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AI ADOPTION AND APPARENT LABOR PRODUCTIVITY IN MEDIUM-SIZED ENTERPRISES IN THE EU

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Abstract: *Artificial intelligence is frequently suggested as a factor that can increase productivity, but its spread among enterprises does not automatically lead to better financial results. The study analyzes the relationship between the adoption of AI and apparent labor productivity in medium-sized enterprises in 25 EU member states, using Eurostat secondary data for 2021 and 2023. The analysis is quantitative, comparative and exploratory and includes descriptive statistics, national rankings, Pearson correlation and simple linear regressions for 2023 levels and changes over the period 2021–2023. In the cross-sectional analysis, AI adoption is positively and significantly associated with productivity ($r = 0.652$; $R^2 = 0.425$). The result is maintained after excluding Luxembourg and after logarithmic transformation of productivity. In contrast, the increase in AI adoption is not significantly associated with the evolution of productivity over the analyzed period. From a human resource management perspective, the results show that technology is linked to better performance when integrated into work organization, skills development, and other complementary practices. However, the data do not support a causal relationship.*

JEL Classification: J24, M54, O33, C21

Keywords: adoption of artificial intelligence, apparent labor productivity, medium-sized enterprises, human resource management, European Union

1. INTRODUCTION

Artificial intelligence is at the center of many management discussions, and expectations regarding its role in increasing productivity are high. Companies are encouraged to use AI to automate repetitive tasks, process information faster, and support decisions. Experience from previous stages of digitalization shows that investments in technology only create value if they are accompanied by changes in work organization and management practices (Bresnahan et al., 2002; Brynjolfsson & Hitt, 2000). There is no reason to believe that AI would work otherwise. The subject is important for human resource management. The adoption of AI matters not by the existence of applications, but by the way it changes the division of tasks, performance evaluation, skills development, autonomy and well-being of employees (Foris, 2016). From a resource-based perspective, technology becomes a strategic resource only when it is combined with quality data, organizational knowledge, routines and skills that are difficult to copy (Barney, 1991). Therefore, the link between AI and productivity is also about the organization of work, not just about information systems.

Medium-sized enterprises are a suitable sample for analysis because they have not been sufficiently studied. They typically have better-organized personnel functions and processes than small businesses, but they have fewer resources than large corporations to integrate, control, and evaluate the AI systems. Existing research often focuses either on individual perceptions and acceptance of the technology or on large organizations. Comparisons between countries' economies, made separately for medium-sized enterprises, are still underexplored.

The study examines whether AI adoption is associated with apparent labor productivity in medium-sized enterprises in the EU. Two relationships are investigated. The first one is the relationship between the level of AI adoption and the level of productivity in 2023. The second one is the relationship between the change in AI adoption and the rate of productivity growth in the period 2021–2023. Separating them allows us to compare the position of states in a given year with their short-term evolution.

The data are aggregated nationally and the analysis is based on 25 observations and a short period. For this reason, the results highlight statistical relationships and differences between states, without demonstrating a direct effect of AI adoption on labor productivity. The study uses formal and standardized indicators that can support prioritization of skills development, work organization and technology investment.

The paper has two contributions. First, it brings together two Eurostat indicators in a comparative analysis dedicated to a category of enterprises that is not sufficiently studied separately. Second, it interprets the results through themes specific to human resource management, such as, job design, performance appraisal, capacity, motivation, autonomy and well-being. Thus, the analysis does not assume that technology adoption directly leads to performance, but focuses on the organizational conditions in which AI can be used effectively.

2. LITERATURE REVIEW

2.1. The strategic role of HRM in the adoption of AI

Human resource management is no longer limited to personnel management, but also has a strategic role, related to organizational culture, motivation, employee development and the use of skills (Foris, 2016). In this framework, the adoption of AI is relevant only if it changes the organization of work and helps the company to achieve its goals, not just if it adds new applications.

The resource-based perspective supports the idea that competitive advantage does not come only from the possession of resources, but also from the combination of valuable, rare, hard to imitate and non-substitutable resources (Barney, 1991). In the case of artificial intelligence, technology does not automatically become a strategic resource. Its value depends on the skills of employees, the quality of data, the accumulated knowledge and the routines through which information is transformed into decisions and actions.

2.2. Digitalization of the human resources function and data-driven decisions

Rapid digitalization is changing the entire human resources activity. Ammirato et al. (2023) show that Industry 4.0 is changing work, learning, leadership, recruitment and relationships in organizations. Priyashantha et al. (2024) describe the transition from e-HRM to digital HRM, smart HRM and HRM 4.0, which forms the way technology is used in recruitment, coordination, evaluation and development.

Digitalizing human resources means more than converting documents into electronic format or automating some operations. Strohmeier (2020) differentiates between digitization, digitalization, digital transformation and digital disruption and shows that the change concerns the objectives, processes, roles and relationships of the HR function. A new application may simplify a task, but transformation only happens when the organization changes the way it works.

The connection to data-driven decisions is clear. Foris (2016) shows that personnel decisions are made under conditions of certainty, risk or uncertainty, and risk can be reduced by quickly obtaining the necessary quantitative and qualitative information. AI, machine learning and natural language processing increase the ability to analyze employee data and can improve the quality and efficiency of decisions (Úbeda-García et al., 2025). These tools do not replace the manager's judgment, but can provide him with better information for decisions.

Marler and Boudreau (2017) show that managerial interest has grown faster than academic evidence, and advanced analytical practices are still underused. Tursunbayeva et al. (2018) note that many contributions are conceptual and that research on the actual use of data analytics in organizations is needed. Angrave et al. (2016) warn that data can lead to overly simplistic recommendations when HR specialists do not distinguish between statistical association and causation.

Labor productivity is important both as an economic outcome and as a benchmark for decisions about staff allocation, work organization, and performance evaluation. The literature supports the use of comparative data in decision-making, but does not claim that the adoption of AI automatically produces productivity. The present analysis starts from the difference between the existence of the technology and its use in the organization.

2.3. Technology adoption and organizational capabilities

At the individual level, the AI adoption can be defined by the well-known models of technology acceptance. The TAM model relates intention to use and actual use to perceived usefulness and how easy it is to use (Davis, 1989). UTAUT adds performance and effort expectations, social influence, and conditions that support the use (Venkatesh et al., 2003). These models show that the traditional adoption of AI by an organization does not guarantee its consistent and productive use by employees.

At the organizational level, the resource-based perspective and dynamic capabilities theory emphasize the combination and adaptation of resources, in which technology supports performance only when connected to other resources and processes (Barney, 1991). At the same time, the organization must integrate, reorganize, and update its competencies as technology changes (Teece et al., 1997). The framework proposed by Priyashantha (2024) applies the same idea as disruptive technologies in human resource management.

The sociomaterial perspective complements these models and shows that technology, employees, and the organizational context are interconnected. Ammirato et al. (2023)argue that the actions of people and technology cannot be separated when explaining organizational outcomes. The idea is close to the connection between people, structure, technology, and goals described by Foris (2016). The same AI solution can produce different results depending on skills, culture, division of authority, and job design.

2.4. Human-AI collaboration and the reorganization of work

Digital transformation changes routines and the way tasks are managed and divided between people and technology, as well as the way they are coordinated. Klein et al. (2024) show that digitalization impacts an organization's identity and routines, and from a human resources perspective, this means redistributing responsibilities, updating performance criteria, and clarifying roles. Repetitive and informative tasks can be automated, and employees can focus more on interpretation, communication, and decision making.

The relationship between AI and humans is based on collaboration. AI systems can easily analyze large amounts of information and identify patterns, but humans are the ones who understand context, interpret unclear situations, and take responsibility for decisions (Jarrahi, 2018). Raisch and Krakowski (2021) explain this relationship through the paradox of automation and augmentation: AI can take over certain tasks, but at the same time transform or expand the role of humans in other activities.

New job design and skills are becoming important requirements for the use of technologies. Parker and Grote (2022) show that technologies can change autonomy, feedback, use of skills, task variety and work intensity. AI can support human performance when it improves work resources. It can also have negative effects if it increases monitoring, system dependence or unclear responsibilities.

Work organization is the theoretical mechanism connecting AI adoption to productivity. Investment can reduce processing time and improve access to information. It can also guide to fragmented responsibilities, too much information, or unclear decisions. From an HR perspective, AI integration requires analyzing jobs, updating job descriptions, clarifying the relationship between algorithmic systems' recommendations and human decisions, and preparing employees for the new requirements.

2.5. AI, complementary investments and productivity

Research on technology and productivity shows that other investments are also needed in this context. Brynjolfsson and Hitt (2000) show that the benefits of information technology depend on changing organizational processes and practices. Bresnahan et al. (2002) highlight the connection between technology, workplace reorganization, and highly skilled employees. In the case of AI, the apparent productivity paradox can be explained by adaptation costs, learning periods, intangible investments, and the time needed to reorganize activities (Brynjolfsson et al., 2018).

The distinction between AI adoption and AI capability is also important. Mikalef and Gupta (2021) define AI capability as a combination of technological, human and organizational resources, not the only existence of an application. The Eurostat (Eurostat, n.d.) indicator used in the study measures the percentage of enterprises using at least one AI technology, but does not show how intensively it is used, how well it is implemented, or how mature the organization's capabilities are.

2.6. Algorithmic management, transparency and fairness

Algorithmic management is different from the simple digitization of administrative activities. Automated systems can take tasks previously performed by managers, such as task allocation, monitoring, evaluation, and personnel recommendations (Kinowska & Sienkiewicz, 2023). In performance evaluation, processing speed and consistent application of criteria can reduce some errors related to evaluator subjectivity (Foris, 2016).

At the same time, algorithmic management brings a new form of control. Kellogg et al. (2020) show that algorithms can direct work, evaluate behaviors, and discipline employees, changing the traditional relationship between manager and employee. Tambe et al. (2019) show that there is a gap between the promises of AI in HR and its actual use. This gap is related to the complexity of human outcomes, data quality, issues of equity and accountability, and employee reactions to automated decisions.

Automation does not eliminate the risk of bias, but it can change its state, as Storm et al. (2023) show, unconscious biases can affect human resources processes, and models based on historical data can repeat or amplify them. Úbeda-García et al. (2025) consider transparency, fairness, explainability and protection of well-being as conditions for the responsible use of AI. Lack of transparency reduces the possibility for employees to understand and contest a decision that affects their evaluation, reward or career.

The risk is not limited to technical errors only. A systematic literature review by Köchling and Wehner (2020) shows that algorithmic decisions in recruitment and human resource development can produce direct or indirect discrimination and change the perception of the fairness of the process. Therefore, the evaluation of a system should track both the accuracy of predictions and the different effects on groups of candidates or employees.

The literature highlights a paradox of objectivity regarding the fact that algorithms can apply the same criteria more consistently and reduce differences between evaluators, but they can also introduce systematic errors, sometimes more difficult to notice compared to human errors. Therefore, the ability to explain the decisions of a system must be seen as a responsibility issue in human resource management, not just as a technical requirement. Periodic verification of models, data quality control, final accountability by a person, and clear procedures through which employees can challenge decisions that affect them are necessary. Regarding productivity, the conclusion must be formulated with caution. A faster evaluation system is not necessarily more effective if it reduces trust, cooperation or acceptance of criteria. A more precise feedback and identification of development needs can support performance, while excessive monitoring and unclear evaluations can reduce it. Algorithmic management must be evaluated by efficiency, fairness and acceptance in the organization.

2.7. Employee skills, motivation and autonomy

The Ability–Motivation–Opportunity (AMO) model explains the relation between human resource practices and performance. Bos-Nehles et al. (2023) show that ability, motivation, and opportunity to contribute should be analyzed together, as they influence each other. In the case of AI, performance can increase when employees have the necessary skills, find the technology useful, and have enough autonomy to use the recommendations in their work.

Self-determination theory provides an important explanation for employee motivation. According to Ryan and Deci (2000), autonomy, sense of competence and good relationships with others support both motivation and well-being. AI can have a positive effect when it helps employees solve problems more easily and make better use of their skills. Conversely, motivation may decrease if technology is perceived as a means of control or as a replacement for professional experience.

The Job Demands–Resources model allows for the analysis of AI as both a resource and a job requirement (Bakker & Demerouti, 2007). Technology is a resource when it provides information, feedback, and support for task performance. It becomes an additional condition when it produces too much information, pressure to adapt, constant monitoring, or role ambiguity. The effect on performance depends on the balance between the resources provided and the new requirements.

Motivation involves the ability to choose between behaviors that guide to the achievement of personal goals (Foris, 2016). Algorithmic management can increase the capacity for action through rapid access to information. Also it can limit autonomy if the system permanently sets the rate, order, and standards of work. Kinowska and Sienkiewicz (2023) describe this shift from traditional time control to an "algorithmic tyranny," in which monitoring and disciplining materialize without direct interaction with the manager.

From the perspective of employees, digitalization is not just about accepting or rejecting technology. They can see both the benefits and the pressures and difficulties brought by change (Klein et al., 2024). Artificial intelligence can reduce repetitive tasks and provide more useful information, but it can also speed up the pace of work, reduce uncertainty and increase the pressure of continuous evaluation. In this context, human resource management must support employees through clear communication, involvement in the change process, training and defining responsibilities.

2.8. Technostress, well-being and sustainability of human resources

Technostress is a possible consequence of the use of AI in everyday work. Úbeda-García et al. (2025) indicate the psychological effects of intelligent systems and methods for reducing technostress as important research directions. The link with productivity is direct: stress can cause delays, attention errors and difficulties in decision making, affecting the efficiency of the organization (Foris, 2016).

Empirical evidence supports this connection. Tarafdar et al. (2007) show that stress caused by the use of information technologies is associated with role stress and individual productivity. Further research shows that the development of technological skills can reduce some of the negative effects, along with self-confidence, information literacy and employee involvement in technological projects (Tarafdar et al., 2015). Therefore, training should be seen as a process of adaptation and uncertainty reduction, not just as technical training. The literature does not show an identical effect of AI on productivity in all situations. The outcome depends on the combination of skills, motivation, autonomy, work design and level of monitoring. A rapid increase in the rate of work can be undone by errors, burnout, employee departure or loss of trust. For human resource managers, responsible integration requires analyzing both employee performance and experience.

Sustainable human resource management takes the idea of technostress further. Ren et al. (2023) suggest combining economic, social, and environmental objectives, and Hronová and Špaček (2021) highlight the need to treat employees as strategic resources and to include them in reporting on sustainable practices. In the case of AI, efficiency must be analyzed together with equity, human capital development and the organization's ability to resist and adapt in the market.

2.9. Evidence on AI's impact on productivity

Recent studies based on task and employee level show that AI can increase productivity in certain situations. For example, Noy and Zhang (2023) identified better performance in professional writing activities, and Brynjolfsson et al. (2025) observed increases in productivity in customer service, with important differences between employees. The effects depend on the type of activity, the tool used and the context of the organization. For this reason, the conclusions cannot be automatically applied to all sectors or economies.

2.10. Conceptual framework and limitations of existing literature

The literature reviewed highlights three important limitations for this study. It focuses more on individual perceptions, acceptance, and well-being, while comparisons between country economies are not sufficiently explored. Medium-sized enterprises are not enough analyzed as a separate group, despite having a fairly well-organized human resources function, but also limited resources for artificial intelligence control. In addition, studies on employee experience and productivity often evolve separately, although work organization connects the two areas. The conceptual framework proposed of the study analyses a possible association between AI adoption and apparent labour productivity. Competencies, organizational capabilities, work design, autonomy, motivation, transparency and well-being are conditions that help to interpret the relationship. Eurostat indicators do not measure them directly. Therefore, they are not tested as mediators or moderators, but are used to theoretically explain differences between countries. This formulation does not imply a causal relationship. The data may show that some countries have high or low levels of both adoption and productivity, but it cannot prove that AI produced the observed differences. Eurostat indicators are official, standardized and multi-dimensional statistical data, not Big Data in the strict technical sense. They can be used for comparisons that support technology and human resource decisions.

Table 1. Summary of the theoretical framework

Domain	Main sources	Conclusion from the literature	Role in the study
Strategic HRM and data-driven decision making	(Ammirato et al., 2023; Angrave et al., 2016; Barney, 1991; Foris, 2016; Marler & Boudreau, 2017; Strohmeier, 2020; Tursunbayeva et al., 2018; Úbeda-García et al., 2025)	AI can improve information analysis and decision making, but its value depends on how it is integrated into the workforce strategy.	AI adoption is analyzed as a human resource management decision, and productivity is treated as an important outcome of the organization of personnel.
Adoption and work organization	(Davis, 1989; Jarrahi, 2018; Parker & Grote, 2022; Priyashantha, 2023; Raisch & Krakowski, 2021; Teece et al., 1997; Venkatesh et al., 2003)	The effects of AI depend on employee skills, organizational routines, work organization, and the sociotechnical context.	Differences between countries are explained by organizational mechanisms that are not directly measured in the analysis.
Algorithmic management	(Kellogg et al., 2020; Kinowska & Sienkiewicz, 2023; Köchling & Wehner, 2020; Storm et al., 2023; Tambe et al., 2019; Úbeda-García et al., 2025)	Automation can apply criteria more uniformly, but it can also introduce bias or reduce the transparency of decisions.	The interpretation of productivity is accompanied by issues of equity, system verification, and maintaining human accountability.

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AMO, autonomy and technostress	(Bakker & Demerouti, 2007; Bos-Nehles et al., 2023; Klein et al., 2024; Ryan & Deci, 2000; Tarafdar et al., 2007)	Performance depends on employee skills, motivation, and the ability to contribute, and technological stress can be reduced by the benefits of AI.	The relationship between AI and productivity may not appear in all models, which is why the results should be interpreted with caution.
Sustainable HRM	(Hronová & Špaček, 2021; Ren et al., 2023)	Increased efficiency must be balanced with employee development, equity, and the organization's ability to adapt.	The recommendations aim at the responsible integration of AI, not just achieving rapid productivity increases.
AI, complementarities and productivity	(Bresnahan et al., 2002; Brynjolfsson et al., 2018; Brynjolfsson & Hitt, 2000; Mikalef & Gupta, 2021; Noy & Zhang, 2023)	Productivity also depends on complementary investments, work reorganization, skills, and time needed for learning. Simply adopting AI does not mean that the organization already has the capacity to use it effectively.	The relationship between adoption levels and productivity is analyzed separately, along with their evolution over time. Thus, the lack of an immediate effect can be explained theoretically.

Source: own synthesis based on the analyzed literature.

Overall, the literature supports a comparative analysis of AI adoption and productivity, but does not consider technology as a sufficient factor for performance. The benefits also depend on other investments, reorganization, skills, and learning time. Therefore, the study analyzes the relationship between levels and the relationship between changes separately. The lack of an immediate dynamic association is theoretically possible.

3. RESEARCH METHODOLOGY

The research has a quantitative, comparative and exploratory design and uses secondary data from Eurostat (Eurostat, n.d.). The objective is to analyze the relationship between the adoption of artificial intelligence and apparent labor productivity in medium-sized enterprises in the European Union Member States.

The analysis has two parts. The first examines the relationship between the level of AI adoption and the level of productivity in 2023. The second examines whether the change in AI adoption is associated with the rate of productivity growth between 2021 and 2023. The research answers the following questions:

RQ1: Is there an association between AI adoption and apparent labor productivity in 2023?

RQ2: Is the increase in AI adoption associated with changes in labor productivity over the period 2021–2023?

Based on the literature on the link between technology, human capital and work organization, two hypotheses were formulated:

H1: AI adoption is positively associated with apparent labor productivity in 2023.

H2: Increased AI adoption is positively associated with the productivity growth rate over the period 2021–2023.

The hypotheses follow statistical associations and do not assume the existence of a causal effect.

The data come from two Eurostat sets: isoc_eb_ai, on the use of artificial intelligence technologies in enterprises, and sbs_sc_ovw, which includes structural business statistics by size class and economic activity. Medium-sized enterprises, defined as enterprises with 50–249 employees, were selected. The AI adoption indicator shows the percentage of enterprises using at least one of the technologies included in the Eurostat methodology.

Productivity is measured by apparent labor productivity, expressed in thousands of euros per person employed. The indicator shows, at an aggregate level, the value created in relation to the labor used.

The two Eurostat sets do not cover exactly the same sectors. The AI indicator excludes agriculture, mining and the financial sector, while the productivity indicator covers the business economy. This difference limits comparability.

Table 2. Definition of variables

Description	Definition	Unit
IA_2023	Medium-sized enterprises using at least one AI technology in 2023	%
Productivity_2023	Apparent labor productivity in 2023	thousand euros/person
ΔIA	The difference between AI adoption in 2023 and 2021	percentage points
Productivity_increase	Percentage change in productivity between 2021 and 2023	%

The change in AI adoption is calculated as a difference in percentage points, and the change in productivity as a percentage growth rate. The analysis started from the description of the data by mean, median, standard deviation and minimum and maximum values. Then, the states were compared with each other, with an emphasis on Romania's position. Continued with the relationship between AI adoption and productivity was analyzed for the year 2023 by Pearson correlation and linear regression. Separately, it was checked whether the change in the adoption of artificial intelligence during the analyzed period is associated with the rate of productivity growth. To check the stability of the results, the models were re-estimated after removing outliers. In the case of 2023 productivity, logarithmic transformation was also used to reduce the influence of very large values. Analysis was performed in Microsoft Excel at a significance threshold of 0.05. Results are presented as coefficients, p-values and R^2.

The study uses public and nationally aggregated data. For this reason, the conclusions cannot be applied directly to a company or an employee. The small sample, the short period analyzed and the lack of control variables limit the interpretation of the results. Also, the inverse relationship cannot be inferred, as more productive economies may have more resources for AI adoption. Therefore, the results indicate associations between variables, not causal effects.

4. RESULTS

The analysis begins with an overview of the data and the position of each country. It then examines the link between the use of artificial intelligence and productivity in 2023. The results are then checked through robustness tests, and finally changes over the period 2021–2023 are analyzed. The conclusions only highlight associations between variables, not cause and effect relationships.

4.1. Descriptive statistics, rankings and position of Romania

The average AI adoption increased slightly, from 12.78% in 2021 to 13.24% in 2023, by 0.46 percentage points. The median decreased from 13.07% to 11.17%. This difference shows an irregular evolution which can be understood as increases in a few countries with high values compensated for stagnation or decline in other economies. The standard deviation of AI adoption fell from 8.01 to 6.74 percentage points, showing that the countries' values have converged. The average apparent labor productivity increased from 64.07 to 66.36 thousand euros per employed person, and the median from 53.83 to 61.37 thousand euros. The standard deviation decreased from 38.27 to 31.84 thousand euros, but the distance between the minimum and maximum values remains large.

Table 3. Descriptive statistics for the sample of 25 states

Description	N	Mediate	Median	Standard deviation	Minimum	Maximal
AI 2021	25	12.78	13.07	8.01	1.90	37.25
AI 2023	25	13.24	11.17	6.74	2.38	26.40
Productivity 2021	25	64.07	53.83	38.27	20.93	175.07
Productivity 2023	25	66.36	61.37	31.84	26.65	162.11

Source: own contibution based on Eurostat data.

In 2023, the top of AI adoption were in Finland (26.40%), Belgium (22.99%), Denmark (22.56%), Malta (21.01%), and the Netherlands (19.75%). At the opposite end were Poland, Greece, Hungary, Bulgaria, and Romania. Romania ranked last in the sample, with 2.38% of medium-sized enterprises using AI.

The productivity ranking was led by Luxembourg (162.11 thousand euros per employed person), Ireland (111.28), Belgium (102.81), Sweden (98.79) and the Netherlands (95.63). Romania ranked 24th, with 31.12 thousand euros, ahead of Bulgaria.

The highest increases in AI adoption, measured in percentage points, were in Spain (+6.21 pp), Belgium (+6.10 pp), Luxembourg (+4.77 pp), Ireland (+4.60 pp) and Malta (+3.19 pp). Romania increased by 0.48 pp and was in 16th place. However, in terms of productivity growth, Romania ranked first, with +28.86%, followed by Bulgaria, Latvia, Croatia and Poland.

Romania clearly shows the difference between level and evolution. An economy can start from a low productivity and have a high growth rate without quickly reaching the level of the top economies.

Table 4. Summary of rankings for 2023 and the period 2021–2023

Description	The top five states	The last five states	Romania
AI adoption, 2023	Finland; Belgium; Denmark; Malta; Netherlands	Poland; Greece; Hungary; Bulgaria; Romania	25th place; 2.38%
Productivity, 2023	Luxembourg; Ireland; Belgium; Sweden; Netherlands	Greece; Latvia; Croatia; Romania; Bulgaria	24th place; 31.12 thousand euros
Increasing AI adoption (pp)	Spain; Belgium; Luxembourg; Ireland; Malta	Italy; France; Slovenia; Sweden; Denmark	16th place; +0.48 pp

Productivity growth (%)	Romania; Bulgaria; Latvia; Croatia; Poland	Sweden; Malta; Ireland; Finland; Netherlands	1st place; +28.86%

Source: own contibution based on Eurostat data.

4.2. The cross-sectional relationship between AI adoption and productivity in 2023

The Pearson correlation coefficient between AI adoption and apparent labor productivity in 2023 is $r = 0.652$. The positive sign indicates that countries where more medium-sized enterprises use AI tend to have higher productivity.

The relationship is statistically significant, $t(23) = 4.124$, $p = 0.000413$. Therefore, the null hypothesis of no linear correlation is rejected. The result does not show the direction of influence. High productivity can facilitate investment in AI, and both variables can be influenced by common factors, such as capital, digital skills, infrastructure and sector structure.

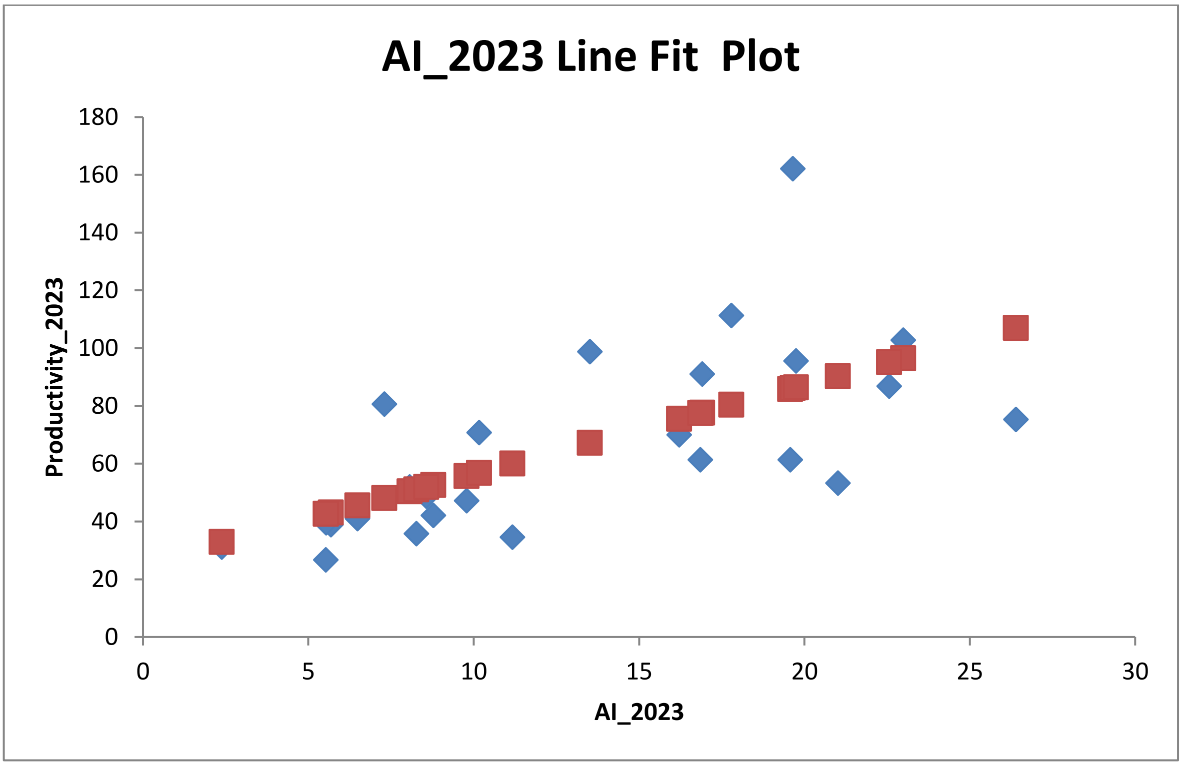

Figure 1. AI adoption and apparent labor productivity in medium-sized enterprises, 2023

Source: own contibution based on Eurostat data. Each point represents a country.

Simple linear regression analyses apparent labour productivity as a function of the level of AI adoption. The model is statistically significant, $F(1,23) = 17.007$, $p < 0.001$. The R^2 value =

0.425 shows that 42.5% of the productivity differences between the analyzed countries are linearly associated with differences in AI adoption. The result indicates a link between the two variables, without demonstrating a direct causal effect.

The coefficient of AI adoption is positive and significant B = 3.082, SE = 0.747, t = 4.124, $p < 0.001$, 95% CI [1.536; 4.629]. Across the model units, a difference of one percentage point in the share of enterprises using AI is associated with an average difference of approximately 3.08 thousand euros in apparent productivity per person employed.

The constant of 25.554 shows the estimated productivity for a hypothetical AI adoption rate of zero. It is primarily a mathematical function and should not be used as an economic forecast outside of observed values. The AI coefficient describes an association, not an "effect" of the technology, because the model analyzes a single year and does not include control variables.

Table 5. Regression of apparent labor productivity by AI adoption, 2023

Description	**B**	**ES**	**t**	**p**	**95% CI**
Constant	25,554	11,055	2,311	0.030	[2,684; 48,423]
AI adoption, 2023	3,082	0.747	4,124	<0.001	[1,536; 4,629]

Source: own contibution. N = 25; $R^2 = 0.425$; Adjusted $R^2 = 0.400$; $F(1.23) = 17.007$.

4.3. Robustness checks and dynamic analysis

The analysis of the residuals indicates that Luxembourg is an outlier in the main model. The observed productivity is 162.11 thousand euros, and the value estimated by the model is 86.12 thousand euros. The standardized residual is 3.147 and exceeds the indicative threshold |3|. The observation was retained, as there is no sign of a recording error and it may reflect real economic particularities.

After excluding Luxembourg, the coefficient of AI adoption remains positive and significant B = 2.597, SE = 0.580, t = 4.481, $p < 0.001$. The model explains 47.7% of the productivity differences ($R^2 = 0.477$), and all standardized residuals are below |2|. Therefore, the positive association is not produced by the Luxembourg case alone.

Table 6. Comparison of the main model with the model without Luxembourg

Description	N	B AI	SE	p	R^2	Adjusted R^2
Main model	25	3,082	0.747	<0.001	0.425	0.400
Without Luxembourg	24	2,597	0.580	<0.001	0.477	0.453

Source: own contibution based on Eurostat data.

To reduce the influence of very large monetary values, productivity was transformed by natural logarithm. The model is significant, $F(1,23) = 24.626$, $p < 0.001$, and has $R^2 = 0.517$. The IA coefficient is $B = 0.04898$, $SE = 0.00987$, $t = 4.962$, $p < 0.001$.

In the semi-logarithmic model, the exact calculation $100 \times [\exp(0.04898) - 1]$ shows a difference of about 5.02% in productivity associated with an additional percentage point in AI adoption. The logarithmic transformation reduces the standardized residual for Luxembourg from 3.147 to 2.137 and shows that the result does not depend on the use of a linear monetary scale.

The model for 2023 shows that levels of AI adoption and productivity are correlated. To test whether higher adoption growth was accompanied by higher productivity growth, a model of change was estimated. The predictor is the percentage point change in AI adoption, and the dependent variable is the percentage rate of productivity growth.

The model is not statistically significant $F(1,23) = 1.366$, $p = 0.255$. The ΔIA coefficient is positive but insignificant ($B = 0.853$, $SE = 0.730$, $t = 1.169$, $p = 0.255$), and the confidence interval includes zero [−0.657; 2.364]. $R^2 = 0.056$ shows that the model explains only 5.6% of the differences in productivity growth rates.

The result does not mean that AI is not relevant to productivity. It only shows that, in the sample and period analyzed, adoption increases are not consistently related to productivity increases. Two years may not be enough for effects to materialize, and the nominal indicator may be influenced by inflation, changes between sectors, and the economic recovery after the pandemic.

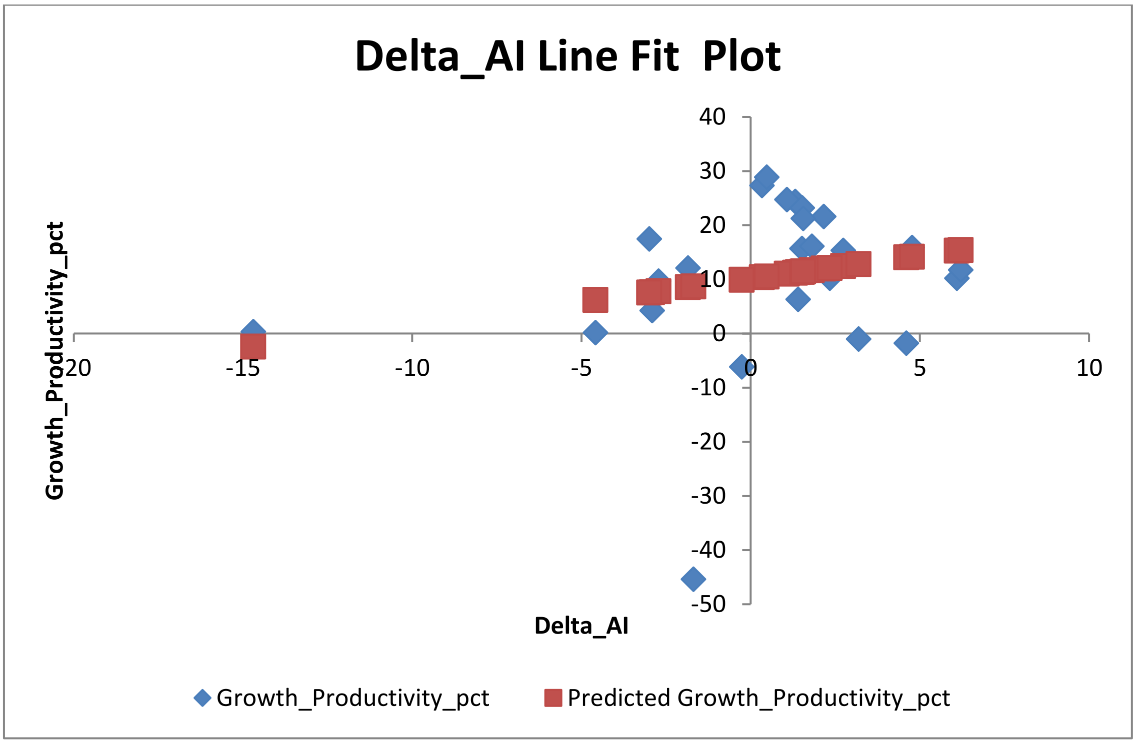

Figure 2. Change in AI adoption and apparent productivity growth, 2021–2023

Source: own contibution based on Eurostat data.

Table 7. Dynamic model of productivity growth

Description	B	SE	t	p	95% CI
Constant	10,104	3,032	3,332	0.003	[3,831; 16,377]
Changing AI adoption	0.853	0.730	1,169	0.255	[−0.657; 2.364]

Source: own contibution . N = 25; R^2 = 0.056; Adjusted R^2 = 0.015; F(1,23) = 1.366.

In the full model of change, the Netherlands has a standardized residual of −3.663. This value occurs together with a very large decrease in productivity of −45.38% and a change in AI adoption of −1.69 percentage points.

After removing this observation, the model remains insignificant, F(1,22) = 1.383, p = 0.252, R^2 = 0.059. The ΔIA coefficient decreases to B = 0.566, but the confidence interval still includes zero [−0.432; 1.565]. Therefore, the lack of a significant dynamic relationship is not explained by the case of the Netherlands alone.

Table 8. Comparison of dynamic models

Description	N	B ΔIA	SE	p	R^2	Adjusted R^2
Full sample	25	0.853	0.730	0.255	0.056	0.015
Without the Netherlands	24	0.566	0.481	0.252	0.059	0.016

4.4. Summary of results and limits of interpretation

The five models conducted to a clear, but not simple, result. In the analysis for 2023, AI adoption is positively and significantly associated with productivity. The result remains after excluding Luxembourg and after the logarithmic transformation of productivity. However, models based on changes from 2021–2023 do not find a statistically significant relationship.

Table 9. Summary of estimated models

Model	Dependent variable	predictable	B	SE	p	R^2	N
M1	Productivity 2023	AI 2023	3,082	0.747	<0.001	0.425	25
M2	Productivity 2023	AI 2023	2,597	0.580	<0.001	0.477	24
M3	ln(Productivity 2023)	AI 2023	0.04898	0.00987	<0.001	0.517	25
M4	Productivity increase	ΔIA	0.853	0.730	0.255	0.056	25
M5	Productivity increase	ΔIA	0.566	0.481	0.252	0.059	24

Source: own contibution . M2 excludes Luxembourg and M5 excludes the Netherlands.

The main result is that economies where more medium-sized enterprises use AI tend to be more productive, but increased adoption is not automatically followed by an immediate increase in productivity. The conclusion is consistent with the idea that technology, skills and work organization complement each other. Adoption may be important, but the benefits depend on training, reorganization and learning time. These mechanisms are theoretical explanations and are not directly measured by the indicators used.

Adopting AI does not guarantee employee performance and in this case organizations need to incorporate technology into work processes, develop employee skills, and clarify the autonomy and responsibility for decisions between humans and AI. This interpretation is consistent with the literature on Industry 4.0, the AMO model, and the sociomaterial integration of technology (Ammirato et al., 2023; Bos-Nehles et al., 2023; Úbeda-García et al., 2025).

The results are limited by the level of analysis and the models used. The unit of analysis is the state, not the enterprise or the employee. The sample of 25 observations does not allow for the consistent inclusion of control variables for GDP, capital, education, digital skills or sector structure. Productivity is expressed in nominal euros, not in purchasing power standards or real values, and the period 2021–2023 may include post-pandemic and inflation effects.

The comparison of data is also limited by the breaks in the series marked by Eurostat and the differences in sectoral coverage between the two indicators. In addition, the association may be explained by reverse causality or by variables that were not included. More productive economies may have more resources for investment in AI. For these reasons, the conclusions are exploratory and cannot be automatically applied to a company level.

5. CONCLUSIONS AND DISCUSSIONS

The study investigated whether the adoption of AI is associated with apparent labor productivity in medium-sized enterprises in the European Union. The analysis for 2023 provided an affirmative answer. Countries where more medium-sized enterprises used AI also tended to have higher productivity. The relationship is moderately high and statistically significant ($r = 0.652$; $R^2 = 0.425$). The result remains after excluding Luxembourg and after logarithmic transformation of productivity.

The result changes when trends are analyzed. The increase in AI adoption between 2021 and 2023 is not significantly associated with the rate of productivity growth. The conclusion remains the same after excluding the outlier observation of the Netherlands. The difference between levels and trends is the central result of the paper. It does not show that AI does not matter, but that, in the short term and at the level of countries' economies, increased adoption is not automatically followed by a measurable growth in productivity.

The human resource management interpretation emphasizes the connection between several factors. Technology, skills, and work organization perform together. The benefits of adoption depend on training, task redistribution, clarification of the relationship between algorithmic recommendations and human decision, and the time required for learning. The explanation is in line with the productivity paradox literature and the AMO model, but is not directly tested, as the Eurostat indicators do not measure job design, autonomy, or well-being.

For mid-sized companies, the bottom line is not that investment in AI should be increased. The priority for them is to integrate the technology into clear work processes, develop skills, and maintain human responsibility for decisions that affect employees. Work pressure should be tracked, evaluation should be transparent, and employees should be able to challenge decisions. A faster system is not necessarily more productive if it reduces trust, cooperation, or acceptance of criteria.

The comparative results suggest different recommendations for different situations. Economies with low adoption and productivity, including Romania, need both investment in technology and development of the capacity to use it. However, Romania also shows the difference between level and evolution. It is in last place in AI adoption and second to last in productivity in 2023, but in first place in nominal productivity growth between 2021 and 2023. The ranking position should be used to guide decisions, not as a verdict on an economy.

The study has several limitations. First, the analysis is conducted at the level of states, not enterprises or employees, so the results cannot be directly applied to a firm. Second, the sample of 25 observations is small and does not allow for the constant inclusion of control variables such as the level of economic development, investment, education, digital skills or sectoral structure. Productivity is expressed in nominal euros, which means that values can be influenced by inflation, the price level and the intensity of capital use. Also, the period 2021–2023 is short and may not capture the time required for learning, reorganization of activities and effective integration of artificial intelligence. The comparability of the data is also limited by the gaps in some Eurostat series and by the differences in sectoral coverage between the indicators. Furthermore, reverse causality cannot be carried, as more productive economies may have more resources for AI investment. For these reasons, the results should be interpreted as exploratory associations between AI adoption and productivity.

Future research could use firm-level data, longer periods and variables on capital, education, digital skills and sectoral structure. Direct measurement of professional training, work organization, autonomy, transparency and employee well-being would allow verification of the mechanisms examined in the paper and would explain more clearly the conditions under which the adoption of AI can contribute to increased productivity.

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1. Ammirato, S., Felicetti, A. M., Linzalone, R., Corvello, V., & Kumar, S. (2023). Still our most important asset: A systematic review on human resource management in the midst of the fourth industrial revolution. Journal of Innovation & Knowledge, 8(3), 100403. https://doi.org/10.1016/j.jik.2023.100403
2. Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: Why HR is set to fail the big data challenge. Human Resource Management Journal, 26(1), 1–11. https://doi.org/10.1111/1748-8583.12090

3. Bakker, A. B., & Demerouti, E. (2007). The Job Demands-Resources model: State of the art. Journal of Managerial Psychology, 22(3), 309–328. https://doi.org/10.1108/02683940710733115
4. Barney, J. (1991). Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. Https://doi.org/10.1177/014920639101700108). 17, 99–120. https://doi.org/https://doi.org/10.1177/014920639101700108
5. Bos-Nehles, A., Townsend, K., Cafferkey, K., & Trullen, J. (2023). Examining the Ability, Motivation and Opportunity (AMO) framework in HRM research: Conceptualization, measurement and interactions. International Journal of Management Reviews, 25(4), 725–739. https://doi.org/10.1111/ijmr.12332
6. Bresnahan, T., Brynjolfsson, E., & Hitt, L. (2002). Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence. The Quarterly Journal of Economics, 117, 339–376. https://doi.org/10.1162/003355302753399526
7. Brynjolfsson, E., & Hitt, L. M. (2000). Beyond Computation: Information Technology, Organizational Transformation and Business Performance. Journal of Economic Perspectives, 14(4), 23–48. https://doi.org/10.1257/jep.14.4.23
8. Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at Work. The Quarterly Journal of Economics, 140(2), 889–942. https://doi.org/10.1093/qje/qjae044
9. Brynjolfsson, E., Rock, D., & Syverson, C. (2018). Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics. In The Economics of Artificial Intelligence: An Agenda (pp. 23–57). University of Chicago Press. https://www.nber.org/books-and-chapters/economics-artificial-intelligence-agenda/artificial-intelligence-and-modern-productivity-paradox-clash-expectations-and-statistics
10. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008
11. Eurostat. (n.d.). Eurostat. Retrieved 9 July 2026, from https://ec.europa.eu/eurostat/
12. Foris, T. (2016). MANAGEMENTUL RESURSELOR UMANE.

13. Hronová, Š., & Špaček, M. (2021). Sustainable HRM Practices in Corporate Reporting. Economies, 9(2), 75. https://doi.org/10.3390/economies9020075
14. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007
15. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at Work: The New Contested Terrain of Control. Academy of Management Annals, 14(1), 366–410. https://doi.org/10.5465/annals.2018.0174
16. Kinowska, H., & Sienkiewicz, Ł. J. (2023). Influence of algorithmic management practices on workplace well-being – evidence from European organisations. Information Technology & People, 36(8), 21–42. https://doi.org/10.1108/ITP-02-2022-0079
17. Klein, S. P., Spieth, P., & Söllner, M. (2024). Employee acceptance of digital transformation strategies: A paradox perspective. Journal of Product Innovation Management, 41(5), 999–1021. https://doi.org/10.1111/jpim.12722
18. Köchling, A., & Wehner, M. C. (2020). Discriminated by an algorithm: A systematic review of discrimination and fairness by algorithmic decision-making in the context of HR recruitment and HR development. Business Research, 13(3), 795–848. https://doi.org/10.1007/s40685-020-00134-w
19. Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR Analytics. The International Journal of Human Resource Management, 28(1), 3–26. https://doi.org/10.1080/09585192.2016.1244699
20. Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. In Information and Management (Vol. 58, Issue 3). Elsevier B.V. https://doi.org/10.1016/j.im.2021.103434
21. Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. Science, 381(6654), 187–192. https://doi.org/10.1126/science.adh2586

22. Parker, S. K., & Grote, G. (2022). Automation, Algorithms, and Beyond: Why Work Design Matters More Than Ever in a Digital World. Applied Psychology, 71(4), 1171–1204. https://doi.org/10.1111/apps.12241
23. Priyashantha, K. G. (2023). Disruptive technologies for human resource management: A conceptual framework development and research agenda. Journal of Work-Applied Management, 15(1), 21–36. https://doi.org/10.1108/JWAM-10-2022-0069
24. Priyashantha, K. G., De Alwis, A. C., & Welmilla, I. (2024). Disruptive human resource management technologies: A systematic literature review. European Journal of Management and Business Economics, 33(1), 116–136. https://doi.org/10.1108/EJMBE-01-2022-0018
25. Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and Management: The Automation–Augmentation Paradox. Academy of Management Review, 46(1), 192–210. https://doi.org/10.5465/amr.2018.0072
26. Ren, S., Cooke, F. L., Stahl, G. K., Fan, D., & Timming, A. R. (2023). Advancing the sustainability agenda through strategic human resource management: Insights and suggestions for future research. Human Resource Management, 62(3), 251–265. https://doi.org/10.1002/hrm.22169
27. Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. American Psychologist, 55(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68
28. Storm, K. I. L., Reiss, L. K., Guenther, E. A., Clar-Novak, M., & Muhr, S. L. (2023). Unconscious bias in the HRM literature: Towards a critical-reflexive approach. Human Resource Management Review, 33(3), 100969. https://doi.org/10.1016/j.hrmr.2023.100969
29. Strohmeier, S. (2020). Digital human resource management: A conceptual clarification. German Journal of Human Resource Management, 34(3), 345–365. https://doi.org/10.1177/2397002220921131
30. Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. California Management Review, 61(4), 15–42. https://doi.org/10.1177/0008125619867910

31. Tarafdar, M., Pullins, E. Bolman., & Ragu-Nathan, T. S. (2015). Technostress: Negative effect on performance and possible mitigations. Information Systems Journal, 25(2), 103–132. https://doi.org/10.1111/isj.12042
32. Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., & Ragu-Nathan, T. S. (2007). The Impact of Technostress on Role Stress and Productivity. Journal of Management Information Systems, 24(1), 301–328. https://doi.org/10.2753/MIS0742-1222240109
33. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and Strategic Management.
34. Tursunbayeva, A., Di Lauro, S., & Pagliari, C. (2018). People analytics—A scoping review of conceptual boundaries and value propositions. International Journal of Information Management, 43, 224–247. https://doi.org/10.1016/j.ijinfomgt.2018.08.002
35. Úbeda-García, M., Marco-Lajara, B., Zaragoza-Sáez, P. C., & Poveda-Pareja, E. (2025). Artificial intelligence, knowledge and human resource management: A systematic literature review of theoretical tensions and strategic implications. Journal of Innovation & Knowledge, 10(6), 100809. https://doi.org/10.1016/j.jik.2025.100809
36. Venkatesh, V., Morris, M., Davis, G., & Davis, F. (2003). User Acceptance of Information Technology: Toward a Unified View. Management Information Systems Quarterly, 27(3). https://aisel.aisnet.org/misq/vol27/iss3/5