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Awareness of the Impact of IT/AI on Energy Consumption in Enterprises: A Machine Learning-Based Modelling Towards a Sustainable Digital Transformation

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Abstract

The integration of artificial intelligence (AI) and information technology (IT) is transforming business operations while increasing energy demand. A scalable and nonintrusive method for assessing the adoption of energy-conscious IT governance without direct measurements of energy use is lacking. To address this gap, a machine learning framework is developed and validated that infers the presence of energy-conscious IT governance from five indicators of digital maturity and AI adoption. Enterprise survey data were used to train five classification algorithms—support vector machine, logistic regression, decision tree, neural network, and k-nearest neighbors—to identify organizations implementing energy-efficient IT/AI management. All models achieved strong predictive performance, with SVM achieving 90% test accuracy and an F1 score of 89.8%. The findings demonstrate that an enterprise's technological profile can serve as a reliable proxy for assessing sustainable IT/AI practices, enabling rapid assessment, benchmarking, and targeted support for green digital transformation. This approach offers significant implications for policy design, ESG reporting, and managerial decision-making in energy-conscious governance, supporting the alignment of digital innovation with environmental objectives.

Keywords: AI technologies; energy consumption; machine learning; digital transformation; enterprises; sustainability

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1. Introduction

In recent years, the widespread implementation of IT/AI technologies, including machine learning, big data, and cloud and fog computing, has transformed the way modern industries and small and medium-sized enterprises (SMEs) operate. Available solutions offer on-demand access to computing resources and data services, enabling SMEs to use advanced artificial intelligence (AI) models and big data (BD) analytics frameworks. However, this technological shift comes with growing environmental costs associated with sustainable energy consumption management, both in the deployment and development of AI-driven technologies. The rapid growth of IT/AI systems, combined with the increasing complexity and number of data processing tasks in enterprises, has driven to a significant

increase in energy demand. Operations such as training advanced machine learning architectures, particularly deep learning systems, involve substantial computational loads that place considerable pressure on energy infrastructure. The resource intensity of these processes, from data center operations to high-performance computing, highlights the environmental trade-offs associated with the large-scale development of artificial intelligence [1]. It is predicted that global energy demand related to artificial intelligence will grow rapidly—potentially doubling by 2026 and tripling by 2030—eventually reaching around 1.3% of total global electricity consumption [2]. Complementary to a growing body of research, a significant acceleration of clean energy technology development in Europe could be achieved through the implementation of artificial intelligence [3]. However, the dominant discourse in the field of information technology (IT) and artificial intelligence focuses mainly on sustainable energy and IT/AI-based solutions, with relatively less attention paid to corporate awareness of the impact of IT/AI energy consumption and the potential environmental effects of their use by businesses in the context of the ongoing digital transformation.

Artificial intelligence is being implemented in many organizations simultaneously as interest in promoting sustainable development grows. The United Nations Sustainable Development Goals (SDGs) and new European Union regulations concerning Environmental, Social, and Governance (ESG) reporting are entering a phase of dynamic growth [4]. Across industries, AI technologies: automation, machine learning, and real-time analytics are used to improve ESG performance, particularly energy efficiency and emissions reduction within digital transformation [5]. This policy context centers managerial decisions on whether appropriate governance controls are in place, which motivates our focus on energy-conscious IT/AI governance developed in the remainder of the paper.

As computing infrastructure and digital operations continue to expand, enterprises are under increasing pressure to adopt energy-conscious IT/AI governance to curb the carbon footprint of their activities. Enterprise data centers, networks, and devices already account for an estimated 2% of global CO_2 emissions, underscoring the significance of "energy-conscious" IT governance as a component of corporate sustainability [6]. Despite growing recognition of the need for sustainable IT management, systematically measuring the uptake of energy-conscious governance across organizations remains challenging.

A significant obstacle is the assessment gap: traditional methods for evaluating the adoption of energy governance practices in IT/AI—such as surveys, interviews, or dedicated readiness audits—are labor-intensive and not easily scalable across large samples of firms. For example, Molla et al. developed a detailed "Green IT Readiness" instrument to gauge an organization's capacity for ecological IT initiatives [6], but deploying such direct assessments broadly requires extensive data collection and active organizational participation. Many companies are reluctant or unable to divulge detailed sustainability practices, and self-reported data can be inconsistent or biased. Consequently, there is a need for non-intrusive, scalable approaches to infer whether enterprises have embraced energy-efficient IT/AI governance without directly surveying each organization about its sustainability initiatives.

Emerging research in information systems suggests that an organization's digital innovation profile can provide latent clues about its environmental IT posture. In this study, an indirect inference approach is adopted for assessing "green"/eco-friendly IT/AI, in particular energy-conscious governance. Instead of directly collecting information about sustainability policies, key indicators of enterprise digital maturity and IT/AI adoption are examined as proxy predictors of these policies. The literature consistently highlights that gathering information about digital maturity indicators is generally more informative and methodologically robust than conducting direct surveys among companies [7–9]. This

approach enables the use of both objective, quantitative metrics and qualitative assessments, which together provide a multidimensional view of an organization's digital capabilities and readiness for transformation. Specifically, five organizational indicators of digital maturity and intelligent technology integration are leveraged:

- Level of embedded AI in smart systems—the extent to which AI capabilities are built into core products and processes [10–12].
- Operationalization of AI-based automation—a score reflecting the extent to which AI-driven automation is implemented in operations [13].
- Depth of analytics integration (ML methods)—the sophistication and breadth of machine learning and data analytics employed in decision-making [14,15].
- Digital intelligence intensity in operations—the degree to which digital intelligence (algorithms, data-driven insights) permeates routine business workflows [15].
- Coverage of intelligent interface applications—the range of user-facing applications or services enhanced by AI (such as smart chatbots and adaptive interfaces) [12,16].

By analyzing these five dimensions of enterprise technology usage, the likelihood of energy-conscious IT/AI governance adoption is modeled as a binary outcome (adopted vs. not adopted). This approach enables an organization's green IT/AI, energy-conscious governance stance to be inferred indirectly from its digital transformation footprint, eliminating the need for direct inquiries about sustainability practices.

There is currently no scalable and non-intrusive way to infer whether enterprises have adopted energy-conscious IT/AI governance from readily available digital-maturity indicators, existing assessments rely on labor-intensive surveys or audits. To address this gap, the objective is to develop and validate a machine-learning framework that predicts the presence of energy-conscious IT/AI governance using five indicators of digital maturity and AI adoption—without any direct energy-consumption data. Five different supervised machine learning classifiers -support vector machines (SVM), logistic regression (LR), decision trees (DT), neural networks (NN), and k-nearest neighbors (KNN)—were trained and evaluated to predict the binary dependent variable (presence or absence of energy-conscious IT/AI governance) based on five input indicators.

The paper is organized as follows. Section 2 reviews the relevant literature and provides the background information. Section 3 details the research design and methodology, describing the data sources for the digital maturity indicators, the operationalization of the energy-conscious IT/AI governance variable, and the machine learning modeling procedure (with classifier configurations and cross-validation setup). Section 4 presents the results of the conducted analysis, comparing the performance of the five classifiers and examining the importance of each indicator in predicting the adoption of green/eco-friendly IT/AI governance in energy-conscious manner. Section 5 provides a discussion of the findings and their implications for both practice and theory (bridging digital transformation and sustainability initiatives), and addresses the limitations of the study.

2. Literature Review

Theoretically, incorporating IT/AI technologies aligns with principles of sustainable energy use and contributes to the development of a resilient, low-carbon economy. However, the importance of AI applications is relatively rarely sustained with energy-aware consumption. Some attention has been given to carbon emissions and the energy requirements of AI, bringing the concept of "green AI" [17]. As posited by [18], not all AI analytical solutions based on large models remain "green" in themselves, and businesses tend to be unaware of the environmental implications of AI during its development and deployment phases. That is why a growing body of literature exists on "green AI" and "red AI" appliances [19–21]. The concept of green artificial intelligence, as understood from the vantage

point of technology developers and the environments in which they operate, encompasses the design of algorithms that exhibit reduced energy requirements [18]. Moreover, these algorithms are developed with the explicit consideration of the carbon footprint associated with their operation, a critical element in the broader context of environmental impact.

The majority of extant studies on the application of artificial intelligence in sustainability focus on specific sectors and technological use cases. For instance, research by [22–24] demonstrate that the implementation of AI systems in the energy and construction sector can significantly contribute to more sustainable energy consumption and innovative applications of technology. In a similar vein, refs. [25,26] investigate the impact of AI on other natural resources, including water, emphasizing the growing relevance of AI applications in the context of resource scarcity [27], when [28] additionally focuses on reviewing the application of AI in agriculture and climate protection. The discussion on the environmental cost of deploying AI models like ChatGPT cannot be overlooked. More often than analyses of the industry or particular SMEs, they focus on sustainable urban development and AI in smart city development [24], particularly on bolstering energy sectors and mitigating climate change [29]. Many authors highlight the high interest in research on resource demand (such as water) involved in training and operating large language models [26], with postulates from [30] on greater transparency and data to guide policymaking, and encourage harnessing AI as a tool for sustainability. In this way, digital technologies are helping industries and specific sectors of the economy become smarter and more eco-friendly by improving resource utilization and reducing environmental impact [31].

However, there are still significant challenges to be addressed, including the high initial costs of AI deployment and limited ecological awareness of resource management, particularly in energy management, among enterprises. For enterprises' AI sustainable energy management, in particular the concept of "green AI sensing", proposed by [32] might be "a call" for the inclusion of efficient, sustainable, and equitable technology, simultaneously highlighting gaps in the literature on practices related to an ecologically conscious approach to AI deployments. As [33] notes, manufacturing SMEs harm the environment in various ways, including excessive resource use, significant energy consumption, and a lack of awareness of environmental greening. From the perspective of enterprises and industry professionals, there is increased interest in big data analytics and artificial intelligence in specific contexts, such as integrating green supply chain processes [34] or implementing general sustainable digital transformation within an AI-driven circular economy and environmental sustainability framework [35]. Supportive regulations and well-crafted policies play a crucial role in creating an optimal environment that fosters the successful integration and adoption of digital technologies. IT/AI applications used by enterprises require substantial computational resources and significant energy and power consumption [36,37]. However, there remains a lack of research examining how these technologies enhance enterprises' the environmental performance from the perspective of energy awareness or sustainable energy consumption strategies.

A significant component of energy awareness and management in the context of AI, as emphasized by [23] pertains to challenges associated with end-user behavior and awareness of environmental, in particular, the knowledge on energy consumption in particular of AI technologies. Additionally, according to [38], the extent of public acceptance is pivotal element in ensuring the effective integration of technology in general. Given that the successful use of technology is contingent not only on its developers but also on the stakeholders who are interested in its outcomes. Conversely, the conscious management of energy resources at the user level (enterprise), as opposed to the technology developer level, necessitates, above all, research into the correlation between the resource intensity

of the technologies employed, including IT/AI, in everyday decisions, as well as the continuous dissemination of information among employees and organizations regarding the sustainable utilization of these resources. This process appears to be both challenging and time-consuming. Furthermore, the monitoring of conscious energy management in decisions made using modern IT/AI applications is subject to inaccuracy, privacy issues, and errors resulting from the measurements taken. An additional limitation, as noticed by [39], indicates psychological explanations behind AI's unrecognized environmental impact—like lack of information, behavioral constraints, and present bias and sentiment, referring to the pessimistic approach that no matter how one acts, environmental degradation will occur, since others do not act in line with the environmental awareness and responsibility for future generations.

The majority of contemporary approaches concentrate on individual behavior, as evidenced by [40] the preponderance of models such as the Technology Acceptance Model, the Theory of Planned Behavior, and the Unified Theory of Acceptance and Use of Technology. These are complemented by the Hybrid Model of Energy Policy Adoption, which adds a broader, macro-level view by combining economic and political factors with behavioral theories to facilitate a more comprehensive understanding of the acceptance of energy policies. However, this also reveals a gap in the literature: there is very little analysis at the organizational level—especially when it comes to how AI might affect management behaviors related to sustainable energy use within organizations. The study by [41] examines how AI technologies and AI-driven solutions can shape sustainable workplace behaviors. It focuses on promoting general pro-environmental behavior and green behavior within the context of artificial intelligence—by bringing valuable insights integrating AI technologies with behavioral theories, organizations can better understand how AI interventions influence employee engagement in environmental sustainability initiatives, and how individuals assess threats and coping mechanisms in response to sustainable energy management challenges. In the context of AI, ref. [41] shows how AI tools facilitate decision-making regarding pro-environmental and energy-saving behaviors. Additionally, the use of AI-based apps for real-time carbon footprint tracking is highlighted, providing employees with a means to reduce resource consumption without disrupting daily operations.

The context for energy awareness should consider "green AI" practices for assessing and optimizing the carbon footprint of these systems. AI energy efficiency work, which considers performance and cost when allocating deep learning training and inference jobs given dynamic electricity prices, was conducted by [42] based on statistical modeling—But it is essential to note the challenge of accurately measuring AI electricity consumption, given the lack of prioritization and its absence as a key selling point, even for companies specializing in AI models [17]. Even AI and cloud-fog-based industries, such as IT itself, examined by [37], note that it is crucial to assess the IT community's knowledge of efficient AI deployments. However, only 10% of respondents reported using energy metrics, and most were unfamiliar with multi-level energy consumption measurement techniques. Similarly, ref. [43] assumed that organizations are in the early stages of reducing AI's environmental impact, focusing on monitoring, mitigation, and challenges. Notably, only one participant in their study reported monitoring AI's environmental impact using the CloudCarbon tool [44] to track carbon footprint. Most companies lacked any monitoring practices, often without clear justifications. The demand for transparent reporting from AI developers and data center operators would enable users to make more informed and environmentally conscious decisions [26]. The model efficiency "green AI" tools review [17] highlights the trade-offs between accuracy and efficiency, citing the example of the NVIDIA Deep Stream SDK as a "green AI" tool developed with a specific focus on achieving 30% energy savings.

The integration of information technology and artificial intelligence into business processes and decision-making presents several challenges. As outlined in existing literature, IT/AI tools have the potential to transform resource management, particularly in addressing energy shortages. This is due to their capacity to enhance efficiency, optimize consumption, and improve decision-making across a range of sectors and industries. However, concerns are mounting regarding the substantial energy inputs required to train and operate such large models, thereby raising questions about their environmental impact, particularly in terms of energy consumption and associated emissions.

The above-mentioned findings highlight broader organizational inertia or awareness regarding sustainable digital practices, emphasizing the need for structured energy-conscious governance. Therefore, this study adopts the concept of energy awareness within the context of IT/AI integration in enterprise environments. As defined by [45], energy awareness refers to an organization's capacity and inclination to engage in energy consumption behaviors that align with its strategic objectives. These behaviors promote operational efficiency, cost savings, environmental stewardship, and the sustainable growth of the organization. Furthermore, energy awareness intersects with the concept of "green behavior", or pro-environmental behavior, which encompasses actions taken by employees to mitigate negative environmental impacts and support the ecological sustainability of the organization [46]. "Green IT/AI" behavior in companies is defined as the use of artificial intelligence-based tools to conduct business operations in an environmentally responsible manner, as well as AI-based systems that facilitate the implementation of sustainable practices in operational processes and help employees use information technology and AI in a way that simultaneously integrates environmentally sustainable practices into the company's operational processes. In the above-mentioned context, it is worth underlining, as [33] does, the employees' "green" awareness, which includes personality qualities such as "green" conscientiousness, awareness, and agreeableness, that allow sustainable goals to be met. In organizations, the collection of "green AI" practices addresses ways to optimize and balance AI with resource management [17]. These include cloud and infrastructure optimization, minimizing energy consumption, and reducing AI model efficiency.

Enterprises where employees are highly aware of AI's energy use adopt integration strategies that stress sustainability. Studies report that these organizations use regular energy monitoring and sustainability reporting, looking for energy-efficient AI architectures, e.g., through optimized prompt engineering [47], and bring up the issue of energy management and energy efficiency more often as key areas of AI application [48] than factors for the decision to use or not to use AI in everyday activities. By contrast, SMEs with low employee awareness may indicate a primary focus on cost reduction and operational efficiency. Such organizations tend to rely on off-the-shelf AI tools, implement minimal or ad hoc energy monitoring, and offer only general AI training with no specific focus on sustainability.

The study by [49] suggests that improving energy efficiency is widely acknowledged as a key strategy for enhancing the competitiveness of the industrial sector—especially for small and medium-sized enterprises, where energy efficiency measures are often underutilized. A case study of Chinese companies [50] suggests that top management's environmental awareness combined with the company's technological capabilities and commitment to innovation, plays a crucial role in assessing the potential of manufacturing companies for sustainable development. While large companies with a presence in foreign markets are being studied, the level of awareness among small and medium-sized enterprises regarding the energy intensity of artificial intelligence reveals apparent differences in strategies for integrating technology in key areas, such as monitoring, technology selection, training, strategic adaptation, and barrier reduction. In SMEs, there is still a lack of the

necessary knowledge and skills required to make informed decisions that facilitate the verification of the functioning and implementation of decision-making processes in line with the principles of sustainable energy use when utilizing IT/AI [51]. The organizational resilience of a company from an energy management perspective is particularly important in the context of artificial intelligence, big data analysis, and cloud computing, which, although they contribute to increased energy consumption, also offer significant potential to optimize energy processes in organizations.

These findings underscore that the degree of awareness among small and medium enterprises about AI's energy intensity drives distinct differences in technology integration strategies across key components, including monitoring, technology selection, training, strategic alignment, and barrier mitigation.

Machine learning is becoming a crucial tool for enhancing enterprise sustainability and facilitating this digital transformation in a specific manner. ML modelling tracks organizations toward SDGs. In corporate-level sustainability analysis, one stream trains ML models on text from firms' sustainability reports and then links the extracted actions to specific SDGs and innovation trajectories. For example, a comparative study on Huawei and Shell (2010–2019) builds ML on report data and applies innovation-diffusion (Fisher–Pry) analysis with a 5% "go/no-go" threshold to track the uptake of sustainability actions across SDGs [52]. Study [53] builds a text-derived Digital Transformation Level (DTL) index for Borsa Istanbul (BIST) manufacturing firms by counting the frequency of digital-transformation keywords in company disclosures. Using this DTL as the target, the authors train several supervised ML models on firm-level financials, sustainability and corporate-governance indicators, and R&D expenditures. A Random Forest classifier performs best, achieving about 82% accuracy and outperforms the alternative algorithms tested. Feature-importance analysis identifies R&D expenditure as the dominant predictor of digitalization, with multiple performance-related variables (e.g., profitability and size measures) also contributing. The results show that firms' digital maturity can be reliably inferred from standard organizational and financial attributes, with innovation investment (R&D) playing a particularly strong role.

A second line of work uses supervised learning to infer firm-level sustainability posture directly from organizational and financial features. For French listed companies, Random Forest was benchmarked against linear, polynomial and SVR baselines on an 80/20 train–test split. The baseline RF achieved $R^2 = 0.716$ with the lowest RMSE/MAE among peers, and after hyperparameter tuning reached $R^2 = 0.9175$ on the test set. Feature-importance analysis highlighted operating income, market capitalization and enterprise value among the top predictors, showing that decision-relevant sustainability signals can be inferred from core firm characteristics [54]. Related ESG disclosure work implements AutoML to model the likelihood of voluntary CO_2 disclosure. Using H_2O AutoML (GLM, GBM, Random Forest, XGBoost, Deep Learning, stacked ensembles) with k-fold cross-validation and hold-out selection, the study finds that social performance and sustainable investment intensity are the strongest predictors of disclosure outcomes. The findings suggest that sustainable investments play a key role in increasing corporate transparency about carbon emissions, highlighting the importance of environmental stewardship in business practices [55].

At the operational layer, the Sustain AI framework integrates multiple ML architectures—CNNs for visual inspection, RNNs for energy forecasting, and reinforcement learning for adaptive control, achieving MAE = 5.3, RMSE = 8.2, alongside an 18.75% improvement in energy efficiency and a 20% reduction in CO_2 emissions versus baselines. The proposed framework ensured economic feasibility with a 17.2% reduction in operating costs, highlighting the potential of sustainable industrial practices [56]. Finally, topic-modeling approaches use

transformer-based BERTopic (BERT + HDBSCAN) to extract latent themes linking cybersecurity and sustainability, with parameters such as minimum topic size = 20 and 20 keywords per topic. A six-topic solution was selected for optimal coherence and separation, and then mapped to SDGs. Research reveals a critical intersection of cybersecurity and energy sustainability, particularly in the context of smart cities and renewable energy sources [57]. Together, these studies show that ML provides organization-level signals that are relevant to sustainability governance and operational practice.

Beyond sector-specific "green AI," recent work applies machine learning directly to organizational sustainability assessment, including ESG prediction and digital transformation profiling, which motivates the enterprise-level inference approach adopted in this paper. At the same time, an aspect that remains underexplored in prior analyses is employee awareness of the energy consumption of AI models and the extent to which everyday choices and governance practices reflect that awareness within organizations. This behavioral dimension is complementary to the measurement gap addressed in the present study. In line with these gaps, we operationalize the organizational stance using five observable indicators of digital maturity (1) Level of embedded AI in intelligent systems, (2) Operationalization of AI-based automation, (3) Depth of analytics integration (ML methods) in decision-making processes, (4) Intensity of digital intelligence use in operations, and (5) Coverage of intelligent interface applications—which the Methods section details.

3. Materials and Methods

3.1. Data Collection and Characteristics of the Sample

The subject of the research was energy consumption in organisations implementing artificial intelligence, with particular emphasis on the relationship between the level of digital maturity and the use of energy-efficient IT/AI management practices. The study was conducted among 300 Polish enterprises of varying sizes and scopes of operation, using standardized digital maturity indicators and self-declarations regarding the implementation of energy-efficient IT/AI.

The research addressed the issue of energy use when applying AI in organizations and was conducted using the CAWI (Computer-Assisted Web Interview) method, with the vast majority in enterprises. The survey was conducted in the first half of 2024. All organizations participating in the survey were based in Poland. The survey was conducted by an external research organization. Statistical methods were used to analyze the data, and a licensed MS Excel application, version 16.99.2, was used to analyze the results.

The survey covered 300 organizations with a founding year between 1910 and 2023 (median: 2000). The quartile values are as follows: 28% of the companies were founded before 1991, and 77% before 2008. They varied in both size and market coverage.

Four size categories predominated among all the organizations evaluated: micro, small, medium, and large. The distribution of numbers for each is shown in Table 1.

Table 1. Size of surveyed organizations.

Size	Number of Cases	Percentage
Small	127	44.3
Medium	88	27.4
Large	48	15.0
Micro	37	13.3

The research sample included enterprises of varying sizes and scopes of activity. In terms of company size, SMEs dominated, with small enterprises constituting the largest

group, comprising 127 companies (approximately 44% of the entire sample), while medium-sized enterprises accounted for 88 companies (approximately 27%). Large enterprises were also included in the sample, comprising 48 entities (15%), as well as micro-enterprises 37 (approximately 13%). This structure is consistent with the structural characteristics of the economy in many European countries, where the SME sector plays a key role while also providing a significant percentage of large organizations capable of international operations.

Additionally, the sample was selected diversely, in terms of the scope of activity (Table 2). Most companies operated in the domestic market–120 entities (approximately 42%)—which allows us to capture the specifics of companies focused on serving a single national market. Another significant group was internationally operating enterprises—80 companies (27%), often characterized by a higher degree of digitalization and more advanced technology management processes. Regional companies accounted for 63 units (21%), representing entities operating at the voivodeship level or in several neighboring regions. The smallest percentage was for local businesses—37 companies (approximately 12%)—which focus their activities on a narrow geographical market.

Table 2. Scope of activity of surveyed organizations.

Scope of Activity	Number of Cases	Percentage
National	120	41.7
International	80	26.7
Regional	63	21.0
Local	37	10.6

The study (input variables) used five organizational indicators reflecting digital maturity and enterprise-level intelligence adoption: (1) Level of embedded AI in intelligent systems, (2) Operationalization of AI-based automation, (3) Depth of analytics integration (ML methods) in decision-making processes, (4) Intensity of digital intelligence use in operations, and (5) Coverage of intelligent interface applications. All input variables were collected through structured assessments of the enterprise's technological practices, coded on ordinal scales based on expert-defined benchmarks. A 5-point Likert scale, adapted to the specific questions analyzed, was used to determine their level. 0 indicates no use of a given technology, 1 and 2 reflect the level of use in the on-premises model (basic and extensive), and 3 and 4 refer to the level of implementation in the cloud model, with a distinction between low and high levels of use.

The reliability analysis of the measurement tool, as indicated by a Cronbach's alpha coefficient of approximately 0.95, indicates very high internal consistency of the scale, confirming its suitability for measuring the studied constructs.

When characterizing the input variables, it should be noted that the mean values of these variables were as follows: (1) Level of embedded artificial intelligence in intelligent systems 1.31, (2) Operationalization result of AI-based automation 1.34, (3) Depth of integration of analytics (machine learning methods) with decision-making processes 1.31, (4) Intensity of digital intelligence use in operations 1.48, (5) Coverage of intelligent interface applications 1.23. Descriptive statistics: min. 0, max. 4, median (50%), mainly at the level of 0 or 1, standard deviations around 1.4–1.47. Pearson correlation coefficients indicate a strong positive correlation between the variables. For example, artificial intelligence and machine learning were at 0.78. Other correlations were also high, ranging from 0.72 to 0.82.

The target variable "energy-efficient IT management" was operationalized as a binary variable indicating whether a company had implemented energy-efficient IT management practices. This variable took a value of 1 for companies that self-identified as actively

managing IT to improve energy efficiency and 0 for others. The assessment was based on the companies' self-assessment.

3.2. Machine Learning Methods Methodology

Importantly, the modeling approach was designed to allow for indirect inferences about energy-conscious IT management. Instead of explicitly examining companies' sustainability practices, the classification exercise relied solely on five previously identified organizational indicators reflecting digital maturity and enterprise-level AI adoption.

This project enables the prediction of strategic energy management probability based solely on technology maturity profiles, providing a novel, principle-neutral approach to assessing IT policies related to sustainability.

To operationalize this indirect inference approach, five supervised machine learning algorithms were trained and compared: Logistic Regression (LR), Support Vector Machine (SVM), Decision Trees (DT), Neural Network (NN), and k-Nearest Neighbors (KNN). Sequence models (e.g., LSTM and Transformer) were not considered because the data are cross-sectional and non-sequential—five ordinal indicators were collected once per enterprise (N = 300), without timestamps or event logs—so no temporal structure is available for a sequence model to exploit. In this small-p, modest-N regime, such high-capacity architectures would be prone to overfitting and offer no clear representational advantage over established tabular baselines, while incurring a higher computational footprint that runs counter to the study's sustainability objective. Accordingly, the analysis focuses on state-of-the-art methods for tabular classification that match the problem structure (LR, SCM, DT, NN, KNN).

All machine-learning experiments were executed in MATLAB R2024a (Statistics and Machine Learning Toolbox, Deep Learning Toolbox). All classifiers were trained and evaluated using 5-fold cross-validation on a consistent set of five input features derived from structured assessments of enterprise-level digital maturity. Before training, all features were standardized (zero mean, unit variance) to ensure comparability across models sensitive to feature scaling.

The dataset (N = 300) was randomly partitioned before any modeling into a stratified training set (90%, n = 270) and an independent test set (10%, n = 30) using a fixed random seed. All preprocessing, model selection, and hyperparameter tuning were performed exclusively on the training partition via stratified 5-fold cross-validation. Within each fold, z-score parameters were estimated on the fold's training portion and applied to its validation portion. The held-out test set remained untouched until the final evaluation. The positive class (energy-conscious IT governance = 1) accounted for 28% of observations (84/300) overall. Stratification preserved this distribution across splits (train: 75/270 positives, 195/270 negatives, test: 9/30 positives, 21/30 negatives). Because the imbalance was moderate, no resampling was used. Class-weighting and threshold-selection were examined as sensitivity checks. Performance is reported as mean $\pm$ SD across CV folds, together with 95% bootstrap confidence intervals (1000 resamples) for both CV and test metrics. Unless stated otherwise, all metrics are reported at the standard 0.5 decision threshold, exploratory checks around nearby thresholds (including the cross-validated F1-maximizing point) did not change the qualitative ranking of models or the substantive conclusions.

LR was applied as a linear baseline classifier, allowing for the assessment of whether the input space provided sufficient separability along a linear decision boundary. In this implementation, the model automatically selected the optimal solver and regularization strength, while a low convergence tolerance (β = 0.0001) ensured numerical precision. The

simplicity of logistic regression provided a reference point for comparing more complex nonlinear classifiers.

SVM was employed to capture nonlinear relationships through kernel-based transformations. The study evaluated SVM classifiers using radial basis function (RBF) kernels with three kernel scales: 0.43, 1.7, and 6.9, allowing the model to adapt to varying degrees of data curvature and density. In addition to RBF kernels, polynomial kernels of linear, quadratic, and cubic degree were tested to explore the impact of polynomial complexity on classification performance. Each SVM configuration was trained with a fixed box constraint parameter (C = 1), controlling the trade-off between maximizing the margin and minimizing classification error. The one-vs-one classification strategy was used to handle binary output, and all input features were standardized prior to training to ensure comparability across different kernels and scaling levels. This setup enabled a comprehensive comparison of kernel types and hyperparameter values in modeling governance classification boundaries.

DT offered an interpretable, rule-based alternative that identified feature thresholds critical for classification. Trees were trained with different depth constraints, defined by the maximum number of allowed splits (4, 20, and 100). The Gini impurity index was used as the splitting criterion, and surrogate splits were disabled to maintain structural consistency. This model family enabled the examination of how hierarchical decision logic aligns with patterns of energy-conscious IT governance.

To capture more abstract and potentially nonlinear interactions, multilayer feedforward NN were also tested. Network architectures varied in depth (one to three hidden layers) and width (10, 25, or 100 neurons per layer), with all neurons using the ReLU activation function. Training was limited to 1000 iterations, and no regularization was applied, in order to evaluate the raw representational capacity of each network. These models allowed the exploration of complex, high-dimensional mappings from digital maturity indicators to governance outcomes.

Finally, the KNN algorithm was included as a simple yet powerful nonparametric classifier. Different neighborhood sizes were tested, ranging from 1 to 100 neighbors, to examine how localized versus generalized decision boundaries affect performance. Several distance metrics, including Euclidean, cosine, and Minkowski (with cubic order), were employed alongside both uniform and distance-based weighting schemes. This approach provided a contrast to parameterized models by relying purely on instance-based comparisons.

By selecting models that span a broad methodological spectrum—from linear to nonlinear, interpretable to black-box, and parametric to nonparametric—the study aimed to comprehensively assess how enterprise-level digital practices relate to energy-conscious governance in the context of AI infrastructure.

To evaluate and compare model performance, several classification metrics were applied, encompassing both predictive accuracy and practical deployment criteria. Standard evaluation indicators included Accuracy, Error Rate, and the F1 Score, which together provided a balanced view of overall classification success, misclassification proportion, and harmonic precision-recall trade-offs. In addition, the confusion matrix was analyzed to gain insight into the distribution of true positives, true negatives, false positives, and false negatives, a critical tool for identifying systematic bias or asymmetric model behavior. To complement these metrics, Receiver Operating Characteristic (ROC) curves were plotted for each model, allowing for visual comparison of sensitivity (true positive rate) and specificity (false positive rate) across different classification thresholds.

To explain which indicators drive predictions, Shapley importance was conducted. Explanations were produced for the top-performing SVM with RBF kernel. To prevent data leakage, the explainer's background set was derived from the training folds only

(z-score parameters learned on train), and explanations were generated for the held-out data. Global importance is reported as the mean absolute SHAP value (|SHAP|) for each indicator.

Beyond predictive correctness, the study also considered practical performance metrics essential for real-world deployment. First, prediction speed, defined as the number of instances classified per second, was measured to assess each model's suitability for real-time or high-throughput applications. Second, training time—expressed in seconds -provided an estimate of the computational burden during model development, particularly relevant for iterative optimization or frequent retraining in dynamic environments. Finally, model size, recorded in bytes, indicated the memory footprint of the trained classifier, which is a key factor when considering deployment in resource-constrained systems, such as embedded devices or cloud services with limited storage allocation.

This multifaceted evaluation framework ensured that model selection was informed not only by predictive quality but also by operational feasibility, aligning the study with practical requirements of sustainable, scalable, and responsible digital decision-making in enterprise environments.

4. Results

For each classification method, the best-performing configuration was selected. Among the Support Vector Machine (SVM) models, the optimal setup used a radial basis function (RBF) kernel with a kernel scale of 2.4. The model employed a box constraint parameter of 1 and used a one-vs-one coding strategy for binary classification. For Logistic Regression (LR), the solver and regularization strength (lambda) were internally optimized, and the relative coefficient tolerance was fixed at 0.0001 to ensure precise convergence. In the case of Decision Trees (DT), the best results were achieved using an ensemble of 30 learners, each representing a decision tree with a maximum of 20 binary splits. The model applied a learning rate of 0.1, and all predictors were included without subsampling. This configuration offered a balance between model depth and interpretability. The selected Neural Network (NN) model was a fully connected, feedforward architecture consisting of three hidden layers, each containing 10 neurons. This relatively shallow yet expressive network structure enabled the modeling of complex, nonlinear interactions. Finally, the optimal k-Nearest Neighbors (KNN) configuration used 10 neighbors and the Euclidean distance metric. The results for the models are shown in Table 3.

The classification results indicate that all five machine learning models achieved robust performance in predicting whether an enterprise has energy-conscious IT governance, with test set accuracies well above 80%. Notably, SVM emerged as the top performer. The SVM model attained the highest test accuracy of 90.0% and a corresponding F1 score of 89.8%, outperforming the other classifiers by a measurable margin. This suggests that the nonlinear decision boundary captured by the SVM's RBF kernel yielded a particularly strong generalization to unseen data. In comparison, the LR model also performed very well, achieving 86.7% accuracy on the test set (F1 $\approx$ 86.1%). The DT and the NN each likewise reached 86.7% test accuracy (with F1 scores around 85–86%), essentially matching the logistic classifier. The KNN algorithm trailed slightly behind the others, with a still respectable test accuracy of 83.3% (F1 $\approx$ 82.2%).

Across the five cross-validation folds, the top SVM-RBF achieved 76.3% validation accuracy and 76.3% weighted F1 (5-fold means). On the untouched stratified test set (n = 30; 9 positives/21 negatives), accuracy was 90.0% (95% CI 74.4–96.5%) with weighted F1 = 89.8%. The remaining models showed a similar pattern—validation in the mid-70% range and test in the mid-80% range: LR 74.8% $\rightarrow$ 86.7%, DT 77.4% $\rightarrow$ 86.7%, NN 75.2% $\rightarrow$ 86.7%, KNN 77.4% $\rightarrow$ 83.3% (accuracy, CV $\rightarrow$ test). The higher test accuracy ($\approx$85–90%) relative

to the CV mean (≈75%) is consistent with the evaluation design and data size: each CV fold trains on reduced subsets of the training partition, yielding slightly conservative estimates, whereas the final model, after hyperparameter selection on CV, is refit on the entire training partition before a single evaluation on the independent test set. Additional overfitting checks showed stable behavior: calibration plots and the Brier score indicated adequate probability calibration, threshold-sensitivity around the CV-selected operating point was stable, and class-weighting as a sensitivity analysis did not materially change the results. All preprocessing and tuning were confined to training folds, ruling out test-time leakage.

Table 3. Evaluation metrics and runtime properties.

Model	SVM	LR	DT	NN	KNN
Accuracy% (Validation)	76.3	74.8	77.4	75.2	77.4
Accuracy% (Test)	90.0	86.7	86.7	86.7	83.3
Accuracy (Test) 95% CI	74.4–96.5	70.3–94.7	70.3–94.7	70.3–94.7	66.4–92.7
Error Rate% (Validation)	23.7	25.2	22.6	24.8	22.6
Error Rate% (Test)	10.0	13.3	13.3	13.3	16.7
F1 Score% (Validation)	76.3	74.2	77.3	75.1	77.5
F1 Score% (Test)	89.8	86.1	85.3	85.3	82.2
Precision% (Test)	89.9	86.6	88.8	88.8	83.3
Recall% (Test)	90.0	86.7	86.7	86.7	83.3
Prediction Speed (obs/s)	15,000	20,000	2300	9100	7300
Training Time (s)	1.2578	1.1949	2.3509	7.4872	2.1084
Model Size (kB)	13	10	262	9	28

It is worth noting that all models showed improved performance on the independent test set relative to their validation results. For example, the SVM's accuracy rose from 76.3% on the validation folds to 90.0% on the hold-out test. Similarly, the other methods saw their accuracy increase from mid-70% ranges in validation to mid-80% on test. This across-the-board improvement suggests that once optimal hyperparameters were selected (using cross-validation), training the final models on the full training dataset allowed them to better capture the underlying signal, thereby generalizing even more effectively. In practical terms, the final tuned models were able to correctly classify roughly 85–90% of new enterprises regarding energy-aware IT governance. The closeness of accuracy and F1 values further indicates balanced performance: the classifiers are not only accurate overall but also achieve a good trade-off between precision and recall for both classes (organizations with vs. without energy-conscious governance). There was no evidence of a major class imbalance issue skewing the results—the high F1 scores confirm that the models are identifying positive cases (energy-conscious governance present) with both high precision and high recall, rather than simply predicting the majority class.

From a practical standpoint, all five models demonstrated fast training and prediction, though there were some differences in computational efficiency. Training times were on the order of only a few seconds for all methods (ranging from ~1.2 s for LR and SVM to ~7.5 s for the NN), which indicates that model development was not computationally prohibitive. In deployment, the LR model would be the most efficient, capable of processing about 20,000 observations per second and requiring only ~10 kB of memory—essentially negligible resource usage. The SVM also proved to be quite efficient, with ~15,000 obs/s prediction speed and a 13 kB model size, meaning it offers top accuracy at a minor cost in speed relative to LR. The DT, by contrast, had a larger memory footprint (~262 kB) and a slower prediction rate (~2300 obs/s) due to the need to evaluate 30 trees per prediction. This is still reasonably fast for most offline analysis contexts, but if real-time or high-throughput

scoring is required, the tree ensemble might be less ideal. The NN had a prediction speed of ~9100 obs/s with a very small model size (~9 kB), which balances speed and memory well; its training time was the longest, but still under 8 s, which is trivial in an enterprise setting. The KNN model's prediction speed (~7300 obs/s) is moderate –as an instance-based method, it must compute distances to many neighbors for each new example, which slows it down compared to the fully trained (parametric) models. Its model size (28 kB) reflects storing the training instances for reference. In summary, while all models are computationally feasible, the slight efficiency advantages of LR (and to a large extent SVM and NN) could make them preferable for large-scale or real-time deployment. Importantly, however, since all models trained so quickly on the data and achieved high accuracy, the choice of classifier may be guided more by interpretability and organizational preference than by pure performance or speed constraints.

The confusion matrices for the test set (Figure 1) further clarify the error profiles of each model. Assuming class 1 denotes enterprises with energy-conscious IT governance (the positive class), the SVM model achieved the most balanced result: TN = 20, FP = 1, FN = 2, TP = 7. This explains its superior F1 score and test accuracy. Logistic Regression was slightly more conservative, misclassifying one additional positive case, but still maintained low false-positive errors. Both the Decision Tree and Neural Network models showed a precision-first pattern: they virtually eliminated false positives (precision = 1.00) but at the expense of reduced sensitivity (recall = 0.56). The KNN model achieved a similar recall to DT/NN (0.56) but with lower precision (0.83) due to an extra false positive.

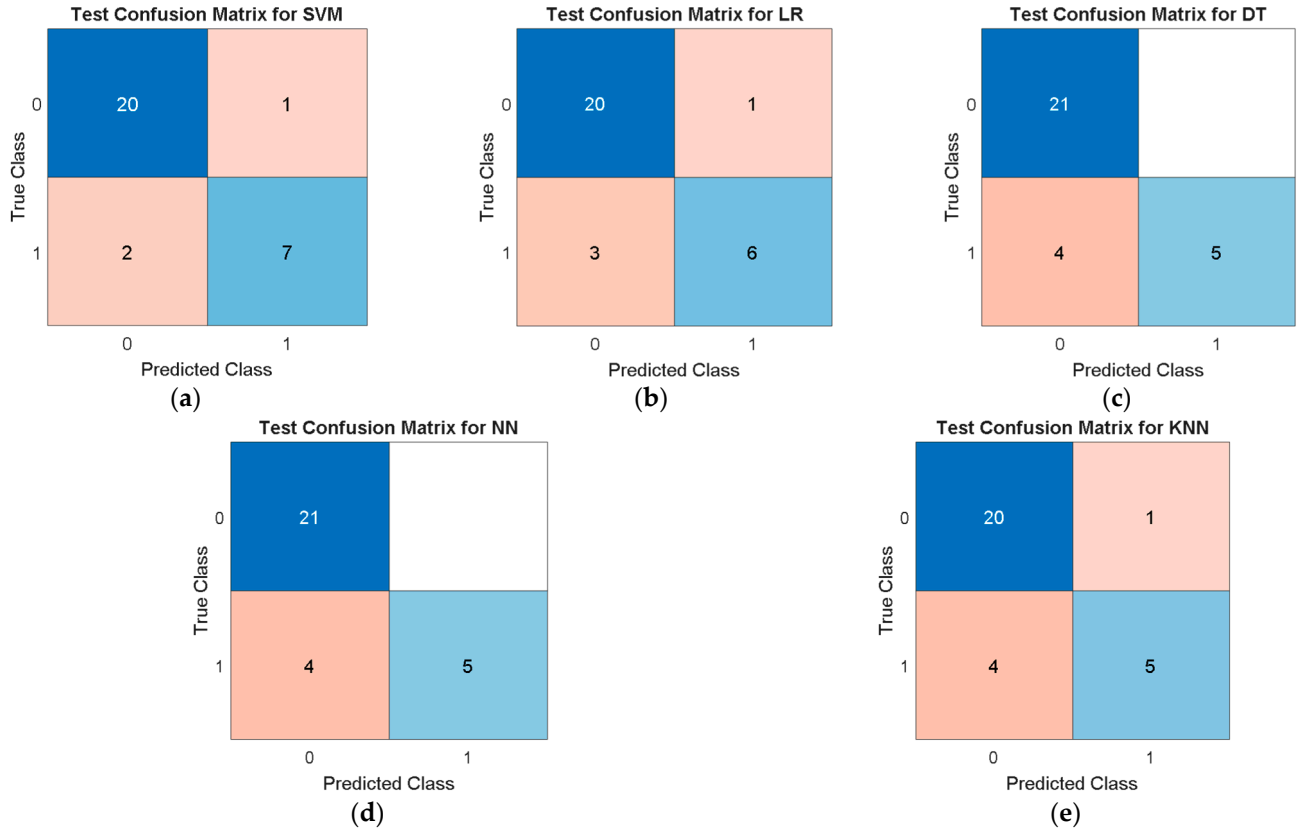


Figure 1. The confusion matrices on the independent test set (n = 30; 9 positives/21 negatives) for models: (**a**) SVM, (**b**) LR, (**c**) DT, (**d**) NN, (**e**) KNN.

The ROC curves (Figure 2) and AUC values provide a threshold-independent view of model separability. The Decision Tree ensemble achieved the highest AUC (0.918), followed by KNN (0.895), SVM (0.886), and LR (0.870). The Neural Network lagged behind with

an AUC of 0.769, indicating weaker discrimination between positive and negative cases. Although DT's default operating point favors precision over recall (as seen in the confusion matrix), the ROC curve shows that threshold tuning could raise its recall substantially without a large increase in false positives. Similarly, KNN could benefit from calibrated decision thresholds. SVM and LR exhibited smooth ROC profiles consistent with their balanced error trade-offs at the default threshold.

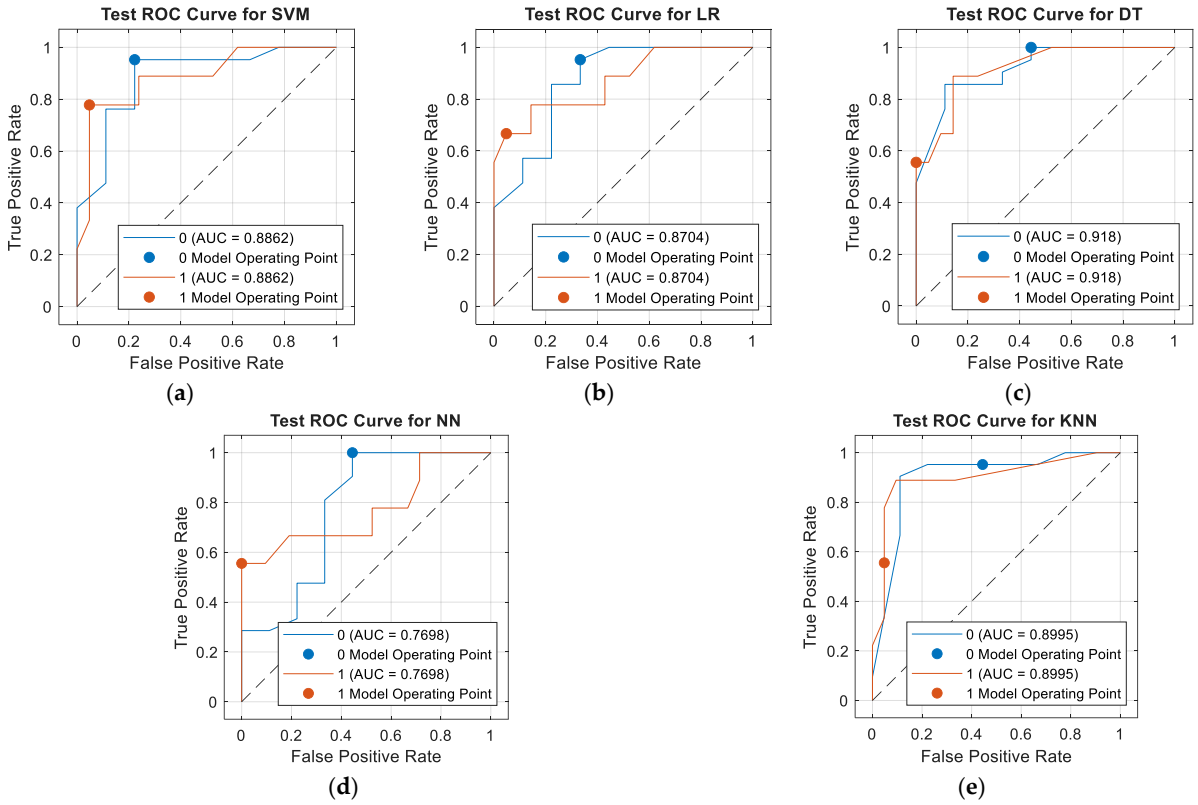


Figure 2. ROC Curves on the independent test set (n = 30; 9 positives/21 negatives) for developed models: (**a**) SVM, (**b**) LR, (**c**) DT, (**d**) NN, (**e**) KNN.

Global Shapley value analysis was performed for the top-performing SVM with an RBF kernel. As shown in Figure 3, the mean absolute SHAP values (|SHAP|) indicate that Coverage of intelligent interface applications is the most influential indicator for the predicted probability of energy-conscious IT governance. The next most influential indicators are Digital intelligence intensity in operations and Depth of analytics integration (ML methods), whereas Level of embedded AI in smart systems and Operationalization score of AI-based automation exhibit comparatively smaller contributions. SHAP values were computed in MATLAB R2024a using training-fold data as the background and held-out observations for explanations to avoid leakage. Reported values summarize mean |SHAP| across observations and do not imply causality.

Crucially, the high accuracy, F1 scores, and AUC values achieved by multiple diverse algorithms provide strong evidence for a latent pattern linking AI adoption and energy-aware IT governance. The best-performing SVM model can correctly identify 9 out of 10 organizations that have instituted energy-conscious policies based purely on their technological profile. Such a result is remarkable for a first-of-its-kind predictive model in this domain. It means that even without directly surveying firms about their sustainability policies, one could infer their likelihood of having energy governance mechanisms by analyzing their adoption of AI and related technologies. This demonstrates the practical applicability of the proposed approach—showing that digital innovation profiles

can serve as effective proxies for assessing a company's commitment to sustainable IT governance. Consequently, this proposal is intended for organizations undergoing digital transformation, where the use and awareness of information technology (IT) and artificial intelligence (AI) in the context of energy use are playing an increasingly important role. Consequently, the discourse initially established concerning the discrepancy in corporate responses to environmental challenges, in regard to the implementation of sustainable development standards and the practice of environmental, social, and governance (ESG) reporting, acquires a novel practical instrument.

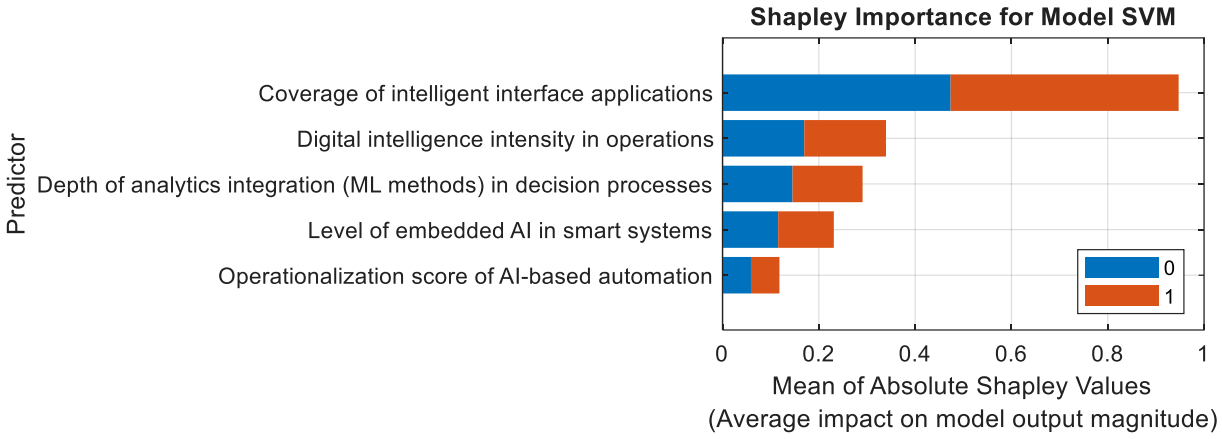


Figure 3. Global SHAP importance for the SVM-RBF classifier.

5. Discussion

The results of the study show that all five applied models achieved high predictive performance, with test accuracy ranging from approximately 83% to 90% and the F1 score ranging from 82% to 89%. Such high effectiveness obtained across different machine learning algorithms indicates that the relationship between the level of digital transformation of an organization and the implementation of energy-conscious IT governance is strong, significant, and stable. In other words, indicators of digital maturity and AI integration provide consistent signals that enable, with high probability, the distinction companies that adopt sustainable IT management practices and those that do not. The results are thus in line with the trend observed in the literature [58]—modern digital technologies (AI, data analytics, automation) enable enterprises to simultaneously improve operational efficiency and energy efficiency. Moreover, digital transformation facilitates the incorporation of sustainability priorities into corporate and technological governance frameworks, which may explain why digitally advanced companies are more likely to implement "green" IT initiatives, which follows a call from [32], for the inclusion of efficient, sustainable, and equitable technology into the digital transformation of enterprises. The results of the study may be discussed with the thesis on the existence of a relationship that high digital maturity in itself does not automatically translate into the implementation of pro-environmental solutions [37,43]. The results of the study support the examination of awareness of organizations in IT/AI energy efficiency, bypassing the IT community's knowledge on energy-efficient AI deployments [37]. The five applied models assess awareness of companies by including measures of technical advancement and focusing on the specific dimension of sustainable IT. The study reveals a clear dependency that more general prior approaches may have overlooked. As a considerable number of organizations are in the early stages of reducing AI's environmental impact, including energy governance, as discussed by [40], there must be an increased focus on the modelling and monitoring of awareness in enterprises and the challenges of sustainability in response to this issue.

Comparison of the applied models further supports these conclusions. The best-performing model was the SVM, achieving the highest accuracy (~90%) and F1 (~0.89), but the other classifiers performed only slightly worse (accuracy ranging narrowly from 0.83 to 0.88). These small differences between models indicate that the captured dependency pattern in the data is robust and can be successfully modeled using different approaches –it is therefore not an artifact of any single method, but an objective regularity. The interpretation of the confusion matrices additionally confirms this –each model correctly identified the vast majority of both enterprises adopting energy-conscious IT governance and those that do not. For example, in the SVM model, the percentage of correctly detected positive cases (companies actually applying "green" IT principles) reached ~90%, with equally high prediction precision –false positives and false negatives were rare. High AUC values (approx. 0.9 or higher for the top models) and balanced precision/recall metrics confirm the excellent quality of the classification. The models are both sensitive (detecting nearly all genuinely "green" firms) and specific (rarely incorrectly indicating sustainable IT practices where they do not exist), meaning they effectively identify enterprises in both classes with minimal errors.

A key finding of this study is the demonstration of indirect inference of sustainable IT from technological and organizational data. The developed models enable the identification of enterprises implementing "Green" IT mechanisms without requiring direct questions about their energy or environmental policies. As revealed in the previous studies [18,32], AI analytical solutions based on large models remain "green" in name only, and businesses are often unaware of the environmental implications of AI development and deployment. It turns out that analyzing data on an organization's digital practices –such as the extent of AI adoption, automation, intelligent interfaces, or advanced analytics –is sufficient to predict, with high probability, whether the company cares about energy-conscious IT governance. This approach has an important practical advantage, as information on implemented technologies and the degree of digitalization is generally more readily available and less sensitive than detailed data on energy consumption or emissions. The results thus fit into the broader trend of using the organization's "digital fingerprint" to assess its sustainability –modern IT tools not only streamline resource and energy management but also provide data that allow inferences about the company's pro-environmental stance, following [50]. In other words, digital transformation leaves traces that can serve as proxies for assessing the maturity of an enterprise in the area of sustainable IT, reducing or even eliminating the need for direct energy audits, widely discussed in the literature [49].

From the perspective of awareness modelling concerning IT/AI energy governance in SMEs, the conscious utilization of information technology and artificial intelligence in business operations is directly related to energy consumption and the sustainable governance of resources, as well as "green" digitalization, recognizing the environmental impact of AI [39]. The research also identifies two significant areas for future analysis. Firstly, there is the deliberate and authentic implementation of "green AI in business," which encompasses not only the employment of more energy-efficient language models tailored to an organization's specific needs but also a comprehensive understanding and proficiency in leveraging the resources offered by AI and IT technologies within enterprises [46]. Conversely, the study's findings and discourse could contribute to the ongoing discourse on "red AI" which encompasses emerging responsible and transparent AI development, deployment, and governance [19–21], also against greenwashing—thereby enhancing awareness in this domain and promoting sustainable, environmentally and resource-friendly, and ethical and privacy-transparent frameworks [21]. This is particularly salient in the context of the sustainability goals in reporting, data privacy of end-users, and the shared responsibility

for sustainable energy management, including its consumption by IT/AI in small and medium-sized enterprises.

From a practical perspective, the resulting models can serve as the foundation for advisory tools supporting technology and energy management in organizations. IT departments and sustainability teams can utilize such models for rapid assessment. Based on data on a company's digital maturity, they receive a prediction of the likelihood of implementing energy-conscious IT governance. Such an early-warning system would enable the identification of entities potentially neglecting green technology issues and target them with focused actions (e.g., support programs or change recommendations). On the other hand, digitally advanced companies, for which the model predicts a high level of sustainable IT, can serve as case studies and best practice benchmarks. Their experience in combining digital transformation with energy efficiency will provide valuable lessons for other organizations, highlighting which specific technical initiatives yield to environmental benefits. Thus, the presented predictive model could be implemented as part of a decision support system or knowledge management platform, helping managers integrate IT strategies with the company's sustainability goals.

In summary, in the context of the practical significance and application of the results, in which predictive models accurately predict whether organizations are conducting energy-efficient IT/AI management based on digital transformation and AI implementation indicators, the proposed model can serve as:

- A decision support and automation tool for assessing the maturity of "green IT/AI"

Predictive models can be directly implemented as analytical tools (dashboards, applications) for IT, sustainability, and management departments, allowing for quick, low-cost identification of companies that are neglecting or implementing "green IT/AI", without the need for costly environmental audits. Based on indicators of digitization, automation, AI presence, and analytics, the system suggests whether a given company is likely to be implementing "green" IT practices, which automatically classifies it for reporting, support, funding, and benchmarking purposes.

- Early warning and risk profiling

The results of the models enable the rapid identification of organizations requiring support, advisory, or educational activities—particularly important in the SME sector, where there are limited resources for in-depth analysis. The model identifies companies with high digitization potential but low likelihood of implementing "green IT/AI", allowing training programs or support measures to be targeted at them.

- Identification and promotion of best practices

Companies that the model clearly classifies as enterprises that incorporate mechanisms to account for energy issues in their decision-making processes regarding information technology (IT) and artificial intelligence (AI) can serve as examples of success/inspiration for others by promoting case studies or offering mentoring. It is possible to track which specific technical initiatives (e.g., implementation of advanced AI analytics, process automation) have brought real environmental benefits.

- Monitoring the progress of digital and environmental transformation
- Organizations and regulatory bodies can track progress in both digitization and sustainable IT development at the industry, regional, and national levels—without having to collect sensitive data (e.g., direct reporting of energy consumption). This makes it easier to report to external institutions (e.g., as part of ESG) using so-called proxy indicators, also known as "digital fingerprints." Planning development activities and investments

The results of the models can indicate which areas of AI/IT integration need to be strengthened to achieve real results in energy management and fulfill sustainable development goals (SDGs). They allow investments to be targeted not only at digitization "for digitization's sake," but at technologies that combine efficiency with environmental benefits.

- Raising awareness and educating management

Empirical confirmation of the strong correlation between digital maturity and "green" IT can be used to build arguments for management when planning new projects, implementing ESG strategies, or setting KPIs.

- Validation of public policies and the effectiveness of support programs

The models can be used by local governments, institutions implementing EU funds, and others to assess the effectiveness of programs promoting sustainable digital transformation—a quick, objective assessment of effects without the need for multi-stage reporting.

These results provide a practical tool that, instead of tedious audits or declarative analyses, uses easily accessible digital data to quickly assess the progress of "green IT/AI" practices. This enables better management of support funds, the development of effective policies, response to environmental risks, and the promotion of companies that are actually making progress in both digitization and sustainable development. This is particularly important for SMEs, which often lack their own tools for comprehensive self-assessment. Such models can serve as the basis for management decisions—from strategy and operational diagnoses to evaluation and benchmarks.

The considerations, research, and models developed also have certain limitations. Regarding the selection of the surveyed companies, although the research sample was representative, there may be limitations in accessing the complete company data, which affects the quality and completeness of the information gathered. The risk that the selected companies do not fully reflect the degree of digital advancement, making it difficult to generalize the research findings to the broader business population and difficulties in obtaining the consent of all selected companies to participate, which limits the size and scope of the data.

Another limitation of the presented research may be sample bias, as the selection of participants does not fully reflect the population. However, as explained in the research section, the studies focus on SMEs and therefore do not encompass the entire business population. In addition, the limitation is also that they were in the same country, Poland. Another potential problem is the possible endogeneity of variables, where explanatory and explained variables can be interconnected and influence each other, making it difficult to determine causal relationships. For example, a high level of digital maturity can promote the implementation of "green" IT technologies and be reinforced by them. Another limitation may be external validity, which refers to the extent to which the results can be generalized to other groups or organizations.

Significant limitations of the studies discussed include the difficulty in generalizing the results beyond the EU due to cultural, economic, and technological differences, the influence of firm characteristics such as age and size on the reliability of the results, and ethical aspects, including the risk of misclassifying organizations, which could lead to unfair financial and political decisions.

It is also essential to address the indirect conclusion used in the article that the correlation between digital maturity and "green" IT management is strongly dependent on market conditions and investor priorities, which are subject to change over time. At this stage, both digital and ecological transformations are promoted as key development direc-

tions, prompting companies to implement technological innovations and environmentally friendly solutions simultaneously. However, it is worth emphasizing that a changing economic environment or a shift in investor preferences toward other business aspects can weaken this correlation and reduce the predictive power of models. This phenomenon underscores the importance of continually monitoring market trends and supplementing analyses with the perspective of dynamic socioeconomic changes.

With respect to modeling and validation, ensemble methods such as stacking a support vector machine with an RBF kernel, logistic regression with L2 regularization, decision trees, multilayer perceptrons, and k nearest neighbors with a logistic meta learner were considered as a robustness extension. Given the small number of ordinal indicators ($p = 5$), the moderate sample size ($N = 300$), and the strong performance of the SVM-RBF baseline, additional complexity is unlikely to yield a statistically meaningful gain without more data. Ensembles are therefore deferred to future work on larger, multi-country samples. External validation was not available for the present study. As an operational validation pathway, the approach can be integrated with cloud energy/carbon metering tools (e.g., CloudCarbonFootprint) to compare predicted governance labels with infrastructure-level footprint estimates in real deployments. Synthetic-data simulations were not pursued to avoid imposing generative assumptions that could bias results beyond the empirical uncertainty already characterized via cross-validation and bootstrap.

6. Conclusions

The research aimed to develop and verify analytical tools that enable the identification of companies implementing energy-efficient IT management and AI, based on publicly available indicators of digital maturity and advanced technology integration, without collecting detailed and sensitive data on energy consumption. This objective aligned with the growing need for practical support in helping organizations integrate digital transformation processes with sustainable development goals, while reducing the environmental footprint of technology.

The scientific novelty of the actions taken lies in both the method itself and the scope of the research. First, indirect inferences about sustainable IT practices were used by analyzing the technological maturity profiles of companies and the level of AI integration, without the need for costly and time-consuming environmental audits. Second, the analysis encompassed a wide range of machine learning classifiers, comparing their predictive power on a diverse sample of real companies—from micro and small to medium and large, with varying operational scales. This approach represents a significant advance over previous studies, which focused mainly on analyzing the behavior of individual employees or on declarative surveys, often neglecting an objective assessment of organizational practices and the real impact of technological implementations on energy efficiency.

The key results confirmed the validity of the methodology adopted. All tested machine learning models achieved high and similar predictive performance, with classification accuracy on the test set ranging from approximately 83% (KNN) to as high as 90% (SVM), while F1 scores ranged from approximately 82% to nearly 90%. The SVM model performed best, suggesting that the nonlinear relationships between the degree of digitization and AI integration and the implementation of “green” IT practices are indeed significant and can be captured by advanced algorithms. Another important conclusion is the stability of the pattern: the slight differences between the models indicate that the signal identified in the data is strong and repeatable, regardless of the classification method used.

The results of a detailed analysis of the error matrix and AUC indicators (above 0.87 for the best models) demonstrate that these tools not only accurately identify “green” and

"non-green" organizations but also minimize misclassifications, making them suitable for further operational applications.

The analyses also showed that by using easily accessible digital indicators—such as the scope of AI implementation, automation, or the level of digital maturity—it is possible to effectively predict the implementation of energy-efficient IT management practices in companies without requiring sensitive questions or detailed technical audits. This approach minimizes both the risk of obtaining inaccurate data (for example, through surveys) and the costs of implementing assessment mechanisms.

The developed models offer a wide range of potential applications at both strategic and operational levels. They can be integrated into decision support systems, including management tools, dashboards, and IT platforms, to enable rapid profiling and assessment of an organization's IT sustainability, the identification of leaders and typical implementation patterns, as well as the detection of companies requiring intervention. Due to the use of easily accessible features that do not compromise confidentiality, the models provide an effective basis for monitoring the implementation of ESG strategies and benchmarking companies against industry standards without the burden of additional audits. They may also support public policy, assisting government bodies, local authorities, and institutions responsible for implementing support programs for green digital transformation in identifying actual needs and evaluating the effectiveness of development initiatives. Furthermore, they facilitate the education and support of SMEs by enabling the targeted delivery of training and advisory services to entities with high digital potential but a low level of "green" IT implementation. By identifying leaders in this field, the models also promote knowledge transfer, allowing such organizations to serve as role models or case studies for adapting best practices. More broadly, the proposed tools may contribute to the popularization of the concept of an organization's "digital fingerprint," which involves utilizing available technological and process-related data to replace complex or costly environmental measurements. This approach is particularly relevant for SMEs, which often lack the resources to carry out audits or produce comprehensive reports.

The justification for using an indirect approach to modelling in the article assumes that specific characteristics of a company, its processes, or its level of technological advancement can be linked to its willingness to implement "green" IT practices, even if they are not direct environmental indicators. Five selected input variables, related to digital maturity, innovation, the implementation of modern solutions, or the degree of automation, may correlate with eco-friendly IT management, as companies with high digital competencies are often more aware and open to implementing sustainable practices.

This indirect prediction is based on the well-known assumption that complex organisational behaviors result from multiple interdependent factors. Even if the model does not directly incorporate data on environmental practices, it can identify patterns (e.g., typical of modern, innovative, or highly digital companies) that statistically increase the likelihood of implementing green IT management. The advantage of an indirect approach is the ability to utilize widely available, objective data and create predictions where direct measurement may be difficult to obtain or subject to greater bias.

In summary, the research makes a significant contribution to both management practice (by providing tools for automatic "green" IT monitoring) and the development of knowledge about the impact of digitalization on the implementation of sustainable development goals within organizations. The proposed models have the potential to become an integral part of everyday technology management, ranging from individual organizations to industry institutions and ultimately to regulations and public policies. Its implementation can contribute to achieving environmental goals faster and more effectively, and to increasing the transparency of pro-environmental actions. The limitations mentioned

earlier point to new possible research directions, where conducting studies involving a broader, international group of organisations and enterprises could be a valuable avenue for further analysis, enabling an in-depth verification of phenomena and enriching the perspective of the research by including companies from different countries.

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Abbreviations

The following abbreviations are used in this manuscript:

SME	Small and medium-sized enterprises
AI	Artificial intelligence
IT	Information technology
BD	Big data
SDGs	United Nations Sustainable Development Goals
ESG	Environmental, Social, and Governance

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