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INTELLIGENT TECHNOLOGIES IN BUSINESS: THE IMPACT OF ARTIFICIAL INTELLIGENCE ON SUSTAINABLE DEVELOPMENT

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Abstract. The *purpose* of the paper is to evaluate the impact of artificial intelligence (AI) adoption on enterprise-level sustainability in the context of digital transformation. The study aims to determine how different levels of AI implementation and business process automation influence key sustainability indicators – namely, energy efficiency, CO_2 reduction, and cost savings. *Metodology.* The research is based on a synthetic dataset generated through a simulation approach using probabilistic distributions and literature-based assumptions. The dataset includes 250 observations and four independent variables: level of AI adoption, investment in AI, automation level, and degree of policy support. The dependent variable is an integrated sustainability index composed of three sub-indicators. Regression modeling was conducted using the Random Forest algorithm to detect both linear and nonlinear relationships, identify key drivers, and ensure model robustness. Model accuracy was evaluated through R^2, RMSE, MAE, and MAPE metrics. *Results.* The model demonstrated a high level of predictive performance ($R^2 = 0.78$), confirming its validity. The most influential factors were the actual use of AI technologies and business process automation. Investment in AI without concrete implementation and state policy support had a lower impact on sustainability outcomes. The feature importance analysis confirmed that energy efficiency, cost savings, and CO_2 reduction are directly correlated with digital implementation rather than with formal spending or subsidies. *Practical implications.* The findings can support enterprise-level strategic planning by highlighting the need for actionable AI integration instead of declarative investment. For policymakers, the study indicates that future support mechanisms should focus on incentivizing outcomes rather than inputs. The proposed model may also serve as a tool for evaluating the effectiveness of national digital and environmental policies. *Value / Originality.* The study provides a novel combination of simulation-based data generation and ensemble modeling to explore the relationship between AI and sustainable development. It offers a transferable methodology for countries with limited access to real enterprise data and contributes to a deeper understanding of digital sustainability transitions in emerging economies.

Keywords: digital transformation of business, artificial intelligence, sustainable development of enterprises, circular business models, regression modeling.

JEL Classification: O33, Q01, C51, L21

1. Introduction

In the contemporary context of growth and dynamic evolution of the digital economy, artificial intelligence (AI) is assuming an increasingly pivotal role in the transformation of business processes and the development of innovative approaches to business management. The implementation of AI technologies has been demonstrated to enhance operational efficiency, optimize management decision-making processes, and facilitate sustainable economic growth (Ahmed, M. Shuaib, 2025). Of particular importance is the integration of intelligent solutions into resource management, financial forecasting, strategic planning, and marketing analytics. Specifically, the integration of AI can enhance energy efficiency, optimize logistics processes, mitigate environmental risks, and effectively manage greenhouse gas emissions. However, it is imperative to acknowledge that the digital transformation underpinned by AI technologies introduces a multitude of challenges

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(Ellen MacArthur Foundation, 2019). These challenges include the necessity of adapting business models to the dynamic shifts in the market environment, addressing cybersecurity threats, navigating regulatory barriers, and enhancing the digital competence of management personnel. Consequently, there is an imperative for a comprehensive study of the economic and environmental aspects of AI's impact on sustainable business development, including the development of models for assessing its implementation. This comprehensive approach enables the formulation of scientifically substantiated recommendations for the optimal utilization of intelligent technologies in contemporary business contexts.

The objectives and purpose of the article are delineated in two areas: first, to assess the impact of artificial intelligence on the digital transformation of business models of enterprises in the context of sustainable development; second, to provide a reasonable analysis of the economic feasibility of introducing intelligent technologies. To achieve this objective, the study employs economic and mathematical methodologies, particularly regression analysis and machine learning (Random Forest), to assess the relationship between the level of AI adoption and indicators of sustainable business development.

2. Literature Review

The role of artificial intelligence (AI) in sustainable business development is a subject of active discussion among foreign scholars. ((Madanaguli et al., 2024) emphasize that AI helps to accelerate the implementation of circular business models, and (Mikalef, Gupta, 2021) confirm that AI allows to predict energy efficiency and manage complex resource flows. Furthermore, (Holzinger and Kieseburg 2021) posit that AI enhances the management of production processes through machine learning, while (Chauhan and Parida, 2022) contend that AI contributes to the development of smart urban systems and urban solutions to reduce CO_2 emissions. In the Ukrainian scientific community, there is a growing interest in researching the implementation of artificial intelligence (AI) in business processes and sustainable development. This research is especially relevant in the context of digital transformation, Industry 4.0, and environmental modernization of the economy, (Gurochkina, 2020; Varnalii, Kulyk, at al., 2022) examines the impediments to the implementation of environmental technologies. The Ukrainian research priority is to adapt artificial intelligence in traditional sectors of the economy, while international research is more focused on innovative business models and the circular economy.

2.1 Digital Transformation and Circular Business Models

Digital transformation is an integral part of the modern business environment, based on the integration of information and communication technologies (ICT), artificial intelligence (AI), big data analytics, and business process automation. The hallmark features of this transformation encompass the evolution of business models, the enhancement of enterprise management efficiency, and the formulation of environmentally sustainable growth strategies(Holzinger, 2021). According to the World Bank, (Matoušková, 2022) the digital economy contributes to improving the living standards of the population by removing barriers to access to financial, information, and educational resources. This is particularly salient in the context of sustainable development, as digital technologies facilitate the mitigation of environmental degradation by optimizing production processes, reducing emissions, and enhancing energy efficiency.

In the context of limited natural resources, the linear economic model, predicated on extraction, consumption, and disposal, is becoming increasingly untenable. Despite the significant potential of the circular economy, its full implementation is hampered by a number of barriers, including the low residual value of waste products, the high costs of their processing, and the lack of effective infrastructure for collecting and sorting materials. The inadequate digitalization of material flows represents a substantial impediment, impeding the capacity to transparently track resources within supply chains (Lu, Serafeim, 2023).

As indicated in the aforementioned studies (Mboli et al., 2020; Garcia-Muiña et al., 2018), the implementation of the Internet of Things (IoT) has been demonstrated to facilitate the creation of durable products, enhance business sustainability, and minimize operating costs through the integration of monitoring and tracking mechanisms. This is a pivotal factor in achieving economic and environmental efficiency.

In the global business landscape, digital technologies are being integrated into circular business models, acting as a catalyst for transformational processes towards sustainable development. The VSM model of digital transformation of the circular economy, proposed by Chauhan et al. (2022), posits that these technologies can provide a sustainable link between business model innovation, digital tools, and the achievement of social, economic, and environmental benefits. In the context of this approach, it is imperative to assess the preconditions, opportunities, and constraints of digital transformation of CE in the national context. Utilizing this model facilitates the identification of pivotal aspects for adapting this concept to the Ukrainian context.

Ukraine possesses the potential for digital transformation; however, the realization of such transformation in a circular economy is constrained by a paucity of digital maturity in numerous sectors. The VSM digital transformation model underscores the pivotal role of technologies such as the Internet of Things, big data, blockchain, and artificial intelligence in facilitating the transition to circular business models (Ahmed, M. Shuaib at al., 2025). The integration of these technologies holds the potential to enhance resource utilization within industrial and agricultural sectors, ensure supply chain transparency, automate material sorting and recycling processes, and facilitate effective emissions and environmental impact monitoring. In the context of Ukraine, the implementation of these solutions holds potential to curtail expenditures related to waste processing, enhance the efficacy of recycling, and establish the foundations for the establishment of closed production and consumption cycles. In conclusion, the implementation of digital transformation holds great potential for Ukraine to advance its circular economy efforts.

Concurrently, the digital transformation of the circular economy in Ukraine is confronted with numerous challenges, including the limited digital integration of enterprises, which predominantly operate on the basis of antiquated production processes; the absence of an incentive regulatory policy, including tax benefits or grant support mechanisms; and constrained investment resources, particularly within the SME sector. The inadequate infrastructure for waste recycling persists as a substantial impediment, with the extant recycling capacity being utilized by less than 10% due to the deficient level of preliminary collection and sorting. Addressing these challenges necessitates the implementation of a targeted government policy that fosters digital innovations, fosters the development of public-private partnerships, and attracts international technical assistance.

In the context of analyzing the role of artificial intelligence (AI) in the emerging field of circular

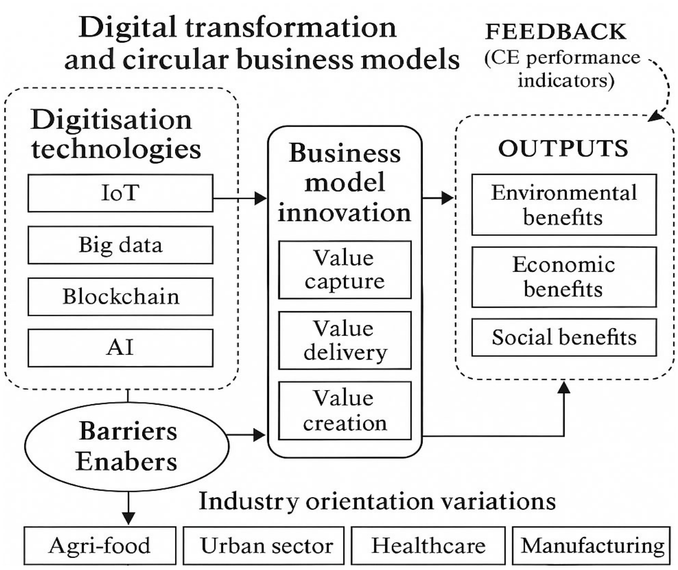

Figure 1. Scheme of digital transformation for the circular economy

Source: (Chauhan et al., 2022)

business models (CBM), it is imperative to recognize that AI endows businesses with a suite of capabilities that extend beyond automation. In contrast to conventional IT capabilities, AI encompasses big data analytics, process optimization, and deep learning, which are pivotal to sustainable development (Mikalef & Gupta, 2021). Consequently, AI is increasingly regarded as a distinct category of digital capabilities, distinguished from traditional IT solutions by its flexibility, learning capabilities, and integration with other technologies (Parida et al., 2019). These capabilities not only complement existing digital tools in enterprises but also significantly transform the logic of value creation and capture within circular strategies. In this regard, digital transformation through the Internet of Things (IoT), big data analytics, and blockchain can be regarded as a foundational stage of development, enabling companies to progressively enhance their capabilities. Conversely, AI represents a more advanced stage of digitalization, characterized by its capacity to deliver profound analytical insights and advanced adaptive resource management systems. Consequently, "while digitalization enables a company to "stand," "walk," and "run," artificial intelligence (AI) allows it to perform a complex "dance" of optimization and innovation, a feat impossible without first mastering fundamental digital skills" (Chauhan, Parida, Dhir, 2022).

2.2 Digital Circular Business Models: Opportunities for Ukraine

According to (Madanaguli, 2023), there are three approaches to the formation of AI-enabled circular business models (AI-enabled CBM): narrowing, slowing down, and closing.

1. AI-enabled narrowing CBM focuses on identifying and eliminating inefficiencies in business processes using artificial intelligence. This enhances resource utilization, improves system efficiency, reduces costs, and strengthens analytical support for managerial decisions.

2. AI-enabled slowing CBM aims to extend system lifespan by predicting component wear and tear through AI-based analytics. Technologies such as digital twins and predictive maintenance support proactive resource management and operational efficiency.

3. AI-enabled closing CBM facilitates resource reuse by simplifying disassembly and recovery processes. AI helps identify reusable components, minimizing reliance on primary materials and supporting circular business practices.

Despite their strong potential to enhance resource efficiency and promote sustainability, AI-oriented circular business models remain of limited applicability in Ukraine due to objective national constraints. Each of the three approaches – narrowing, slowing, and closing resource flows – faces implementation barriers related to technological capacity, infrastructure, human capital, and institutional readiness. For instance, limited digital maturity, poor data quality, lack of integrated IT systems, and managerial resistance to automation hinder the adoption of AI-enabled narrowing CBM. High implementation costs in wartime and post-war conditions further exacerbate these challenges.

The slowing approach, based on predictive maintenance and digital twins, is constrained by the complexity and cost of these technologies, as well as the lack of skilled professionals in Ukraine. The reactive maintenance culture also limits preventive measures. Finally, the closing approach is hampered by the absence of recycling infrastructure, a weak secondary materials market, low automation in sorting and dismantling, and a lack of coordination between producers and recyclers (OECD, 2024). However, despite the existing barriers, the introduction of AI-oriented business models in the context of the circular economy in Ukraine has the potential to yield several advantages, thereby establishing the basis for a technological breakthrough and sustainable economic growth in the post-war recovery period.

Firstly, the flexibility and adaptability of Ukrainian businesses engender an environment conducive to the experimental implementation of innovative models. In particular, small and medium-sized enterprises in Ukraine frequently exhibit high dynamism and a readiness to adopt new solutions in response to the challenges posed by an unstable environment. This dynamic environment fosters opportunities for experimentation through pilot projects in various sectors, including light industry, information technology (IT), logistics, and agriculture. Secondly, the active development of digital infrastructure, particularly through government initiatives such as Diia and Diia.Business, fosters the introduction of AI technologies (OECD, 2024). Thirdly, the possession of a substantial human capital endowment in the domains of information technology and data analytics constitutes a pivotal competitive asset for Ukraine. The presence of skilled IT specialists, analysts, and developers of generative AI facilitates the creation of customized digital solutions that support these models. This, in turn, paves the way for the development of export-oriented products within the green digital economy. Moreover, the imperative to revitalize the economy in the post-war era is prompting a reevaluation of conventional methodologies concerning production, consumption, and resource management.

3. Methodology

In light of the potential benefits and barriers to the implementation of AI-enabled business models of the circular economy in Ukraine, there is a need for a scientifically based assessment of their impact on key parameters of sustainable development. The intricate and multifaceted relationship between the utilization of artificial intelligence and key performance indicators (KPIs) of environmental and economic efficiency necessitates the application of contemporary quantitative analytical methodologies. In this context, we contend that regression modeling of the relationship between AI and sustainable development is a pivotal instrument that will facilitate an objective assessment of the effectiveness of digital technologies in areas such as emissions reduction, energy efficiency, and cost optimization.

In order to ascertain the most suitable model for predicting the impact of artificial intelligence on sustainable business development, it is recommended to employ a model based on decision trees and ensemble methods, such as Random Forest. This approach has been demonstrated to be particularly effective in identifying non-linear dependencies and complex relationships between the implementation of AI technologies and relevant sustainability indicators. The Random Forest model is predicated on the development of an ensemble of decision trees, thereby facilitating enhanced modeling accuracy by diminishing variations. The model's functionality includes the automatic selection of the most informative variables, thereby facilitating a more profound comprehension of the influencing factors (Schott, 2019).

To model the relationship between the level of artificial intelligence adoption and sustainability indicators, we employed the Random Forest algorithm. This algorithm combines ease of implementation with high forecasting accuracy. The fundamental premise of this methodology entails the construction of a set of decision trees, with each tree formulating an independent assumption regarding the value of the target variable. The model's final forecast is defined as the average value of the initial forecasts of all trees. The mathematical description of this process is given by the following formula:

$$a(x) = \frac{1}{N}\sum_{i=1}^{N} b_i(x)$$

$a(x)$ – is the final prediction of the Random Forest model for observation x;

N – is the number of trees in the "forest";

$bi(x)$ is the prediction made by the i-th tree of the model for observation x.

In situations where there is restricted access to pertinent statistical data, particularly when appraising the repercussions that innovative digital technologies-artificial intelligence included-exert on the metrics of sustainable development of enterprises, it is considered beneficial to employ the method of generating synthetic data, also termed the Simulation Approach. This approach involves the utilization of statistical modeling or stochastic simulation methods to generate an artificial yet realistic data set that emulates potential relationships between key variables (Zomchak, 2023).

The methodology for generating synthetic data entails the creation of a hypothetical set of observations (250 observations)[1] [2] based on realistic ranges of variable values as determined by the results of the literature review. For instance, an increase in energy efficiency of businesses following the introduction of AI by 5 to 20 percent has been documented in relevant research. For each indicator, a corresponding

[1] The data used to train the model was first gathered using a generative AI model based on probability distributions and theoretical assumptions.

[2] Source data is available at the link: https://docs.google.com/spreadsheets/d/13F5-s1Q5a4lMMKIoUSIf1Rh18jXZYijD/edit?usp=sharing&ouid=111200014823689941375&rtpof=true&sd=true

statistical distribution is established (normal, uniform, etc.), which reflects the likely behavior of the variable. Furthermore, stochastic relationships between variables are incorporated, modeled on the basis of theoretical assumptions concerning the existence of cause-and-effect relationships. This ensures the internal logic and practical applicability of synthetic data for subsequent analysis. Notably, the primary limitation of this approach stems from the hypothetical nature of the outcomes, which underscores the need for rigorous validation and interpretation of the results to ensure their relevance and reliability in practical applications.

Therefore, the model encompasses four independent variables that embody the primary facets of the digital transformation of enterprises: the extent of AI implementation, process automation, investment potential, and the availability of government support. This methodological approach enables a comprehensive evaluation of the impact of digital technologies on sustainable development indicators (see Table 1).

The model was trained by randomly dividing the synthetic data into two samples: a training sample (80% of observations) used to build decision trees and a test sample (20% of observations) used to evaluate the model's accuracy on new, "unknown" data. The quality of the model was assessed using three standard metrics of regression forecasting quality (see Table 2).

4. Results

The value of the coefficient of determination, R^2, is close to 0.71. This means that the model explains 71% of the variability in the sustainability indicator. This is a high result for data that was simulated. The low MAE value also confirms that the average forecast error is not significant. This makes the model potentially suitable for practical application in conditions of limited information. We also calculated the root mean square error (RMSE) and the mean absolute percentage error (MAPE) to confirm that the model was adequate. The root mean square error (RMSE) is 0.468, which indicates a slight average deviation from the actual values. The MAPE did not exceed 2.83%, which is an acceptable level of accuracy for this type of task. The adjusted R^2 was 0.78, which indicates that the model can explain a lot, even considering the number of variables. Here are the VIF coefficients for the independent variables in the model: Automation_Level: 6.57; AI_Adoption: 6.02; Investment_in_AI: 4.82; Policy_Support: 2.33.

Table 1
Structural and Charakteristical Aspects of Model Variables

Variable type	Variable name	Description
Dependent variable	*Sustainable Impact, Y*	Integral indicator of sustainable development (composite index)
Components of the target integral indicator[3]	*Energy Efficiency*	Increase in energy efficiency of the enterprise (%)
	CO2 Reduction	CO_2 emissions reduction (%)
	Cost Savings	Savings in production and logistics costs (%)
Independent variables	*AI Adoption, X1*	Share of enterprises using AI (%)
	Investment in AI, X2	Share of AI expenses in the total enterprise budget (%)
	Automation Level, X3	Level of business process automation (%)
	Policy Support, X4	Level of state support for digital transformation (0 – none, 1 – partial, 2 – active)

Table 2
Metrics for model quality assessment

Metrics	Characteristics	Resulting value
MAE (Mean Absolute Error)	shows the average absolute difference between the forecasted and actual values. The smaller the value, the higher the accuracy of the forecast.	~ 0.89
MSE (Mean Squared Error)	takes into account error squares, which makes the metric sensitive to large deviations. It is used to identify significant deviations in forecasts.	~ 1,22
R^2	indicates how much of the variance in the target variable is explained by the model. A value close to 1 indicates a high quality model.	~ 0,71

[3] The components of the Sustainable_Impact target index are three sub-indicators: Energy_Efficiency, CO_2_Reduction and Cost_Savings.

This means that the model does not have too many multicollinearity issues, and the predictors do not repeat each other's information.

Figure 2 shows that one of the best ways to see how good a regression model is is to look at a graph. This graph is the ratio of the actual values and the predicted values (y - ŷ).

The model is good because there is a lot of data along the line of correspondence. This data shows that the model can approximate the real values of the target variable in the conditions of simulated data. This means that the model is accurate and consistent, as shown by the lack of systematic shifts and small errors in most observations. The Random Forest Regressor model can predict how well businesses are doing in terms of sustainability and also figure out how important each factor is in achieving that result (see Table 3). This approach helps us identify which factors have the most significant impact on the Sustainable_Impact index.

Table 3
Importance of variables in the Random Forest model

Variable	Importance
AI Adoption, X1	0.564
Investment in AI, X2	0.356
Automation Level, X3	0.061
Policy Support, X4	0.019

We can understand this result in a few different ways.

1) The analysis of the importance of predictors in the Random Forest model demonstrated that the level of artificial intelligence adoption (AI Adoption) exerts the greatest influence on the sustainability indicator. The variable's importance, as determined by the analysis, is 0.557, thereby substantiating the assertion that the pervasive and methodical implementation of AI within the operations of enterprises constitutes a pivotal element in enhancing energy efficiency, curtailing expenditures, and attaining environmental sustainability. This finding is particularly salient in the context of Ukraine, where the demand for technologies that conserve resources and facilitate adaptation to change is on the rise. These technologies have the potential to facilitate Ukraine's economic recovery during a period of transformation, as illustrated in Figure 3.

2) The variable of Automation_Level (importance = 0.365) is the second most important variable, and it reflects the degree of digital automation of business processes. Its role in ensuring sustainable development is also significant, as automation allows for the reduction of dependence on human resources, the optimization of operations, and the reduction of energy losses. For Ukrainian enterprises, particularly in the industry, the introduction of digital platforms and smart solutions is one of the most promising ways to increase competitiveness in the European market.

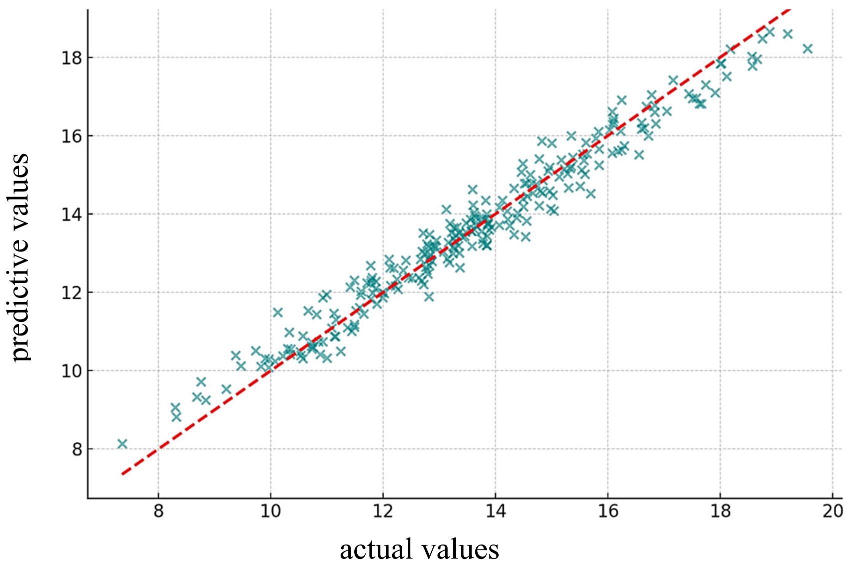

Figure 2. Graph of the correlation between actual and forecasted values

3) Conversely, the Investment in AI variable exhibited a comparatively modest level of influence (0.058), suggesting that the magnitude of investment in AI alone is not necessarily indicative of achieving a sustainable effect, particularly in instances where such investments are not accompanied by the practical implementation and integration of technologies into business processes. For Ukraine, this suggests a transition from mere expenditure on digital transformation to the strategic and effective implementation of innovative solutions.

4) The least significant variable was Policy Support (0.019), which reflects the availability of government support for digitalization. This outcome may signify the inefficacy or fragmentation of government incentives, as well as the absence of coherence between sustainable development policy and digital transformation practices. In the context of Ukraine, this underscores the importance of formulating a systemic state policy that would not only stimulate the use of AI but also create conditions for its large-scale spread among small and medium-sized businesses.

The Random Forest model is a non-linear ensemble machine learning technique based on the collective decision-making of a large number of decision trees. Each tree in the model generates its own prediction based on the conditional branching of variables, and then the model aggregates these values, usually by averaging the predictions of all trees (Figure 4). In contrast to classical linear models, such as linear regression, Ridge, or Lasso, the Random Forest model does not have an analytically expressed formula in the form of a single equation. The ensuing discussion will focus on a specific tree within the ensemble Random Forest model, which was developed using synthetic data concerning the adoption of artificial intelligence (AI) in business enterprises. The accompanying visual depiction elucidates the model's decision-making rationale, predicated on pivotal predictors such as AI_Adoption, Automation_Level, Investment_in_AI, and Policy_Support. Each internal node contains a separation condition, and the end nodes (leaves) contain the predicted value of the target variable Sustainable_Impact. The depth of the tree is limited to three levels to enhance interpretability.

The modeling was conducted on the basis of synthetic data generated under stochastic assumptions, as verified by the extant literature. The obtained results demonstrate the potential of using AI in achieving sustainable development goals; however, further empirical verification on real samples is required.

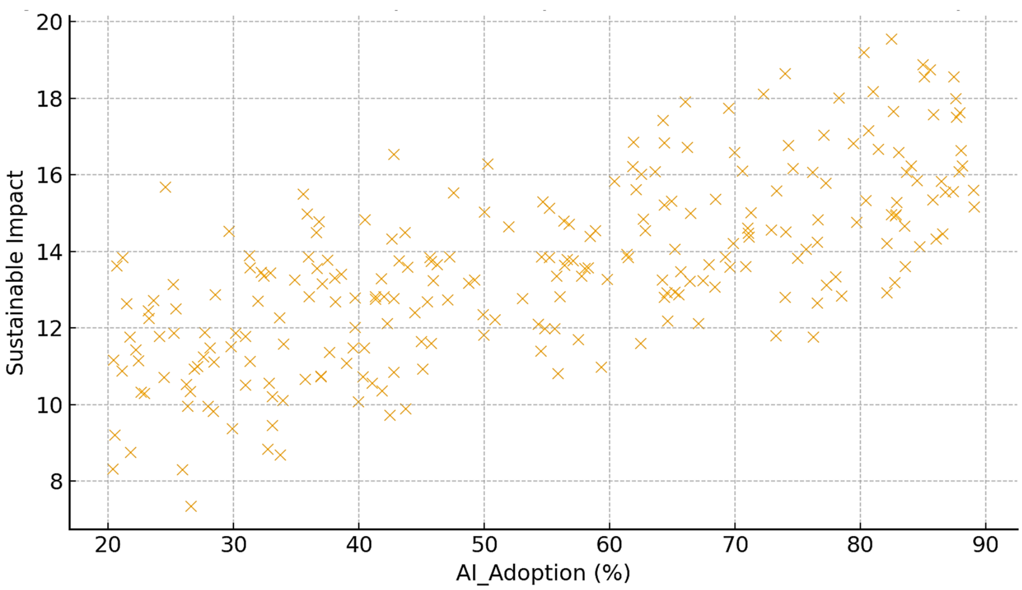

Figure 3. The dependence between the level of AI adoption and sustainable development[4]

[4] When businesses adopt AI more, they're more likely to reduce costs, save energy, and be more environmentally friendly.

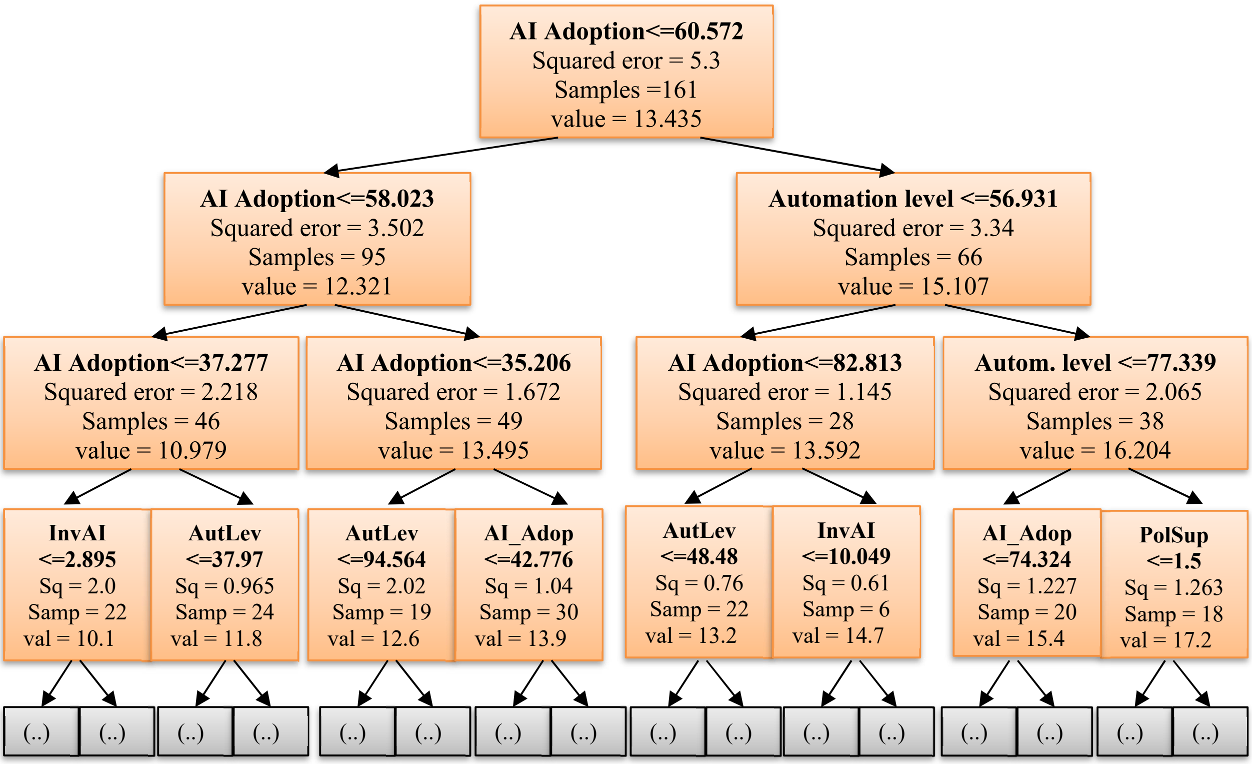

Figure 4. An example of a decision tree that is part of the Random Forest model[5]

5. Conclusions

The aforementioned results demonstrate, albeit in a hypothetical sense, that artificial intelligence is not an end in itself, but rather a functional tool that facilitates energy efficiency, automation of operational processes, and reduction of CO_2 emissions. The findings indicate that the practical implementation of AI technologies, rather than mere investment in these technologies, is the pivotal factor in the positive impact on sustainable development indicators. Digitalization should be integrated into sustainable management strategies, rather than regarded as a discrete technical undertaking. Public policy and institutional support can play an indirect yet strategically significant role in shaping the conditions for sustainable business development. While the Policy_Support variable demonstrated the lowest impact in the model, its significance may become apparent over time, particularly in the context of promoting innovative technologies in the domains of green energy, resource efficiency, and digital ecosystems.

Future research must focus on validating the results with real data from Ukrainian companies, taking into account industry and regional specifics. Additionally, the expansion of the sustainable development model to encompass social indicators such as employment, gender equality, and inclusion holds considerable promise. A rigorous comparison of the effectiveness of various digital technologies (e.g., AI, IoT, blockchain, digital platforms) in the context of sustainability is also recommended. A particular focus should be placed on the assessment of the impact of public policy over time, drawing upon panel data concerning the implementation of digitalization programs across multiple years.

[5] Each node is a test condition (for example, AI_Adoption ≤ 60.57). The left path corresponds to "yes", the right path to "no". In the lower nodes: value is the model's prediction for the corresponding branch.

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