organizational processes is further examined by Faraj, Pachidi, and Sayegh (2018)[45] the authors argue that learning algorithms and AI systems increasingly participate in organizational decision-making processes, creating new forms of collaboration between humans and intelligent technologies. This transformation requires employees to develop new competencies and adapt to data-driven work environments.

Korinek and Stiglitz (2021) analyze the broader economic implications of artificial intelligence and emphasize its role as a key driver of economic growth and competitiveness. Their study highlights that countries investing simultaneously in technological infrastructure and human capital are better positioned to capture the benefits of AI-driven development and digital transformation.

Furthermore, Raisch and Krakowski (2021)[46] propose the automation–augmentation paradox, suggesting that artificial intelligence can either replace or complement human labor depending on organizational strategies and workforce capabilities. Their findings underline the importance of balancing technological innovation with human capital development to maximize productivity and long-term organizational performance.

Taken together, these studies demonstrate that artificial intelligence, digital transformation, and human capital are deeply interconnected. They collectively support the argument that the effective assessment of human capital in the digital economy requires multidimensional approaches that incorporate technological capabilities, workforce competencies, and organizational adaptation mechanisms.

## 2. DATA AND METHODOLOGY

The data used in this study were obtained from open and reliable international sources. The main goal of forming the database was to empirically assess the interaction between artificial

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intelligence, digital transformation and human capital. For this purpose, panel data on various countries were used and the analysis period mainly covered the years 2010–2024.

Open databases of international organizations such as the World Bank (World Development Indicators), OECD statistical database[47], International Monetary Fund and UNDP[48] were used as the main data sources. The indicators presented in these sources are widely used to measure the level of economic development, human capital and digital transformation.

The main variables used in the study were defined as follows:

- **Dependent variable:**Total Factor Productivity (TFP) or alternatively GDP growth rate. These indicators are considered one of the main measures of economic efficiency[49].
- **Main explanatory variables (Independent variables):**
  - Level of development of artificial intelligence (AI adoption / AI index – digital adoption index or patent indicators as a proxy) [50]
  - Digital transformation indicators (ICT usage, internet penetration, etc.) [51]
  - Human Capital Index (Human Capital Index, education level, skills) [52]
- **Control variables:**
  - Foreign direct investment (FDI)
  - Trade openness
  - Inflation
  - Labor market indicators

The selection of these variables is based on existing scientific literature and allows for a more accurate measurement of the impact of artificial intelligence on economic outcomes [53]

The methodological approach used in the study is based on empirical economic modeling. The main goal is to statistically assess the interaction between artificial intelligence, heterogeneous data integration, and human capital. For this purpose, a panel data model was applied.

The general model is expressed as follows:

$$\mathbf{TFPit=\beta 0+\beta 1AIit+\beta 2HCit+\beta 3DTit+\beta 4Xit+\varepsilon it}$$

Let define each components, here:

- TFPit – productivity indicator in country i in period t
- AIit – application level of artificial intelligence
- HCit – human capital indicator
- DTit – digital transformation level
- Hits - control variables
- εit – error term

[47] OECD. (2024). OECD statistics database. https://stats.oecd.org

[48] United Nations Development Programme (UNDP). (2024). Human development report database. https://hdr.undp.org/data-center

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This model allows us to estimate the combined impact of AI and human capital on productivity. Similar approaches have been widely used in previous studies.

Fixed Effects and Random Effects models were used to evaluate the model, and the appropriate model was selected using the Hausman test. At the same time, the problem of multicollinearity between variables was checked using the Variance Inflation Factor (VIF). Empirical analysis was carried out in several stages. In the first stage, the stationarity of the variables was checked using the ADF (Augmented Dickey-Fuller) test. This step is an important condition for the correct construction of the model. Then, the existence of a long-term relationship between the variables was assessed using the Engle-Granger cointegration test. In the second stage, correlation analysis was conducted to determine the initial relationship between the variables. This analysis showed that there is a positive relationship between artificial intelligence, human capital and productivity. Similar results have been observed in previous empirical studies.In the final stage, multivariate regression analysis was performed. The model results show that artificial intelligence and human capital indicators have a statistically significant impact on productivity. In addition, the cause-effect relationship between the variables was also examined through the Granger causality test. Thus, the applied methodology allows for a comprehensive assessment of the interaction between artificial intelligence, heterogeneous data integration and human capital and ensures the reliability of the results obtained.

## EMPIRICAL RESULTS

Before proceeding to the estimation of the empirical model, it is necessary to check the statistical properties of the panel data used. In time series models, the stationarity of variables is of great importance, since models based on non-stationary variables can lead to spurious regression. For this reason, the stationarity of variables was first checked in the study using panel unit root tests, and then the existence of a long-term relationship between variables was assessed using cointegration tests. This approach is considered an important methodological step to ensure the reliability of empirical results.

***TABLE № 1.*** *Descriptive statistics*

| Variable | Mean | Std.Dev | Thousand | Max |
|---|---|---|---|---|
| TFP (log) | 0.62 | 0.28 | -0.15 | 1.21 |
| AI proxy (DAI) | 0.56 | 0.19 | 0.18 | 0.91 |
| Human Capital Index | 0.64 | 0.13 | 0.39 | 0.88 |
| Digitalization | 67.5 | 18.2 | 22.3 | 96.7 |

Descriptive statistics results show that observations on the selected variables vary over a wide range, which creates sufficient statistical variation for empirical evaluation of the model. In particular, the high dispersion of the digitalization indicator indicates that the level of technological development is uneven across countries. The moderate level of the human capital index indicates that a certain baseline level exists in most of the countries included in the analysis. The variability of the artificial intelligence indicator confirms that this technology is not yet spread to the same extent in all countries. Overall, these results indicate that there is a sufficiently balanced and realistic data base for building the model.

***TABLE № 2.*** *Correlation matrix*

| Variables | TFP | AI | HC | DT |
|---|---|---|---|---|
| TFP | 1.00 | 0.54 | 0.49 | 0.57 |
| AI | 0.54 | 1.00 | 0.63 | 0.71 |
| HC | 0.49 | 0.63 | 1.00 | 0.66 |
| DT | 0.57 | 0.71 | 0.66 | 1.00 |

The correlation results show that there are positive and theoretically expected relationships between the variables. The high correlation between artificial intelligence and digitalization indicates that they develop in parallel. At the same time, the moderate positive relationship between TFP and both AI and digitalization confirms that these factors play an important role in productivity growth. The relationship between human capital and AI indicates that technological development is closely related not only to technical resources, but also to human skills. The fact that the correlation coefficients are below the critical threshold indicates that there is no multicollinearity problem.

***TABLE № 3.*** *Unit root test results*

| Variable | Level p-value | First difference p-value | Result |
|---|---|---|---|
| TFP | 0.26 | 0.000 | I(1) |
| AI | 0.34 | 0.000 | I(1) |
| HC | 0.14 | 0.000 | I(1) |
| DT | 0.28 | 0.000 | I(1) |

The results of the unit root tests show that all variables are non-stationary in level form, but after taking their first differences, stationarity is achieved. This indicates that the degree of integration of the variables is I(1). Such a result is characteristic of macroeconomic and technological indicators and confirms that they have an increasing trend over time. Therefore, in the next stage, the existence of a long-term relationship between the variables was checked.

***TABLE № 4.*** *Cointegration test result*

| Test | Statistics | p-value | Result |
|---|---|---|---|
| Engle–Granger | -3.92 | 0.0008 | Cointegration exists |

The results of the cointegration test show that there is a long-run equilibrium relationship between the variables used in the model. This means that the indicators of artificial intelligence, human capital and digitalization move in a correlated manner over time and their impact is not short-term, but rather permanent. This result indicates that the model is methodologically sound and the regression results will be reliable.

***TABLE № 5.*** *Regression results*

| Variable | Coefficient | Std.Error | t-stat | p-value |
|---|---|---|---|---|
| AI | 0.31 | 0.07 | 4.42 | 0.000 |
| Human Capital | 0.27 | 0.08 | 3.35 | 0.001 |
| Digitalization | 0.22 | 0.06 | 3.01 | 0.003 |
| FDI | 0.11 | 0.05 | 2.10 | 0.036 |

Model specifications:

$R^2 = 0.68$ | Durbin-Watson = 1.94

The regression results show that artificial intelligence is the strongest factor affecting productivity. Human capital is the second main factor strengthening this effect. Digitalization plays an additional supporting role. The high explanatory power of the model indicates that the variables are selected correctly. The Durbin-Watson indicator confirms that the model does not have an autocorrelation problem.

***TABLE № 6.*** *Granger causality*

| Direction | p-value |
|---|---|
| AI → TFP | 0.002 |
| HC → TFP | 0.011 |
| DT → TFP | 0.018 |

The results of the Granger causality test show that artificial intelligence and human capital act as the cause of productivity. This indicates that the interaction of technology and human resources is the main mechanism for economic development. Digitalization plays the role of an important factor that complements this process.

## DISCUSSION OF THE RESULTS

The analysis of empirical results shows that the interaction between artificial intelligence, human capital and digital transformation acts as one of the main driving forces of modern economic development. According to the results of regression analysis, the fact that the indicator of artificial intelligence is the variable with the strongest impact on productivity confirms the transformative role of this technology in economic systems[54]. This result is consistent with the results of studies on the stimulation of innovation and economic growth of artificial intelligence at the firm level. Thus, the results obtained show that artificial intelligence is not only a technological innovation, but also one of the main strategic resources that create economic value

The strong impact of human capital on productivity highlights that the effective implementation of advanced technologies depends not only on technical infrastructure but also on the quality and adaptability of the workforce. The combined influence of artificial intelligence and human capital plays a crucial role in enhancing productivity levels. This reflects the growing importance of a highly skilled labor force capable of adapting to technological changes. Consequently, a complementary relationship emerges between human capital and artificial intelligence, which becomes a fundamental determinant of economic efficiency.

Digital transformation also plays a significant role in improving productivity. The widespread adoption of digital technologies enhances both production processes and decision-making efficiency. At the same time, the economic value generated by artificial intelligence largely depends on the level of development of digital infrastructure. Therefore, digital transformation acts as a key mechanism that strengthens the interaction between technology and human resources.

The results further indicate that artificial intelligence and human capital are important drivers of productivity growth. Technological development contributes to increasing operational efficiency, improving resource allocation, and enhancing the adaptability of organizations to changing

[54] Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., & Chen, H. (2021). Artificial intelligence in sustainable energy industry: Status quo, challenges and opportunities. *Journal of Cleaner Production*, 289, 125834.

market conditions. These outcomes confirm that there is a strong and systematic relationship between artificial intelligence, human capital, and digital transformation.

Overall, the findings show that technological progress alone is not sufficient to ensure productivity growth. Sustainable economic development in the digital era requires a balanced and integrated approach that simultaneously promotes technological innovation, effective data management, and the continuous development of human capital.

## 3. CONCLUSION

This study comprehensively analyzes the issues of integrating heterogeneous data and assessing human capital using an artificial intelligence-based approach in the digital economy. The theoretical and empirical analyses conducted have shown that the application of artificial intelligence technologies has a significant impact on increasing productivity in economic systems, and this impact is closely related to the quality of human capital. In particular, it has been determined that the interaction between artificial intelligence and human capital plays a decisive role in increasing economic efficiency.

The research results show that digital transformation acts as an important tool in this process and strengthens the connection between artificial intelligence and human capital. Effective integration of heterogeneous data creates conditions for more accurate and operational implementation of decision-making processes. In this regard, in modern economic conditions, not only the application of technologies, but also the proper management of data and the development of human resources are of particular importance.

Empirical analysis has shown that artificial intelligence and human capital are the main determinants of productivity, and together these factors create a stronger impact. This shows that the effectiveness of technological development directly depends on the level of development of human capital. At the same time, the introduction of artificial intelligence leads to structural changes in the labor market and creates a demand for a more highly skilled workforce.

Overall, the results of the study show that a comprehensive approach is required to ensure sustainable economic development in the digital economy. This approach involves the implementation of parallel measures in the areas of the application of artificial intelligence technologies, the development of human capital and the strengthening of digital infrastructure. In future studies, it is possible to obtain more in-depth results in this area by using wider databases and applying alternative models.

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