

Article

Methodology for Calculating the Human Capital Vulnerability to AI Index

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Abstract

The rapid proliferation of artificial intelligence (AI) technologies is transforming the role of human capital in value creation, generating both new developmental opportunities and substantial risks. This study addresses the following research question: how can human capital vulnerability to AI be systematically measured and compared across countries? The purpose of this study is to develop a methodology for calculating the index for human capital vulnerability to AI and to validate it through cross-country comparative analysis to overcome analytical fragmentation in examining the consequences of AI diffusion. A human capital vulnerability to AI index is constructed as a composite indicator encompassing five interrelated dimensions: national technological readiness, human capital adaptability, institutional protective capacity, structural labour market vulnerability, and migration-related vulnerability. Twenty-four indicators are normalised using the min–max method; subindex weights are determined via principal component analysis. The framework is validated on a sample of six countries—Germany, France, Finland, Estonia, Poland, and Ukraine—selected through cluster analysis, drawing on data from the OECD, Eurostat, the State Statistics Service of Ukraine, and Oxford Insights. Results reveal substantial cross-country heterogeneity, ranging from Finland’s low vulnerability, underpinned by strong institutional readiness, to Ukraine’s critical vulnerability, driven by compounded structural, institutional, labour market, and migration constraints, with Germany, France, Estonia, and Poland occupying intermediate positions shaped by labour market exposure, migration pressures, and limited technological readiness, respectively. The proposed methodology integrates the precision of multivariate statistical tools with conceptual rigour, enabling reliable and interpretable cross-country differentiation of human capital vulnerability under AI-driven transformation for forecasting labour market changes and shaping targeted retraining and social protection policies.



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1. Introduction

The modern development of artificial intelligence (AI) actively transforms, fundamentally changing the structure of working places, the paradigm of the structuralisation of the labour force and the concept of human capital value in organisations and at the level of

countries' economies. AI is used not only in the context of completing routine work and productivity but also in management decisions (Bilal, 2021). Neeliah and Seetanah (2016) proved that between human capital and economic growth exists a bilateral positive and statistically significant relationship. The accumulation and development of human capital are key determinants of economic growth, because they encourage growth in production efficiency, innovative activity and economic system adaptability. At the same time, economic growth strengthens the potential for the reproduction of human capital, ensuring expansion of the resource base for investments in human development. However, in the modern digital economy the value of human capital exceeds the traditional economic growth factor, acquiring the role of the main driver of digitalisation, determining prerequisites for the generation and effective usage of technological innovations in the field of AI (Ionaşcu, 2025). Therefore, human capital remains a main source of resilient competitiveness, innovation and economic growth (Naisho, 2025).

At the same time, AI creates not only some new opportunities for the development of human capital but also real threats for its devaluation and loss (Arntz et al., 2016). Therefore, the problem of human capital preservation under conditions of technological transformation is becoming strategically important for governments, business and educational institutions.

Drawing on the foundational conceptualisation by Chambers (1989), human capital vulnerability encompasses “an external side of risks, shocks and stress to which an individual or household is subject; and an internal side which is defencelessness meaning a lack of means to cope without damaging loss” (Chambers, 1989). Adapting this dual framework to the context of the AI-driven transformation of socio-economic systems, human capital vulnerability to AI is defined in this study as the degree to which a country's human capital is exposed to the risks of technological displacement while lacking sufficient adaptive, institutional, and structural capacity to withstand or recover from such disruptions. Operationally, workers can be classified as “potentially AI-vulnerable” when they combine a high degree of AI exposure with low AI-related job performance requirements (Council of Economic Advisers [CEA], 2024).

Taddeo and Floridi (2018) highlight that AI is not only a new object of regulation but also a powerful transformative power, which changes usual practices, interactions and the environment, so it is essential that this influence is focused on benefits for people. This determines the first dimension of human capital vulnerability to AI, namely labour market structural vulnerability, since AI automates routine cognitive and physical tasks, thereby reducing demand for medium-skilled labour (Arntz et al., 2016; Maslii & Maksymenko, 2025).

A person can use the advantages of modern technologies fully, including AI, only by possessing a wide range of complex cognitive, motoric, sociological and emotional skills (Frey & Osborne, 2017). There is a real risk of the devaluation and deactivation of human capital without such skills and knowledge (Leahy & Wilson, 2014). Digital technologies, including AI, significantly transform the structure of demand for competences and reevaluate the role of human capital in the creation of economic value, increasing the strategic importance of cognitive, creative and digital skills (Frank et al., 2019). This determines the second dimension of human capital vulnerability to AI—human capital readiness to adapt – since the ability of workers to acquire new digital competencies and retrain in response to technological change directly affects their resilience to AI-driven displacement (Frank et al., 2019).

The other dimension of human capital vulnerability to AI is institutional protection capacity. For example, Rondón-Castillo et al. (2026) conducted a systematic review of the international literature on the connection between human capital and growth, with a focus on Colombia. They revealed that the positive influence of human capital on

economic growth in the context of digitalisation is constrained by structural and regional disproportion, corruption, violence, informal employment, institutional fragmentation and the disparity between education and labour market demands. It actualizes the necessity for further research on the institutional and socio-economic contexts on human capital vulnerability to technological challenges, related to the spread of AI.

The spread of AI transforms the instruments and logic of corporate management, enhancing the role of data-driven approaches, automated decision making and projected human resources (HR) analytics (Budhwar et al., 2022). In such an environment, human capital vulnerability increases where digital readiness, skills adaptability and the ability to study do not correspond to new algorithmic work organisation demands (Chowdhury et al., 2023). It was proved by Faqihi and Shah (2023) that the spread of AI changes approaches to talent detection, assessment and development, actualizing the risks of algorithmic prejudice, unequal access to opportunities, opacity of personnel decisions and new requirements for workers' competency (Kozachenko et al., 2018). Tambe et al. (2019) presented the main problems in the usage of modern personnel management methods by using digital instruments. In the research works of Bilal (2021) and Fenech et al. (2019), AI is considered an instrument of HR process automation, and it emphasizes the role of human resources, reformatting from an administrative function to a strategic partner, which manages changes and development of the competencies of personnel. In the continuation of this research direction, Jatobá et al. (2023) emphasized the competencies, structures and HR practices needed for the successful implementation of AI. The aforementioned studies indirectly confirm that the level of skills development, ability to study and retrain and the quality of the durational qualification base are important prerequisites for decreasing vulnerability to AI. Therefore, the theoretical comprehension of AI-driven talent management must be continued through the systematic evaluation of these parameters' influence on the human capital vulnerability to AI formation at the macro level.

An important aspect of modern digital development is the swift increase in generative AI usage. The complex approach of the present literature about AI and generative AI systematisation and further description about the exact ways of how generative AI can change HR processes, practices, relations and results (productivity, employment, welfare, ethics, steady development) was represented in the work of scientists (Budhwar et al., 2023). However, this research is focused mainly on the organisational level and does not expose how these risks are accumulated into systematic human capital vulnerability at the macro level.

A further dimension of human capital vulnerability that has received growing scholarly attention concerns migration dynamics. Empirical evidence from EU member states demonstrates that brain drain negatively affects government AI readiness, as the emigration of skilled professionals depletes the human capital necessary for AI innovation and public sector digitalisation (Socol & Iuga, 2024). This creates a self-reinforcing cycle: countries experiencing higher brain drain face compounded vulnerability, as the loss of information and communication technologies (ICT) specialists and highly educated workers simultaneously reduces both adaptive capacity and institutional ability to respond to AI-driven disruption.

Mastering ICT instruments for solving cognitive tasks in today's world is becoming one of the important factors in labour efficiency and the population in-come increase (OECD, 2023). At the same time, emphasis is placed on the fact that skills, which support higher-order thinking processes, must be developed over a long time, and education plays a key role in this sphere (Faqihi & Shah, 2023). Therefore, it is important to continue research into digital skills and institutional support inequality and their role in shaping human capital vulnerability to AI. This determines a further dimension of human capital

vulnerability to AI, namely technological maturity and AI penetration, since the pace and depth of AI diffusion across economic sectors define the scale and immediacy of the pressure exerted on the existing workforce (Olszewska-Ziemba, 2025).

Quantitative assessments of different measures of human capital vulnerability to AI are limited in the academic literature. For example, in their research paper, Sofrankova et al. (2025) conducted a comparative analysis of the development of digital skills in the EU-27 in 2018–2024 based on the indicators of Digital Economy and Society Index (DESI), which demonstrates a resilient positive connection between the level of digital skills and overall effectiveness of digital transformation. The key empiric result of the conducted digital skills and competences research on human capital in the DESI structure is the confirmation of the inequality in the distribution of human capital digital adaptability prerequisites between countries (Kovács et al., 2022). However, the DESI analytical framework is primarily focused on the evaluation of digital transformation readiness and progress, rather than on the human capital vulnerability to AI as a separate research construct. DESI allows for assessing the prerequisites of adaptation to digital changes, but it does not include the specialized indicators for evaluating the influence of human capital vulnerability to AI (the risk of professional exclusion, tasks transformation, skills polarisation, adaptation inequality, etc.).

Brey and van der Marel (2024) used Eurostat aggregated data on AI implementation at the level of EU countries' enterprises. They show that the level of human capital is the key early predictor of the implementation of AI technologies, as a high level of human capital accelerates AI diffusion and strengthens the complementarity effect between technologies and competences. At the same time, the model does not consider human capital "preservation" and does not propose multivariate indicators, which would connect AI business adaptation with educational standards and government policy. It highlights the analytical gap, within which the transition from digital readiness assessment to operationalisation and human capital vulnerability to AI evaluation demand appears.

The research problem lies in the necessity of considering the influence of separate parameters on human capital development, including digital competences, adaptive skills, professional mobility, educational qualification structure, institutional protection ability, and others, on the ability of society and the labour market to adapt to the spread of AI. In the modern literature, these relationships are covered mostly fragmentarily (Arntz et al., 2016), because of separate analyses of individual digital transformation dimensions, without the formation of a holistic view about how human capital structural characteristics modify the social-economic risks of AI implementation.

Oltulular (2025) proposes a quantitative assessment of the connection between higher education dynamics (by levels and sexes) and economic growth in Turkey based on the Vector Autoregression (VAR) model. A long quarterly series (1982Q1–2021Q4) and VAR analysis were used with four models for the assessment of the dynamic relationships between economic growth and the number of bachelors, master's and PhD students, which allows for analysing not only static correlations but cause-and-effect dynamics over time. However, no direct indicators of vulnerability to innovative technologies or AI were included in the article: there were no variables, related to digital skills, usage of ICT, automation, employment structure by professions or risks of exclusion from work due to technologies.

Acceleration in the pace of AI diffusion in EU countries during 2021–2024 is characterized by inequality and deep structural differentiation of the European space in terms of the level of technological development (Ionaşcu, 2025). Such inequality in AI diffusion causes the formation of different levels of the human capital vulnerability to technological transformations in different countries. In addition, research papers do not consider the

context of a country with an economy devastated by war, where the different shocks of such a state should be taken into account: massive business relocation, shadow employment, and disruptions in educational trajectories, which critically change the methods of human capital preservation.

The synthesis of the reviewed literature allows for identifying five key structural parameters that collectively determine the level of human capital vulnerability to AI-driven transformation at the country level, enabling its measurement through internationally comparable quantitative indicators. First, the structural characteristics of the labour market, particularly the share of employment in routine and automatable occupations, constitute the primary source of direct vulnerability. Second, the adaptability potential of human capital, reflected in digital competencies, educational attainment, and lifelong learning participation, determines the capacity of the workforce to respond to technological disruption. Third, the institutional capacity of the state to protect workers through social safety nets, reskilling programmes, and AI governance frameworks mediates the severity of vulnerability at the national level. Fourth, migration dynamics, particularly the outflow of skilled labour, amplifies structural human capital deficits and reduces the adaptive capacity of the national economy. Fifth, the level of technological maturity and AI penetration defines the intensity and pace of labour market transformation, contextualising the magnitude of vulnerability across countries. These five dimensions, grounded in the existing theoretical and empirical literature, form the conceptual foundation of the proposed index.

Highly appreciating the contribution of these research papers, which studied the level of professional exposure to AI, employment, salary, productivity and workers' subjective welfare dynamics, it should be stated that the majority of the conducted research operates only with fragmented indicators of AI's influence on human capital and does not provide a systematic and complex evaluation. Indexes of AI exposure, job insecurity poll scales, AI-induced human capital obsolescence indicators, reskilling and upskilling investments or highly qualified personnel spatial concentration analysis are used separately and are not combined into a cohesive analytical framework of vulnerability evaluation and human capital preservation in the context of the development and spread of AI. As a result, it is still not clear which country types are the most vulnerable to the negative effects of AI. Also, it is unclear which institutional, educational, and corporative mechanisms really decrease these risks. This gap is especially notable in economies that suffer from war and post-war shocks and where the losses of human capital because of death, forced migration, infrastructure destruction and mental traumas are combined with digital transformation and AI implementation challenges.

This study proposes the following hypothesis. The level of human capital vulnerability to AI is derived from the quality and balance of its structural parameters; developed digital competencies, high-quality educational qualification base, high labour market adaptability and stronger study and retraining institutional mechanisms decrease corresponding risks, whereas their deficit, structural weakness and inequality increase vulnerability to AI-driven transformation.

In this context, the task of developing an integral system of human capital vulnerability to AI evaluation, based on interconnected structural elements and its validation in international comparative analysis, becomes scientifically and practically important. Such a framework must integrate technical exposure to AI, skills obsolescence risks, labour market parameters, educational and retraining investments, workers' institutional protection guarantees, and also demographic and migration processes, including war and post-war contexts. This research focuses on overcoming the existing fragmentation of analytical approaches by developing an integrated methodological approach in the digital transformation era, caused by the spread of AI. Accordingly, this study addresses the following

research question: how can human capital vulnerability to AI be systematically measured and compared across countries?

This paper is structured as follows. Section 2 outlines the methodology for constructing the Human Capital Vulnerability Index to AI. Section 3 presents the empirical results and their interpretation. Section 4 discusses the key findings, their policy implications, the limitations of this study, and directions for future research.

2. Methodology

The objective of this section is to develop a methodology for assessing human capital vulnerability to AI that captures its multidimensional structure through five interrelated dimensions of vulnerability (Figure 1), in contrast to existing fragmented approaches.

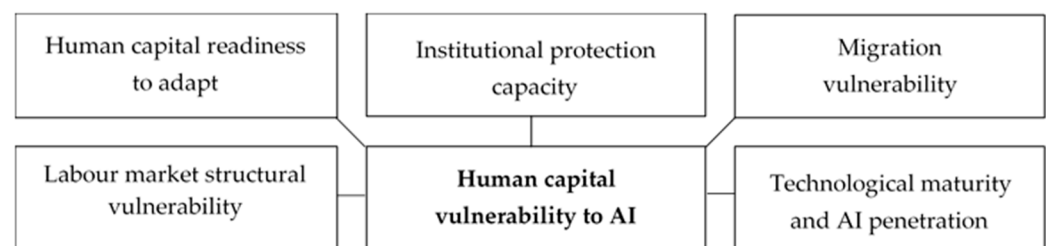


Figure 1. Measurements of the human capital vulnerability to AI according to the author’s methodology.

The relevant list of the indicators is chosen for every measurement, comprehensively representing human capital vulnerability to transformational changes as a result of AI diffusion in the socio-economic relations system (Table A1). The analytical input data array formation was conducted on the basis of official statistical data from the Eurostat and State Statistics Service of Ukraine and also the results of annual EU surveys on the usage of ICT and electronic commerce by enterprises, conducted by Eurostat (Eurostat, 2025).

In contrast to approaches which consider technological maturity only as an external context, in this research, measurement of the “Technological maturity and AI penetration” is a part of the index structure as an independent vulnerability measurement, which represents the intensity of technological pressure on the labour market. A higher level of AI penetration is considered a factor which enhances human capital structural vulnerability under the condition of insufficient institutional and adaptability readiness.

The human capital vulnerability to AI index calculation is preceded by input data array formation based on the determined indicators. For the indicators with biennial data collection cycles, the missing data were recovered via the method of lineal interpolation between adjacent observations within the time series for every country. The EM algorithm method was used exclusively for unpredictable structural omissions, which were not related to the statistics’ collection frequency. Indicators whose calculating methodology was developed after 2019 due to the emergence and spread of AI technologies were not subject to retrospective extrapolation. For such indicators, the first year of their official calculation was considered to be the basic year of analysis. The indicator “population share, who use generative AI” was omitted from the analysis, as its systematic statistical record began only in 2025, which makes it impossible to include as a part of the comparative analysis in the research period of 2019–2024.

Due to the Russian Federation’s full-scale invasion of Ukraine (February 2022), the official statistical reports for Ukraine were stopped and not published for a number of indicators. For 11 out of 24 indicators, which were not published in the period 2022–2024, the method of the Last Observation Carried Forward (LOCF) was used with a fixation on 2021 as the basic year. The remaining 13 indicators remained available and were updated in accordance with official sources. Consequently, Ukraine’s annual vulnerability scores

continue to shift throughout the wartime period, reflecting both the real dynamics of the indicators that are still being measured and the relative repositioning of Ukraine as other countries' values move within the shared index baseline. The gathered data should be considered as a lower/upper bound for vulnerability assessment under the circumstances of wartime structural ambiguity.

The EU countries selected for analysis were purposefully chosen as representative archetypes of structurally distinct European digital economy models, reflecting qualitatively different trajectories of AI development within the EU. To ensure methodological transparency and reproducibility of the selection procedure, cluster analysis was applied in the XLSTAT software (version 2025.1) environment in compliance with a consistent multistage procedure conforming to multidimensional statistical analysis standards. Cluster analysis was subsequently applied to the most recent available data to confirm that these typological distinctions remain statistically robust, thereby validating the representativeness of the selected sample across the entire study period 2019–2024. The within-cluster homogeneity and between-cluster heterogeneity of the sets of units guarantee the selection's meaningful stratification and the representativeness of every selected segment. It allows for avoiding the spontaneous or situational selection of countries, minimizing the subjectivity of the selection and increasing repeatability and methodological transparency of the analytical procedure, which is a principal requirement for cross-country comparative research.

Clustering of the countries was conducted in the space of two quantitative indicators, which represent the structural measurements of AI diffusion: (1) the share of enterprises that use AI instruments (AI_Business), and (2) the share of the population that uses generative AI (AI_Population). At the first stage, the input matrix table was formed $X \in R^{n \times p}$, where n —the number of the countries, $p = 2$ —the number of AI diffusion indicators. Every country $x_i \in R^2$ is described by the feature vector $x_i = (x_{i1}, x_{i2})$. In order to provide comparability across variables, the variables were standardized via z-transformation method, which ensured their equal weight in the process of minimising Euclidean distances (Lloyd, 1982):

$$z_{ij} = \frac{x_{ij} - \bar{x}_j}{\sigma_j}, \quad (1)$$

where x_{ij} —value of j indicator for i country, $\bar{x}_j$ —arithmetic mean, and σ_j —standard deviation of j indicator.

Clustering was conducted using the k -means method (Lloyd, 1982), which minimizes the function of within-cluster variance:

$$\min \sum_{k=1}^K \sum_{z_i \in C_k} \|z_i - \mu_k\|^2, \quad (2)$$

where x_{ij} —value of j indicator for i country, $\bar{x}_j$ —arithmetic mean, and σ_j —standard deviation of j indicator.

To assess the similarity between the objects being clustered, Euclidean distance (Lloyd, 1982) was used:

$$d(i, k) = \sqrt{\sum_{j=1}^p (z_{ij} - z_{kj})^2}, \quad (3)$$

where $d(i, k)$ —distance between country i and country k in the p -dimensional space.

The quality of the cluster structure was assessed using the silhouette coefficient for each object i (Rousseeuw, 1987):

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}, \quad (4)$$

where $a(i)$ —average distance between object i and other objects in its cluster; $b(i)$ —minimal average distance from object i to the nearest neighbouring cluster's objects. A value $s(i) \in [-1; 1]$ close to 1 indicates correct assignment of the object to the cluster.

According to the principle of stratified representativeness, for further analysis of the human capital vulnerability to AI, one country was selected from each cluster, which most fully represents the typical structural characteristics of its group. The object's minimal distance to the centroid of the corresponding cluster served as a criterion for the selection, which provided maximal representativeness of the selected object in its group as a whole.

In order to ensure human capital vulnerability to AI indicator comparability, represented in different units of measurement and scale, all indicators within every vulnerability measurement were subject to normalisation via min–max method. According to economic interpretation of the relationship between the value of an indicator and the level of vulnerability, two modifications of the normalisation formulas were used. For indicators and stimulators (S), where an increase in the values correlates with an increase in vulnerability, the normalisation was conducted using the following formula (OECD & European Commission, 2008):

$$y_{ij}^S = \frac{(x_{ij} - x_j^{\min})}{(x_j^{\max} - x_j^{\min})}, \quad (5)$$

where x_{ijt} is the observed value of indicator j for country i in year t ; $x_j^{\min} = \min_{i,t} x_{ijt}$ and $x_j^{\max} = \max_{i,t} x_{ijt}$ are the minimal and maximal values of indicator j across all countries and all years of the study period, ensuring a unified cross-country normalisation scale. At the same time, the normalised value $y_{ij}^S = 1$ corresponds to the highest vulnerability level, and $y_{ij}^S = 0$ —to the lowest one.

For indicators and destimulators with inverse impact (D), an increase in which corresponds to a decrease in vulnerability, an inverted modification of the normalisation formula was used (OECD & European Commission, 2008):

$$y_{ij}^D = \frac{(x_j^{\max} - x_{ij})}{(x_j^{\max} - x_j^{\min})}, \quad (6)$$

Inversion provides meaningful consistency in the evaluation scales: the country with the highest level of adaptation readiness or the most developed institutional capacity gets a normalised value $y_{ij}^D = 0$, which corresponds to minimal vulnerability, whereas the country with the lowest protection characteristics value— $y_{ij}^D = 1$. The classification of each indicator as a stimulator (S) or destimulator (D), along with the corresponding normalisation direction applied, is provided in Appendix A, Table A1.

Human capital vulnerability to AI integral index is determined hierarchically: at the bottom level—indexes with separate vulnerability measurements (I_{im}); at the top—generalized index (I_i^{HCVAI}).

Subindex calculation using each of the five vulnerability measurements is conducted via the following formula:

$$I_{im} = \sum_{j=1}^m d_{ij} \times y_{ij}, \quad (7)$$

where I_{im} —aggregated value/subindex of the m vulnerability measurement for i country, where $m = (1, 2 \dots 5)$; d_{ij} —weight coefficient, which determines the degree of input of indicator j in the integral index of the m human capital vulnerability to AI measurement for i country; y_{ij} —normalised assessment of j indicator for i country.

Weight coefficients of the indicators were determined using principal component analysis (PCA). The PCA usage allows for avoiding the spontaneity of expert weighting and ensures a statistically justified contribution of every indicator in the general variation of the corresponding measurement.

In dimensions requiring two or three retained components, the final weight for each indicator was computed as the eigenvalue-weighted sum of squared factor loadings across all retained components, normalised to ensure that weights sum to unity within each dimension.

Human capital vulnerability to AI index (I_i^{HCVAI}) is calculated as a weighted sum of the five subindexes, each of which must represent a separate vulnerability measurement:

$$I_i^{HCVAI} = \sum_m d_m \times I_{im}, \quad (8)$$

where d_m —weight coefficient, which determines the subindex degree of input of the m vulnerability measurement to the human capital vulnerability to AI integral index; I_{im} —aggregated subindex of the m vulnerability measurement for the i country, where $m = (1, 2 \dots 5)$. The value I_i^{HCVAI} is in the range $[0; 1]$, where 0—minimal vulnerability, 1—maximal. Weight coefficients of the subindexes d_m are determined statistically by explained dispersion share with the help of the PCA method.

The human capital vulnerability to AI is assessed using the classification scale presented in Table 1, which is based on equal quartiles of the normalised $[0, 1]$ range (0.25, 0.50, and 0.75) to distinguish four vulnerability levels—low, moderate, high, and critical—in accordance with the widely used quartile-based approach to composite index construction relying on min–max normalisation (OECD & European Commission, 2008).

Table 1. The human capital vulnerability to AI assessment scale.

I_i Value	Vulnerability Level	Characteristic
[0–0.25)	Low	Balanced system, high adaptability potential
[0.25–0.5)	Moderate	Challenges and threats exist, preventive measurements are needed
[0.5–0.75)	High	Critical threats, immediate measures are needed
[0.75–1.0]	Critical	Human capital systematic crisis

Compared with alternative approaches, such as median- or standard-deviation-based splits, the quartile method offers greater methodological transparency, independence from the specific data distribution of a given sample, and more intuitive interpretability of thresholds (OECD & European Commission, 2008). The choice of four, rather than three or five, levels reflects two considerations. On the one hand, a three-level scale would not allow moderate and high vulnerability to be distinguished, which is essential for formulating differentiated policy recommendations. On the other hand, further disaggregation (five or more levels) would introduce excessive granularity for a sample of six countries, unsupported by adequate statistical power.

For visualisation of the obtained values, gradient colour scaling in the format of a heat map in the table form was used, where the intensity of the colour represents the level of human capital vulnerability to AI for the corresponding value.

All calculating procedures were implemented in XLSTAT software (version 2025.1), which ensured the repeatability of the results and correspondence of the research to verified quantitative analysis standards. The proposed methodology combines the multidimensional statistical instruments' accuracy with a conceptually meaningful index structure that allows for obtaining a reliable, meaningful, and differentiated assessment of the countries according to the human capital vulnerability level under the technological transformation conditions due to AI development.

The empirical application of the proposed index is presented as a pilot test and preliminary validation of the methodology, intended to demonstrate its diagnostic potential and sensitivity to cross-country structural differences.

AI tools (Claude 4.6 Sonnet, ChatGPT Instant 5.3, and Gemini 3.1 Pro) were used in the preparation of this manuscript. All usage was limited to language editing and organisational support. The authors remain fully responsible for the content, data, and conclusions.

3. Results

3.1. The EU Representative Selection Formation for the Human Capital Vulnerability to AI Index Assessment

According to [OECD \(2025\)](#) data, AI implementation by companies more than doubled during 2024–2025, increasing from 8.7% in 2023 to 20.2% in 2025. The swift spread of universal generative AI instruments caused a rapid increase in individual usage among the population. More than a third of the people in the OECD used AI generative instruments in 2025. At the same time, significant inequality in its usage among different population groups, depending on their age, education and income, is observed. Such tendencies are observed in EU countries and Ukraine (Figure 2).

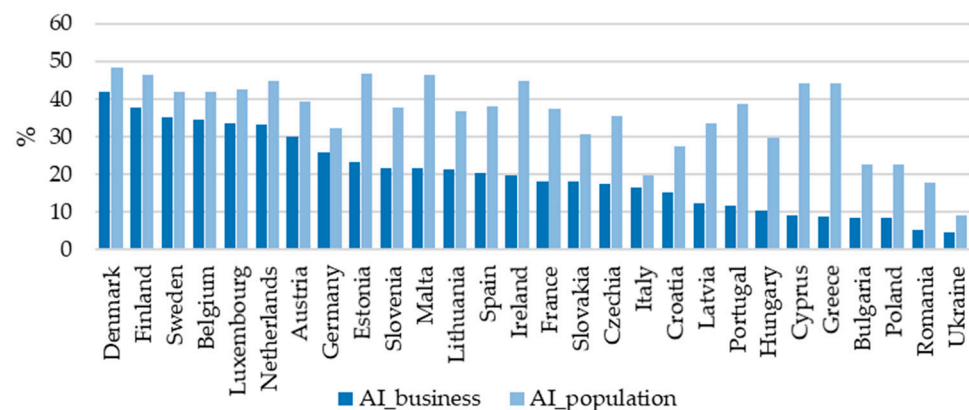


Figure 2. Indicators of AI diffusion among business and the population in EU countries and Ukraine in 2025. Built using [Eurostat \(2025\)](#) data.

AI technology diffusion indicator analysis in EU countries showed significant differentiation in implementation levels. Denmark, Finland, Sweden, Belgium, Luxembourg and the Netherlands are the leaders by implementation both in business and among the population. More than 30% of enterprises and more than 40% of the population used AI instruments in these countries. However, such countries as Romania, Poland and Bulgaria have the lowest AI instrument usage indicators. In 2025, they were used by only 5–9% of enterprises and 7–23% of the population in these countries. In Ukraine, the level of AI instrument usage is even lower—only 4.6% of enterprises and 9.1% of the population used AI in 2025. It should be mentioned that some EU countries, like Estonia, Malta, Ireland, Cyprus and Greece, are leaders in population usage of AI instruments (more than 44%); however, they have a much lower level of business usage of AI instruments (only 9–23% of enterprises).

The discovered inequality in AI implementation determined the feasibility of cluster analysis usage for the group of countries based on the similarity of AI diffusion characteristics, separation of structurally homogeneous countries into clusters and further human capital vulnerability to AI assessment in each of them and comparison of the obtained results with the corresponding indicators for Ukraine in the context of its European integration into the EU Digital Single Market.

To form a representative selection of the countries for analysing human capital vulnerability to AI, the clustering of the 27 EU member states was carried out through two main indicators of AI diffusion among business and the population: (1) the share of enterprises using AI instruments (AI_business), and the share of the population using generative AI (AI_population). To ensure the comparability of the indicators, the standardisation of the input matrix was conducted via the z-transformation method. Standardised indicator values by countries are shown in Table 2.

Table 2. The matrix of AI diffusion standardised indicator values.

EU Country	AI_Business_Std	AI_Population_Std
Belgium	1.372	0.611
Bulgaria	−1.210	−1.648
Czechia	−0.311	−0.160
Denmark	2.116	1.355
Germany	0.521	−0.519
Estonia	0.265	1.147
Ireland	−0.108	0.949
Greece	−1.172	0.852
Spain	−0.046	0.132
France	−0.255	0.084
Croatia	−0.550	−1.067
Italy	−0.430	−1.954
Cyprus	−1.138	0.864
Latvia	−0.846	−0.386
Lithuania	0.057	0.018
Luxembourg	1.280	0.672
Hungary	−1.029	−0.831
Malta	0.078	1.126
Netherlands	1.240	0.922
Austria	0.916	0.311
Poland	−1.229	−1.628
Portugal	−0.913	0.227
Romania	−1.542	−2.197
Slovenia	0.087	0.095
Slovakia	−0.271	−0.688
Finland	1.698	1.104
Sweden	1.422	0.611

As a result of clustering the 27 EU member countries by business and population AI instrument usage using the k-means method, four structurally homogeneous country groups were separated (Table 3).

Table 3. Clustering quality indicators.

Cluster	AI_Business Cluster Centroids	AI_Population Cluster Centroids	Sum of Weights	Within-Cluster Variance
1	1.435	0.798	7.000	0.269
2	−0.998	−1.554	6.000	0.453
3	−0.133	−0.178	8.000	0.256
4	−0.498	0.861	6.000	0.533

The distances between the centroids of the selected clusters are shown in Table 4.

Table 4. Distances between the cluster centroids.

Cluster	1	2	3	4
1	0	3.384	1.847	1.934
2	3.384	0	1.625	2.466
3	1.847	1.625	0	1.101
4	1.934	2.466	1.101	0

The obtained average silhouette value of 0.465 shows good clustering quality and clear segmentation of the groups. The biggest distance is observed between clusters 1 and 2 (3.384), which demonstrates their greatest difference in terms of the level of business and population AI instrument usage. At the same time, the lowest distance is observed between clusters 3 and 4 (1.101), which demonstrates the relatively close characteristics of the countries attributed to these groups.

The obtained cluster structure allowed for distinguishing four levels of AI development in Europe: from countries with lower AI integration in business processes and the social environment to groups with a higher technological level of digital diffusion (Table 5).

Table 5. The countries' division by clusters.

Cluster	1	2	3	4
Number of objects by cluster	7	6	8	6
Sum of weights	7	6	8	6
Within-cluster variance	0.269	0.453	0.256	0.533
Minimum distance to centroid	0.188	0.232	0.179	0.400
Average distance to centroid	0.402	0.566	0.428	0.653
Maximum distance to centroid	0.880	0.842	0.743	0.815
Country	Belgium Denmark Luxembourg Netherlands Austria Finland Sweden	Bulgaria Croatia Italy Hungary Poland Romania	Czechia Germany Spain France Latvia Lithuania Slovenia Slovakia	Estonia Ireland Greece Cyprus Malta Portugal

The within-cluster dispersion analysis shows significant uniformity in the formed groups: the lowest values of variation are observed in cluster 3 ($s^2_3 = 0.256$) and cluster 1 ($s^2_1 = 0.269$). It confirms the high structural compactness of these groups. Clusters 2 and 4 demonstrate slightly higher within-cluster variation ($s^2_2 = 0.453$ and $s^2_4 = 0.533$, respectively). This indicates the higher heterogeneity of the AI development structural characteristics within these groups.

From the countries to leaders by their lowest distance to the centroid (0.402), in other words, from the countries with high values of both corporative and societal usage of AI, Finland was selected for further analysis. This country is considered a leader in the sphere of digital transformation and AI implementation in Europe. It is confirmed by its stable high rankings in international digital economy indexes (European Commission, 2025a) and readiness for AI (Oxford Insights, 2025). It serves as an abstract model for risk assessment in high-technology environments with the developed educational and competency systems.

Germany and France present the cluster of moderate AI development—the biggest and structurally homogeneous group (variation 0.256), with high industrial potential and significant employment share in sectors, which are sensitive to automation. Including these countries allows for studying the transformation risks for large economies with diversified production structures, with special analytical importance for the research.

Estonia represents the cluster of countries with high digital population integration and active implementation of digital solutions in public administration. Despite belonging to a cluster with higher within-cluster variation (0.533), Estonia is a unique case of a small economy with highly developed digital infrastructure and public administration based on AI (Espinosa & Pino, 2024). This provides it with special analytical value as a digital transformation model for small EU member countries. Its inclusion allows for assessing the specifics of vulnerability under digital country conditions and service-orientated economy.

Poland is part of the country cluster with the lowest level of AI diffusion but with a significant share in traditional sectors and moderate level of digitalisation. Poland is the largest economy among the countries in this cluster, and it represents the group of countries at the stage of active national strategy formation in the sphere of AI under conditions of structural limitations (Olszewska-Ziembka, 2025). It is relevant for the analysis of the transition economies and has structural characteristics, similar to Ukraine.

Thus, the five EU countries selected for analysis—Finland, Germany, France, Poland and Estonia—were purposefully chosen as representative archetypes of structurally distinct European digital economy models, reflecting qualitatively different trajectories of AI development within the EU. Cluster analysis was subsequently applied to the most recent available data to confirm that these typological distinctions remain statistically robust, thereby validating the representativeness of the selected sample across the entire study period (2019–2024). It forms the empirical foundation for the pilot cross-country validation of the proposed methodology, enabling preliminary assessment of human capital vulnerability to AI across EU countries and Ukraine.

3.2. Evaluation and Assessment of the Human Capital Vulnerability to AI Subindexes

The input dataset comprises 24 out of 25 indicators (Table A1) from Eurostat (2025), the State Statistics Service of Ukraine (2025), and Oxford Insights (2025), structured into five dimensions of human capital vulnerability to AI across six countries over the period 2019–2024. The indicator X5.2 is the share of the population that uses generative AI, and it was not included in this study because of the absence of the corresponding statistical data for the analysed period. To ensure the comparability of the indicators, expressed in different units of measurement, all indicators were normalised using the min–max method in a range [0; 1]. Descriptive statistics of the obtained normalised indicator values are shown in Table 6.

Table 6. Descriptive statistics of the normalised indicator values.

Indicator	Observations	Median	Mean	Variance	St. Dev.
X1.1	36	0.208	0.209	0.044	0.209
X1.2	36	0.637	0.530	0.101	0.318
X1.3	36	0.598	0.562	0.075	0.273
X1.4	36	0.340	0.390	0.088	0.296
X1.5	36	0.215	0.385	0.122	0.349
X2.1	36	0.609	0.598	0.090	0.300
X2.2	36	0.478	0.475	0.123	0.350
X2.3	36	0.416	0.425	0.086	0.293
X2.4	36	0.580	0.551	0.098	0.314
X2.5	36	0.382	0.409	0.117	0.342
X2.6	36	0.183	0.312	0.103	0.321

Table 6. *Cont.*

Indicator	Observations	Median	Mean	Variance	St. Dev.
X3.1	36	0.238	0.309	0.098	0.313
X3.2	36	0.391	0.427	0.109	0.330
X3.3	36	0.309	0.410	0.097	0.311
X3.4	36	0.221	0.323	0.097	0.311
X3.5	36	0.535	0.534	0.153	0.392
X4.1	36	0.546	0.532	0.018	0.133
X4.2	36	0.435	0.444	0.069	0.263
X4.3	36	0.363	0.421	0.067	0.259
X4.4	36	0.485	0.451	0.076	0.276
X5.1	36	0.846	0.738	0.065	0.254
X5.3	36	0.531	0.540	0.102	0.319
X5.4	36	0.334	0.397	0.093	0.306
X5.5	36	0.407	0.433	0.111	0.334

The average normalised values of the indicators vary in a range from 0.31 to 0.6, which shows moderate levels of the studied characteristics within the normalised scale. The proximity of the average and median values for most of the indicators demonstrates the relatively symmetrical distribution of the data. At the same time, the variation indicators demonstrate different levels of indicator heterogeneity: dispersion changes within a range from 0.018 to 0.153, and the standard deviation is within a range of 0.133 to 0.392, which shows significant differentiation between separate aspects of human capital vulnerability. With this in mind, the next research stage becomes the determination of the indicator weight coefficients using the PCA method. It allows for considering their relative significance in forming the integral index of human capital vulnerability to AI.

The component number, which had been used in weight coefficient evaluations, was determined by the cumulative share criterion of not lower than 70% explained dispersion. According to the obtained data in Table A2 for the “Institutional protection capacity” and “Technological maturity and AI penetration” measurements, the first main component explains more than 75.9% of the total dispersion, which exceeds the threshold of 70%. Because of that, the weight coefficients were evaluated on the basis of one component. For the “Human capital readiness to adapt” and “Migration vulnerability” measurements, two components were used with the cumulative shares of the explained dispersion of 77.0% and 82.2%, respectively. The factor pressure of the vulnerability indicators on the separated components, and their evaluation based on their weight coefficients, is shown in Table A3.

The subindexes of human capital vulnerability to AI across the five measurements for every indicator were established, considering the values of the evaluated weight coefficients. Using the gradient colour scaling of the obtained subindex values, comparative analysis of the human capital vulnerability to AI was conducted through the creation of a heat map in table form (Table 7). Significant country differentiation was discovered across separate human capital vulnerability to AI measurements.

The main risks in most countries are caused by the swift spread of AI despite their insufficient level of technological maturity, since subindex I5 has the highest value, which is close to or exceeds the threshold of high vulnerability (0.5). Finland is an exception to this. Its human capital vulnerability by this measurement is low and demonstrates a positive trend of declining from 0.213 in 2019 to 0.004 in 2024. However, in Ukraine, this problem is especially acute, since its subindex value I5 is critical and, over the whole research period, exceeds 0.95.

Table 7. Comparative heat map * of the human capital vulnerability to AI subindexes in the selected EU countries and Ukraine during 2019–2024.

Country	Year	Labour Market Structural Vulnerability— I_1	Human Capital Readiness to Adapt— I_2	Institutional Protection Capacity— I_3	Migration Vulnerability— I_4	Technological Maturity and AI Penetration— I_5
Finland	2019	0.3565	0.1862	0.0889	0.3791	0.2126
	2020	0.4087	0.1303	0.0598	0.3659	0.1520
	2021	0.3407	0.1599	0.0671	0.3417	0.1288
	2022	0.3059	0.1310	0.0946	0.3470	0.1141
	2023	0.3126	0.1315	0.0556	0.2982	0.1187
	2024	0.3635	0.1102	0.0448	0.2568	0.0042
Germany	2019	0.2679	0.3904	0.2548	0.3379	0.3687
	2020	0.3015	0.4419	0.2253	0.3150	0.3429
	2021	0.2736	0.4543	0.2507	0.2914	0.3821
	2022	0.2406	0.4388	0.3054	0.2809	0.3771
	2023	0.2385	0.4261	0.2552	0.2289	0.3469
	2024	0.2379	0.3975	0.2280	0.2099	0.2484
France	2019	0.5307	0.3635	0.2327	0.3869	0.5933
	2020	0.5538	0.3721	0.1927	0.3814	0.5476
	2021	0.4838	0.3628	0.1931	0.3736	0.5164
	2022	0.4457	0.3735	0.2109	0.3710	0.5411
	2023	0.4486	0.3524	0.2099	0.3460	0.5344
	2024	0.4593	0.3488	0.1747	0.3302	0.4753
Poland	2019	0.2921	0.6293	0.5434	0.6277	0.7894
	2020	0.3196	0.5998	0.5181	0.7221	0.6983
	2021	0.3378	0.5832	0.5264	0.6264	0.6438
	2022	0.2448	0.5622	0.5503	0.5572	0.5688
	2023	0.1848	0.5134	0.4993	0.5487	0.5115
	2024	0.1959	0.4921	0.4556	0.5348	0.4583
Estonia	2019	0.1751	0.3053	0.3764	0.3736	0.6267
	2020	0.3114	0.3184	0.3351	0.3535	0.5824
	2021	0.2789	0.3296	0.3666	0.3850	0.5422
	2022	0.2834	0.2792	0.3749	0.2883	0.5168
	2023	0.2347	0.2496	0.3243	0.3766	0.4800
	2024	0.3080	0.2340	0.2946	0.4574	0.3306
Ukraine	2019	0.7835	0.9803	0.9647	0.7402	0.9522
	2020	0.8274	0.9778	0.9521	0.7469	0.9574
	2021	0.7843	0.9695	0.9547	0.7563	0.9719
	2022	0.8292	0.9365	0.9281	0.8071	0.9669
	2023	0.7662	0.9200	0.9397	0.8567	0.9612
	2024	0.7246	0.9388	0.8882	0.8586	0.9538

* Colour intensity reflects the level of human capital vulnerability to AI, from low (light) to high (dark).

At the same time, the readiness of human capital to adapt in EU countries is estimated as being at a moderate level, since the subindex I_2 in all studied countries exceeds a value of 0.25 during 2019–2024 and is close to the threshold of high vulnerability (0.5). Finland and Estonia are the exceptions, as their level of human capital readiness to adapt demonstrates a positive dynamic because of active government policy in the sphere of AI development and systematic support of population digital competency formation.

The analysis of institutional protection capacity demonstrates its highest levels in Finland, France and Germany. In Finland, the value of the corresponding subindex in 2024 is only 0.04, which shows a minimal level of institutional vulnerability. At the same time, in France and Germany, this indicator also remains relatively low—0.17 and 0.23, respectively (Figure 3), because of existing, well-developed digital administration institutions, active implementation of AI development national strategies and a high level of state regulatory capacity, which complies with the approaches of the EU in building a safe and responsible AI ecosystem (Buriak & Maslii, 2025).

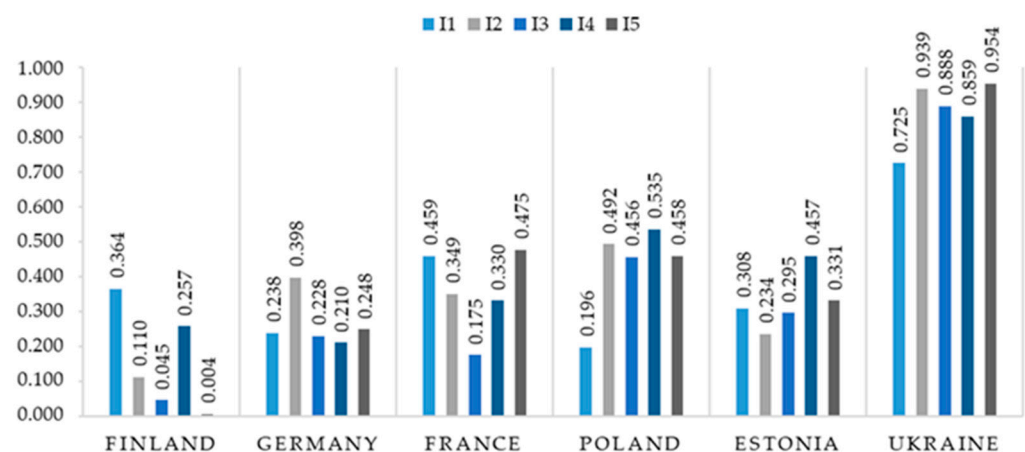


Figure 3. The subindex values of the human capital vulnerability to AI in the EU countries and Ukraine in 2024.

Migration vulnerability has high values in all European countries, which is related to significant human capital outflow. The I4 subindex value in the studied countries varies in a range from 0.20 to 0.55. It shows significant differentiation in migration risk levels and potential loss of human capital. The weight of this problem is the highest in Poland and Ukraine, especially after 2022. In Poland, the increase in the I4 subindex shows a rise in pressure on the labour market under conditions of massive population migration from Ukraine. At the same time, Ukraine has critically high values for this subindex. Such values are formed by a deep migration crisis, caused by the full-scale war, mass outflow of the population and loss of a significant share of human capital.

A moderate level of values is observed for the labour market structural vulnerability subindex I1. Notably, such a trend is common for all studied countries, including Finland, which at the same time demonstrates a high level of human capital readiness to adapt and significant institutional protection capacity. It shows that, even in countries with developed institutions and a high level of human capital adaptability, the structural transformation of the labour market under the influence of AI technologies diffusion remains an important risk factor. First of all, it is about the change in employment structure, redistribution of professional skills demand and the steady exclusion of some professions by automated technologies (OECD, 2023).

Within the pilot sample of six countries, Finland demonstrates the lowest values of human capital vulnerability to AI (Figure 4) and belongs to the group of countries with a high level of AI penetration in all spheres of socio-economic relations, a developed system of digital training, a high level of digital competencies among the population, and a high institutional protection capacity.

Within the testing of the proposed methodology, Germany and Estonia demonstrated moderate levels of human capital vulnerability to AI across all studied dimensions in 2024, while France and Poland exhibit higher variability in subindex values. Notably, France has a significant advantage in terms of its institutional protection capacity (the value of this

subindex is 0.175, and it stays in the low value zone), but at the same time, the structural vulnerability of its labour market is much higher (0.459) when compared with the same indicators in Germany and Poland. Poland is characterised by its low labour market vulnerability (0.196), but the values of its other indicators approached the zone of high risk in 2024.

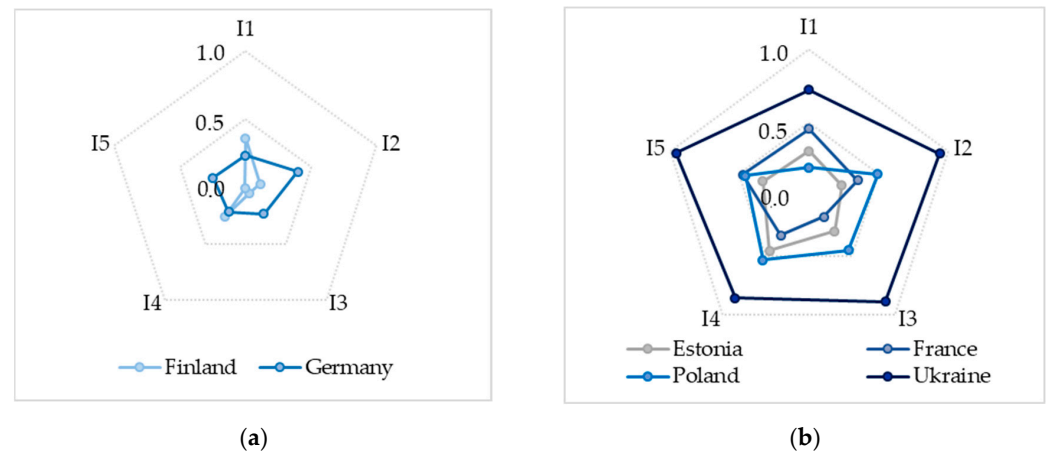


Figure 4. The profiles of the human capital vulnerability to AI subindexes among studied countries in 2024: (a) countries with a lower level of vulnerability (Finland, Germany); (b) countries with a higher level of vulnerability (Estonia, France, Poland, Ukraine).

Within the pilot sample, Ukraine is characterised by critically high levels of human capital vulnerability to AI across all studied measurements, unlike the EU countries. The values of all subindexes remain in the zone of critical values, which indicates significant structural limitations of human capital adaptability to AI technology diffusion.

The discovered differences form an important analytical foundation for developing effective policies for the human capital adaptation to technological transformation and enhancing the institutional capacity of the economy to function in the context of digitalisation.

3.3. Human Capital Vulnerability to AI Integral Index: Cross-Country and Dynamic Analysis

The Human Capital Vulnerability Index to AI (HCVIAI) is calculated as a weighted sum of subindexes I_1 – I_5 with weight coefficients, determined by the PCA method with the values of the subindexes. Based on the results of PCA, the first main component explains 85.3% of the subindexes' general dispersion, which indicates high within-index uniformity of the index structure. The obtained subindex weight coefficients are relatively uniform and comprise the following: $d_1 = 0.150$, $d_2 = 0.218$, $d_3 = 0.220$, $d_4 = 0.204$, $d_5 = 0.208$.

The values of the integral HCVIAI for 2019–2024 for the studied countries are shown in Table 8.

Table 8. The value of the integral HCVIAIs in selected studied countries of EU and Ukraine during 2019–2024.

Country	2019	2020	2021	2022	2023	2024	Average 2019–2024	Vulnerability Level
Finland	0.235	0.209	0.197	0.190	0.173	0.142	0.191	Low *
Germany	0.327	0.327	0.334	0.335	0.304	0.267	0.316	Moderate *
France	0.412	0.398	0.378	0.383	0.372	0.350	0.382	Moderate *
Poland	0.593	0.585	0.555	0.512	0.468	0.441	0.526	High *
Estonia	0.382	0.383	0.386	0.352	0.338	0.324	0.361	Moderate *
Ukraine	0.893	0.898	0.895	0.898	0.897	0.882	0.894	Critical *

* The four-level scale of vulnerability was used: low [0–0.25), moderate [0.25–0.50), high [0.50–0.75) and critical [0.75–1.00].

Within the testing of the proposed methodology, the lowest level of human capital vulnerability to AI during 2019–2024 was discovered in Finland, with a moderate value of HCVAI (0.191), which correlates with a low level of vulnerability. It is due to the high level of institutional protection capacity and technological maturity. The risks of AI implementation for the other studied countries are significantly high, as the moderate values of HCVAI for Germany, France and Estonia correspond to a moderate level of vulnerability and stay in the range of 0.316–0.382. Within the pilot sample, Poland has the highest level of human capital vulnerability to AI among the studied countries, with an average HCVAI value of 0.526, which corresponds to a high level of vulnerability. It is due to a low level of human capital readiness to adapt, a comparatively low level of technological maturity, insufficient institutional protection capacity and migration vulnerability.

Unlike the EU countries, Ukraine is characterised by a critically high level of human capital vulnerability to AI (the average value during 2019–2024 is 0.894) within the pilot sample, because the values of all subindexes stay within the critical value zone. It shows the combination of war, demographic and structural challenges, related to mass forced population movement, labour market transformation and limited adaptability opportunities for human capital regarding digital and technological changes. The existence of systematic structural risks to human capital adaptability to technological transformation under martial law conditions confirms the necessity to implement a comprehensive approach to ensure the information and economic security of Ukraine in cyberspace (Onyshchenko et al., 2023b).

Based on the results of dynamic analysis, a general trend of a decrease in human capital vulnerability to AI during 2019–2024 in the studied countries was discovered (Figure 5). To improve visibility, the interpretation of the HCVAI values, presented in the 0–1 range, was translated into a percentage scale (0–100%).

Within the pilot sample, the highest rate of human capital vulnerability to AI decrease is discovered in Finland (the value decreased by more than 1.5-times during 2019–2024), which is a result of the sustained implementation of the national AI strategy (European Commission, 2021). The decrease in vulnerability during the crisis period of the COVID-19 pandemic was distinctive for Finland and France, and it was accompanied by swift digitalisation and implementation of AI, while all other countries demonstrated the opposite dynamics. The most sensitive impact of active AI implementation on the increase in human capital vulnerability is discovered in Germany and Estonia (HCVAI increased by nearly 1 p.i.); however, there was no significant increase, due to the timely implementation of appropriate measures. In Germany, the National Skill Strategy, regional centres of excellence in labour research and retraining programmes based on AI were established (Bundesministerium für Arbeit und Soziales [BMAS], 2019). Estonia implemented the AI strategy “Kratt”, aimed at training personnel and building national AI infrastructure (Ministry of Economic Affairs and Communications, 2021).

Compared with other EU countries, a decrease in human capital vulnerability in Ukraine is not observed. It is caused by a combination of demographic, migration and institutional challenges (Onyshchenko et al., 2023a). Despite the implementation of digital transformation programmes, the institutional capacity to form an effective development ecosystem and ensure the safe use of AI technologies is still insufficient, which limits human capital adaptability.

These results demonstrate that human capital vulnerability to AI can be systematically measured through a composite index based on multidimensional indicators and meaningfully compared across countries, revealing substantial heterogeneity driven by differences in institutional readiness, labour market structure, technological maturity, and migration-related pressures.

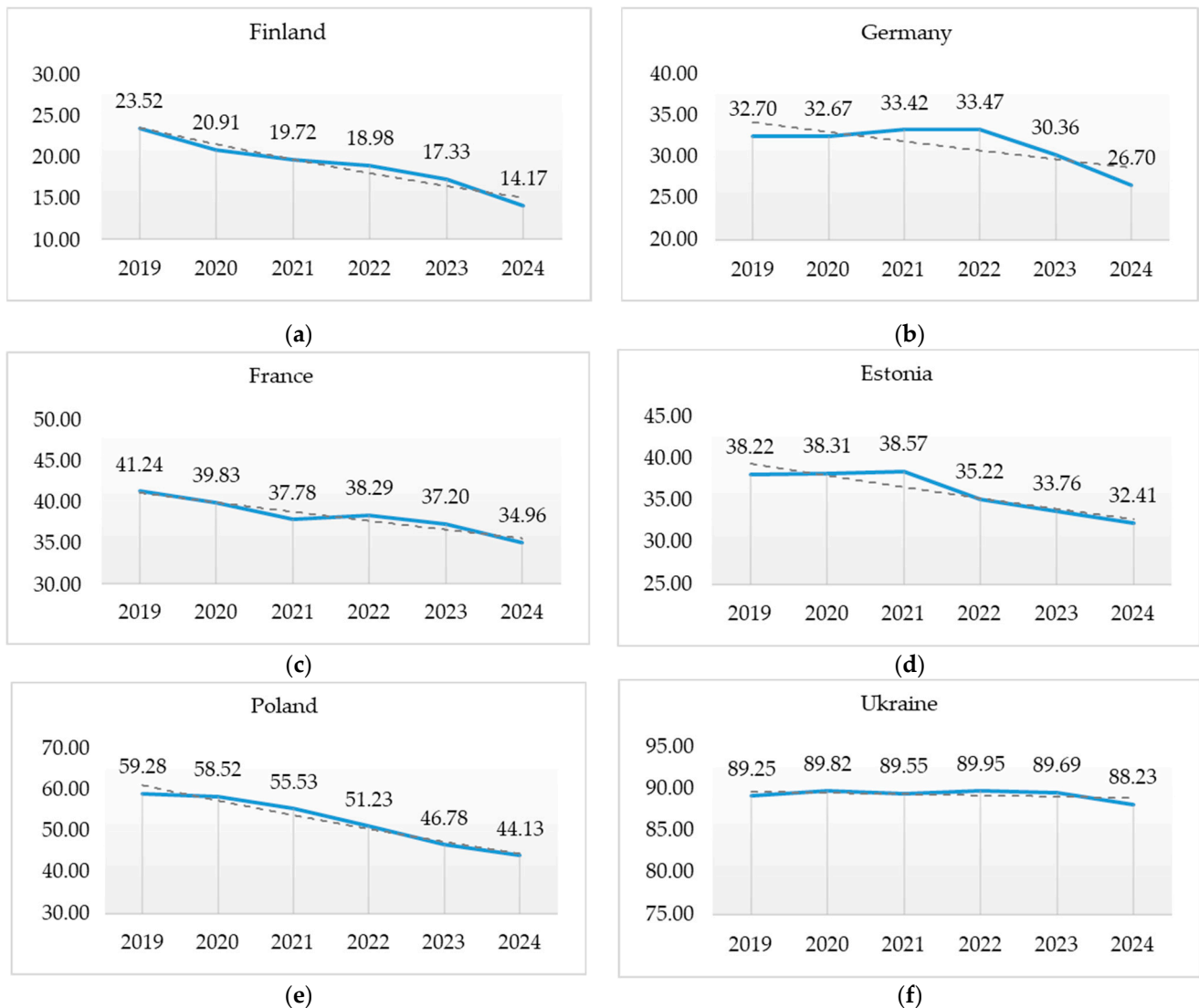


Figure 5. Human capital vulnerability to AI index dynamics during 2019–2024, %: (a) Finland; (b) Germany; (c) France; (d) Estonia; (e) Poland; (f) Ukraine.

4. Discussion

The main aim of this study was to develop a methodology for calculating the Human Capital Vulnerability Index to AI and its validation through cross-country comparative analysis. The suggested index integrates five main measurements: labour market structural vulnerability, human capital readiness to adapt, institutional protection capacity, migration vulnerability, technological maturity, and AI penetration. This ensures a multidimensional and scalable assessment system, suitable for use in different national and sectoral contexts.

The obtained results show that the highest level of vulnerability is found in countries for which a scale of routine manual and routine cognitive tasks, and low demands for the level of education and limited access to retraining programmes, is common in their labour market structure. Administrative support, data management, basic production and transport logistics workers contribute to the higher human capital vulnerability to AI formation, which only confirms the earlier documented uneven distribution effects of automation (Acemoglu & Restrepo, 2020). These conclusions generally correlate with the results of the fundamental research by Frey and Osborne (2017), in which it was proved that approximately 47% of employment in the USA is at high risk of computerisation. It is argued that non-routine cognitive and social tasks are crucial as a protection measure

against automation. In this way, in the OECD research by [Arntz et al. \(2016\)](#), it was emphasized that the distinctive factor of the automation risk is not the name of the profession but the set of tasks within the job position. The methodology proposed in this study develops these results and considers not only variability but also the adaptive capability of human capital—educational level, digital literacy and flexibility of the labour market.

In comparison to the approach of the authors [Acemoglu and Restrepo \(2020\)](#), who analysed automation through the prism of the substitution of labour by capital and the exclusion of tasks in production functions, HCVAI is oriented directly towards the perspective of the worker, fixing the individual and group levels of exclusion risk. This difference is methodologically essential: while macro-level analysis shows a combined production and employment effect, HCVAI is intended to support the key policy measures at the level of specific professional population groups that are most vulnerable to structural changes in the labour market.

The obtained results confirm the feasibility of including the migration vulnerability dimension in HCVAI, as under the conditions of AI diffusion, the key factor is not only the current level of competencies but also the ability of the country to keep, reproduce and accumulate its stock of these competencies. The outflow of young, educated, professionally mobile and highly qualified groups weakens the personnel base of technological adaptation, decreases the potential for acquiring new digital solutions and complicates the formation of a professional critical mass able to integrate into the AI transformation.

It is equally important to include institutional protection capacity in HCVAI, because institutions determine to what extent society can soften the risks of technological exclusion, professional polarisation, uneven access to retraining and asymmetry in adaptive capabilities. Even with relatively high educational and skill potential, the weakness of public regulation, underdevelopment of the lifelong education system, the low effectiveness of retraining programmes, limited social support and the absence of strategic coordination can seriously increase human capital vulnerability to AI.

In this sense, institutional capacity for protection shifts the analysis toward the realm of social resilience, which is particularly important for interpreting cross-country differences. This conclusion aligns with this study's working hypothesis that the vulnerability of human capital to AI is shaped not only by digital and demographic qualification characteristics but also by demographic migration and institutional factors and, at the same time, expands existing approaches, which are predominantly focused on skills, employment, human capital losses due to migration processes and the inequality of institutional protection in the context of technological transformations.

The key methodological contribution of this study lies in the HCVAI composite architecture, which goes beyond binary risk classifications (high/low) and offers a continuous, multidimensional spectrum of vulnerability. This addresses a well-documented limitation of previous automation risk assessment systems ([Naisho, 2025](#)). Including a measure of socio-economic adaptability, which encompasses access to lifelong learning and coverage by the social protection system, enables the index to reflect structural inequalities that either exacerbate or mitigate technological displacement, in line with the broader paradigm of human capital security within the context of EU social policy ([European Commission, 2025b](#)).

Applying the HCVAI methodology to the Ukrainian context reveals specific structural vulnerabilities stemming from the structure of the national economy, the significant share of semi-skilled, routine-intensive employment, and the historically limited reach of digital upskilling programs outside major urban centres. These findings complement existing research on human capital security in wartime conditions ([Lebedynska, 2025](#)), indicating that the risk of displacement due to AI exacerbates existing vulnerabilities related to demographic outflow and labour market fragmentation.

The results of this study also point to several promising avenues for further research. First, the HCVAI methodology requires continuous refinement. The operationalisation of indicators for task redefinition and cognitive complexity relies heavily on occupational classification schemes—primarily ISCO-08 and O*NET—whose descriptions may not fully capture the rapidly changing nature of tasks in the context of active AI implementation. As AI capabilities expand into areas previously considered cognitively complex, regular verification of indicators' validity in cross-country comparisons and the composition of indicators of human capital vulnerability to AI becomes a necessity.

Another methodological challenge is the availability and comparability of data. The international application of the HCVAI is limited by the heterogeneity of employment statistics, competency assessment systems, and labour force survey methodologies across different countries. This limitation is particularly acute in the context of post-socialist economies, where occupational classifications may deviate from international standards, and informal employment significantly distorts official labour market data. For countries under martial law, such as Ukraine, such research is significantly complicated by restrictions on the disclosure and collection of information under special data collection protocols, which limits opportunities to explore the potential of administrative microdata and employer surveys to supplement official statistics.

Another promising area of research concerns the dynamic interaction between the trajectories of AI adoption and vulnerability of human capital. The current version of the HCVAI provides a cross-sectional assessment of vulnerability; however, the temporal evolution of vulnerability under the influence of differentiated rates of technological adoption, firms' investments in automation, and corresponding government policy measures remains insufficiently theoretically grounded. Applying the index in a panel format, combined with difference-in-differences or synthetic control approaches, will significantly strengthen the causal inference regarding the effects of AI diffusion on the labour market.

Finally, the policy implications of the HCVAI methodological framework deserve separate analytical attention. The index was developed not only as a diagnostic tool but also as a decision-making aid in the areas of labour market policy, educational planning, and the design of social protection systems. The precise identification of highly vulnerable occupational groups allows authorities to more effectively direct investments in retraining and upskilling, adjust social insurance parameters in anticipation of structural unemployment, and develop AI governance systems that actively regulate the distributional consequences of the technological transition. In this context, the methodology proposed in this study contributes to the growing body of evidence shaping the EU's strategic agenda on the future of work and the responsible deployment of artificial intelligence.

Another promising area is the mapping and analysis of national and pan-European strategies aimed at improving digital literacy and inclusion, with a particular focus on the role of lifelong learning programs and adult reskilling initiatives in reducing the vulnerability of medium- and low-skilled workers to AI. Such an analysis will integrate human capital vulnerability assessments into national digital transformation strategies and social cohesion policies.

5. Conclusions

As a result of this study, a new methodological approach for human capital vulnerability to AI assessment was proposed. This study confirmed that the vulnerability of human capital to AI is a multidimensional and differentiated phenomenon that cannot be measured by using single indicators. The developed index, which integrates five subindexes (labour market structural vulnerability, human capital readiness to adapt, institutional protection capacity, migration vulnerability, technological maturity and AI penetration),

offers a systematic analytical platform for comparative assessment of countries in terms of their risk of technological displacement. The significance of this approach lies in conceptualising human capital not only as a source of knowledge, skills and a driver of digital development but also as a source of the national economic system's vulnerability to AI-driven transformation. In aggregate, the human capital vulnerability to AI is formed at the intersection between a country's technological maturity to AI, human capital readiness to adapt, institutional protection capacity, national labour market structural vulnerability, and migration vulnerability.

The scientific novelty of this study lies in the development of an integral index for assessing the human capital vulnerability to AI-driven displacement at the national level. Considering all five measurements creates a methodological foundation for the international comparison of the level of human capital vulnerability to AI and gives the opportunity not only to identify the current imbalances but also the deep structural limitations of digital development. The index can be scaled and modified for different regions, industries and countries. Also, it could be a useful analytical instrument to forecast changes in the labour market and to form targeted training and retraining programmes for public servants, educational organisations and businesses. The practical value of the proposed author's methodology lies in its ability to serve as an evidence-based foundation for developing targeted retraining programmes, adjusting social protection mechanisms, and forming national digital transformation strategies.

The application of the proposed methodology revealed significant cross-country differences in the level of human capital vulnerability to AI. Empirical testing based on a sample of Germany, France, Finland, Estonia, Poland, and Ukraine demonstrated the index's sensitivity to cross-country structural differences and confirmed its diagnostic potential. For example, countries that are leaders in digital transformation and the implementation of AI in Europe, represented in this study by Finland, are characterised by low levels of human capital vulnerability to AI. This result was achieved by investments in education for the development of digital skills, a well-established system of lifelong learning and a high institutional protection capacity. The implementation of AI development national strategies with a focus on retraining, improvements in professional skills and cooperation between humans and AI nullifies the risks of human capital exclusion and forms its cognitive resilience and adaptability. As a result, even with high level of AI penetration, a relatively low level of human capital vulnerability to AI is maintained.

For countries with high industrial potential and a significant share of employment in sectors that are sensitive to automation, which were represented in this study by Germany and France, the level of human capital vulnerability to AI is moderate. The transformational risks for large economies with a diversified production structure are minimized by the development of institutional protection capacity and a decrease in labour market structural vulnerability.

It was discovered that for small member countries in the EU with high levels of digital integration of the population and active implementation of digital solutions in public administration, which were represented in this study by Estonia, it is typical to have a moderate level of human capital vulnerability to AI. Highly developed digital infrastructure, systematic support of population digital competency formation and public administration based on AI allow for minimizing the technological risks. Therefore, for such small states, human capital vulnerability is associated with migration challenges.

Among the studied countries in the EU, the highest level of human capital vulnerability to AI was discovered in Poland, which represented the group of countries with economies in transition, with a lower level of AI penetration and less developed resilience strategies. Despite the development of advanced digital skills and the scaling-up of human capital retraining programmes in the EU countries, many of them still have a distinctive gap

between the pace of technological changes and the ability of human capital to adapt to news demands in a digital economy.

In comparison with the EU countries, a critically high level of human capital vulnerability to AI was discovered in Ukraine from the results of the comparative analysis of HCVAI. The reasons for that are different, but interconnected, factors. The long war, which began in 2022, caused structural shocks in the labour market: forced business relocation, loss of workplaces in high-productivity sectors and the outflow of qualified migrants to other spheres. These factors resulted in a decrease in social capital and the ability to adapt. However, despite the significant Ukrainian achievements in the digitalisation of the public services system and its ranking in the global ratings of AI readiness, digital skills and access to advanced knowledge and education remain unequally distributed between regions and sectors. This imbalance shows that a significant share of the labour force does not have sufficient educational adaptability and cognitive flexibility to use the advantages of AI.

The results confirm the main research hypothesis and indicate that the intensity of AI penetration does not necessarily lead to an increase in human capital vulnerability. The decisive factor is the interaction between technological influence, institutional protection capacity and the qualitative characteristics of human capital, including its cognitive, educational and social parameters. Under a favourable combination of these factors, AI does not pose a displacement threat but rather serves as a catalyst for skill enhancement and improved economic efficiency of human capital.

In general, the proposed methodological framework lays the foundation for a new paradigm for the digital future—a model of evidence-based human capital management in the context of AI transformation, which conceptualises human capital not as a passive object of technological influence but as a dynamic and adaptive system capable of coexisting with AI and evolving alongside it, transforming technological challenges into strategic growth opportunities.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
DESI	Digital Economy and Society Index
EU	European Union
HCVAI	Human Capital Vulnerability Index to AI
HR	Human Resources
ICT	Information and communication technologies
GDP	Gross domestic product
LOCF	Last Observation Carried Forward
OECD	Organisation for Economic Co-operation and Development
PCA	Principal Component Analysis
R&D	Research and Development
STEM	Science, Technology, Engineering and Mathematics
VAR	Vector Autoregression

Appendix A

Table A1. The justification for the selected human capital vulnerability to AI measurements.

Vulnerability Measurement	Scientific Justification	Impact Characteristic	List of Indicators
Labour market structural vulnerability (I_1)	Shows the share of employed in the professions with high risk of automation. It is the main measurement of the direct threat from AI for employment structure.	Basic/direct measurable impact. With the growth of labour market vulnerability, the human capital vulnerability to AI grows too. Indicators type: stimulators (S) *.	(X1.1) unemployment level (15–74); (X1.2) young people unemployment (15–24); (X1.3) share of the temporary employment; (X1.4) young people, who do not work, study or retrain (15–24); (X1.5) employment in the sectors with the high risk of exclusion
Human capital readiness to adapt (I_2)	It characterises the ability of work force to adapt to labour market transformations through education, skills and digital literacy.	Moderation/protection characteristic. The low level of adaptability readiness signalises of high vulnerability. Indicators type: inverse, destimulators (D) *.	(X2.1) the basic and high digital skills (16–74); (X2.2) participation of adults in training (25–64, 12 m.); (X2.3) ICT specialists in employment share; (X2.4) enterprises with ICT training; (X2.5) STEM graduates (ISCED 5–8); (X2.6) population with high education (30–34)
Institutional protection capacity (I_3)	Assesses the effectiveness of state institutions, social protection systems and regulative environment in ensuring the protection of the workers against the automation negative consequences.	Contextual/institutional characteristic. The institutional weakness leads to vulnerability growth. Indicators type: inverse, destimulators (D) *.	(X3.1) education expenses, % GDP; (X3.2) R&D expenses (GERD), % GDP; (X3.3) social protection expenses, % GDP; (X3.4) Gov. AI Readiness Index; (X3.5) electronic governance (e-government users)
Migration vulnerability (I_4)	Represents the risks of the qualified personnel outflow under the influence of AI-transformation, which strengthens the human capital structural deficits and decreases the adaptation potential of economy.	Structural/demographic characteristic. The intensity of personnel outflow directly influences the vulnerability growth. Indicators type: stimulators (S) *.	(X4.1) net migration, per 1000 population; (X4.2) the increase of population; (X4.3) the foreign students share (mobility); (X4.4) population ageing
Technological maturity and AI penetration (I_5)	Determines the level of AI spreading and AI technology maturity in the national economy. It is the contextual measurement, which modifies other measurements intensity influence: the high technological maturity simultaneously rises the risks of automation and expands the opportunities for adaptation.	Contextual/modifying characteristic. Dual (contextual) influence, which determines the scale and pace of the transformation. Indicators type: stimulators (S) *.	(X5.1) share of enterprises that use AI; (X5.2) share of population that use generative AI; (X5.3) share of enterprises that have cloud services; (X5.4) share of households that have broadband access; (X5.5) business expenses on R&D (BERD), % GDP

* stimulator (S)—higher indicator values correspond to higher vulnerability, normalised using Formula (5); destimulators (D)—higher indicator values correspond to lower vulnerability, normalised using inverted Formula (6). In both cases, the normalised value of 1 corresponds to maximum vulnerability and 0 to minimum vulnerability, ensuring a consistent directional interpretation of the composite index.

Table A2. Explained variance of principal components.

Vulnerability Measurement	Component	Eigenvalue	Variability (%)	Cumulative %
Labour market Structural vulnerability (I_1)	F1	2.518	50.355	50.355
	F2	1.333	26.665	77.020
	F3	0.559	11.172	88.193
	F4	0.353	7.055	95.247
	F5	0.238	4.753	100.000
The human capital readiness to adapt (I_2)	F1	3.947	65.786	65.786
	F2	1.026	17.101	82.887
	F3	0.538	8.961	91.848
	F4	0.375	6.255	98.103
	F5	0.094	1.572	99.675
	F6	0.020	0.325	100.000
Institutional protection capacity (I_3)	F1	3.797	75.933	75.933
	F2	0.783	15.658	91.591
	F3	0.232	4.641	96.232
	F4	0.133	2.657	98.889
	F5	0.056	1.111	100.000
Migration vulnerability (I_4)	F1	2.360	59.010	59.010
	F2	0.926	23.149	82.159
	F3	0.459	11.471	93.630
	F4	0.255	6.370	100.000
Technological maturity and AI penetration (I_5)	F1	3.038	75.944	75.944
	F3	0.518	12.948	88.892
	F4	0.357	8.933	97.825
	F5	0.087	2.175	100.000

Table A3. Results of PCA for determining the weights of vulnerability indicators.

Indicator	F1 Loading	F2 Loading	Weight Coefficient
X1.1	0.835	0.206	0.223
X1.2	0.147	0.951	0.155
X1.3	0.748	−0.213	0.181
X1.4	0.846	0.265	0.234
X1.5	0.724	−0.521	0.207
X2.1	0.683	−0.635	0.136
X2.2	0.885	0.002	0.186
X2.3	0.972	−0.085	0.225
X2.4	0.772	−0.321	0.148
X2.5	0.701	0.538	0.134
X2.6	0.815	0.472	0.171
X3.1	0.876	-	0.202
X3.2	0.916	-	0.221
X3.3	0.900	-	0.213
X3.4	0.964	-	0.245
X3.5	0.673	-	0.119
X4.1	0.602	−0.728	0.209
X4.2	0.669	0.628	0.221
X4.3	0.914	−0.016	0.307
X4.4	0.846	0.039	0.263
X5.1	0.806	-	0.214
X5.3	0.856	-	0.241
X5.4	0.906	-	0.270
X5.5	0.914	-	0.275

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