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THE IMPACT OF ARTIFICIAL INTELLIGENCE ON THE SMARTIZATION OF ENTERPRISES

Abstract. *The increasing role of Artificial Intelligence (AI) in enterprise transformation necessitates comprehensive assessment models that capture the full spectrum of AI-driven smartization. This study introduces the AI-Enterprise Smartization Index (AIES-Index) — a structured framework designed to evaluate AI adoption across five key dimensions: AI adoption level, decision-making autonomy, explainability and transparency, operational efficiency, and sustainability contributions. Unlike existing AI maturity models, which primarily focus on strategic or financial aspects, AIES-Index integrates quantifiable metrics that measure AI's real-world impact on business operations, decision-making processes, and sustainability efforts.*

The study employs a multi-criteria weighted index methodology, where each category is assigned a specific weight based on its significance in AI-enabled smartization. A min-max normalization approach ensures comparability across enterprises, allowing for objective benchmarking. To differentiate AIES-Index from existing models, a comparative analysis highlights its advantages in measuring AI adaptability, transparency, and ESG alignment, areas often overlooked in traditional AI capability frameworks.

The results demonstrate that AIES-Index provides a more holistic and quantifiable assessment of AI-driven smartization, incorporating both financial and non-financial metrics. The model emphasizes AI's role in enhancing operational efficiency, optimizing business processes, improving explainability, and driving sustainable innovation. A key finding is that AI transparency and decision-making autonomy are critical factors influencing enterprise-wide adoption and regulatory compliance.

Future research will focus on empirical validation of AIES-Index using real enterprise data, enabling practical applications across industries. Additionally, a sensitivity analysis will be conducted to assess the model's robustness by evaluating how variations in specific indicators affect the overall AIES-Index score. These steps will ensure the model's adaptability to dynamic business environments and sector-specific AI implementations.

The proposed AIES-Index framework serves as a valuable tool for enterprises, policymakers, and researchers, offering a structured methodology to evaluate AI's transformative impact on business processes while aligning with modern governance, ethical, and sustainability standards.

Keywords: *AI-Enterprise Smartization Index (AIES-Index), Artificial Intelligence (AI), Smartization, Decision-Making Autonomy, Explainability and Transparency, Operational Efficiency.*

1. Introduction

In recent years, artificial intelligence (AI) has emerged as a transformative force in enterprise management, driving digitalization and automation across various sectors [1]. Smartization refers to the intelligent transformation of business processes, products, and services through AI and other digital technologies [2]. By leveraging AI-driven analytics, automation, and decision-making capabilities, enterprises can enhance efficiency, reduce costs, and improve strategic agility. The integration of AI into enterprise operations facilitates predictive analytics, process optimization, and real-time adaptability, making businesses more competitive in an increasingly digitalized economy.

The aim of this article is to develop and justify the AI-Enterprise Smartization Index (AIES-Index) as a structured framework for assessing the role of Artificial Intelligence in enterprise smartization. The study focuses on quantifying AI-driven transformation by integrating key dimensions such as AI adoption, decision-making autonomy, explainability, operational efficiency, and sustainability contributions. To achieve this goal, the following scientific tasks were systematically accomplished:

1. Develop a structured methodology for assessing AI-driven smartization: define the AIES-Index model, selecting measurable indicators and determining appropriate weighting for key smartization dimensions.
2. Justify the five key categories of AIES-Index: analyze why AI adoption, decision-making autonomy, explainability, operational efficiency, and sustainability are critical factors in enterprise transformation.
3. Compare AIES-Index with existing AI assessment models: identify the limitations of conventional AI maturity and impact assessment frameworks and highlight the advantages of AIES-Index in providing a multi-dimensional evaluation.
4. Apply a quantitative weighting and normalization methodology: develop a formula for calculating the AIES-Index score using expert evaluation, weighted indicators, and min-max normalization techniques.
5. Discuss implications and future research directions: Assess how AIES-Index can be applied to real enterprise data, evaluate its potential sensitivity to changes in input parameters, and propose directions for empirical validation.

By addressing these objectives, the article provides a comprehensive framework for measuring AI-driven smartization, contributing to both academic research and practical enterprise applications. The findings support business leaders and policymakers in evaluating AI's role in enterprise transformation while ensuring alignment with transparency, efficiency, and sustainability goals..

The integration of artificial intelligence into enterprise operations has significantly contributed to the transition towards smartization — a process in which data-driven decision-making, automation, and cognitive computing play a fundamental role. Existing studies have examined AI's impact on enterprise digital transformation, focusing on efficiency gains, cost reductions, and innovation acceleration. However, the need for standardized approaches to evaluating AI-driven smartization remains a critical challenge.

A notable contribution to this discourse is the DIKWP Conceptualization Semantics Standards Version 1.0 [3], which introduces an advanced framework for testing and evaluating AI performance. This model extends the traditional Data-Information-Knowledge-Wisdom (DIKW) [4] paradigm by incorporating Purpose, emphasizing goal-oriented cognitive processing. The DIKWP model conceptualizes AI's ability to transform raw data into actionable insights, aligning with the core principles of enterprise smartization. It highlights AI's role in semantic understanding, bias assessment, value alignment, and decision-making transparency, which are crucial for evaluating AI-driven business transformation.

The management of smartization in enterprises has been explored from both theoretical and practical perspectives. Bashynska (2023) [2] provides a comprehensive examination of the theoretical and methodological aspects of business process smartization in industrial enterprises, defining the key components required for the transition from traditional to AI-enhanced business models. Meanwhile, Bashynska (2020) [5] investigates the role of smartization in ensuring economic security, outlining frameworks for managing smart business processes to enhance resilience, adaptability, and efficiency. These works highlight the importance of structured AI integration within corporate strategies, bridging the gap between digital transformation and long-term business sustainability.

Several assessment methodologies have been proposed to evaluate AI's impact on enterprises. AI maturity models, such as Gartner's AI Maturity Framework [6] and McKinsey's AI Readiness Model [7], classify enterprises into stages based on their level of AI adoption, ranging from experimental implementation to full AI-driven automation. These models provide strategic guidance but often lack the granularity needed to assess AI's cognitive and ethical dimensions within smartization. Meanwhile, The demand for AI transparency has led to the development of frameworks such as DARPA's Explainable AI (XAI) program [8] and the EU Trustworthy AI Guidelines [9]. These approaches emphasize interpretability, fairness, and accountability in AI decision-making.

Beyond technical evaluation, researchers such as Brynjolfsson and McAfee [10] and Kaplan and Haenlein [11] have examined AI's contribution to business efficiency through metrics like productivity gains, cost reductions, and innovation rates. However, a major challenge remains in isolating AI's direct impact from broader digital transformation trends. Other studies, such as those by Binns [12] and Jobin *et al.* [13], have shifted the focus to ethical and socioeconomic assessments, exploring AI's implications for workforce dynamics, regulatory compliance, and privacy concerns. These perspectives highlight the importance of balancing automation with responsible AI governance.

From the perspective of enterprise smartization, existing assessment methodologies remain fragmented. Frameworks such as the Industry 4.0 Readiness Index and the Digital Economy and Society Index (DESI) provide valuable insights into digital transformation but focus primarily on technological infrastructure rather than AI's strategic role in business intelligence and automation. Other studies, such as those by Lee et al. [14] and Xu et al. [15], have proposed enterprise smartness models based on AI-driven process optimization, autonomous decision-making, and adaptability. However, these models still lack a unified standard for measuring AI's integration into corporate decision-making.

Key performance indicators have also been suggested for evaluating enterprise smartization, with research by Porter and Heppelmann [16] and Kagermann [17] emphasizing real-time data utilization, AI-enhanced customer interactions, and predictive maintenance efficiency. Recent developments have further integrated sustainability metrics, with studies such as those by Sauter *et al.* [18] advocating for AI-driven approaches to energy efficiency, resource optimization, and circular economy principles as essential elements of smartization assessment.

While each of these methodologies provides valuable insights, they remain either technologically focused or ethically driven, lacking a comprehensive, multi-dimensional framework for evaluating AI's role in enterprise smartization. The DIKWP model offers a potential bridge between these perspectives by integrating technical performance, cognitive adaptability, and ethical compliance within a structured evaluation approach. This highlights the need for future research to develop standardized, adaptable assessment models that capture AI's strategic business value, adaptability, and long-term sustainability in enterprise environments.

The literature indicates that while AI and smartization are closely linked, there is no integrated assessment model that captures the holistic impact of AI-driven smartization. Developing a comprehensive evaluation framework that integrates AI maturity, enterprise smartization levels, and sustainability indicators would provide businesses with a more actionable tool for measuring progress and making informed decisions..

2. Materials and Methods

2.1. Data collection and sources

The study utilizes primary and secondary data sources:

- Primary data: expert interviews with business leaders, AI specialists, and digital transformation consultants to gain insights into AI-driven smartization strategies.
- Secondary data: analysis of industry reports, academic publications, and publicly available datasets from institutions such as the OECD, World Economic Forum, European Commission, and consulting firms (e.g., McKinsey, Gartner).

2.2. Limitations of the study

While this research aims to provide a comprehensive assessment of AI-driven enterprise smartization, certain limitations exist:

- Theoretical-methodological nature of the model: the AIES-Index developed in this study is theoretical and methodological, meaning that it has not yet been empirically tested on real enterprise data. Future research will focus on validating and refining the model through practical applications.
- Data availability: access to proprietary enterprise AI adoption data may be restricted, limiting the ability to fully verify the model's applicability across different industries.
- Industry-specific challenges: the dynamics of AI-driven smartization vary significantly across industries, making it difficult to create a one-size-fits-all assessment framework. Sector-specific adjustments to the AIES-Index may be necessary.
- Ethical considerations: AI-related risks, such as algorithmic bias, workforce displacement, and regulatory compliance, require further in-depth analysis beyond quantitative assessments, particularly in areas of explainability and fairness.

Given these limitations, future research will focus on empirical validation of the AIES-Index using real enterprise data and conducting sensitivity analysis to refine the model's accuracy and applicability.

2.3. Methodological framework for AI-driven smartization assessment

The study develops the AI-Enterprise Smartization Index (AIES-Index) to measure the extent of AI-driven enterprise transformation. Table 1 presents the key assessment dimensions and indicators.

The **AI-Enterprise Smartization Index (AIES-Index)** is designed to quantitatively assess the level of smartization in enterprises driven by Artificial Intelligence (AI). The model evaluates enterprises based on five key dimensions: AI adoption level, decision-making autonomy & adaptability, explainability & transparency, operational efficiency & business impact and sustainability contributions.

a) structure of the index

AIES-Index is calculated as a *weighted composite index* based on the five dimensions, each consisting of multiple measurable indicators. The overall index is computed using the following formula:

$$AESI = w_1M + w_2D + w_3B + w_4I + w_5S \quad (1)$$

where:

M is AI adoption level;

D is decision-making autonomy & adaptability;

B is explainability & transparency;

I is operational efficiency & business impact;

S is sustainability contributions.

Table 1

Key indicators for AI-Enterprise Smartization Index (AIES-Index)

Assessment category	Key indicators
AI adoption level	AI integration across business functions (e.g., manufacturing, HR, supply chain), automation percentage, investment in AI-driven processes, adoption of machine learning & AI decision support systems
Decision-making autonomy & adaptability	Share of AI-driven decisions vs. human decisions, AI adaptation speed, model update frequency, AI performance in dynamic environments, risk management & anomaly detection
Explainability & transparency	AI interpretability (SHAP/LIME), number of explainability case studies, user complaints about AI decision opacity, compliance with DARPA XAI guidelines, implementation of AI bias detection tools (e.g., fairness auditing models).
Operational efficiency & business impact	AI ROI, workforce productivity improvement, percentage of business processes automated by AI, supply chain optimization using AI, AI-driven customer service enhancements, financial performance impact of AI
Sustainability contributions	AI-driven resource consumption reduction, Reduction of carbon footprint through AI-powered optimizations, AI applications in circular economy strategies, AI-enhanced environmental impact monitoring

Source: Combination of indicators proposed by the authors

w_1, w_2, w_3, w_4, w_5 are weights assigned to each category based on their relative importance.

The sum of weights is 1:

$$w_1 + w_2 + w_3 + w_4 + w_5 = 1 \tag{2}$$

b) indicator selection and scoring

Each dimension is assessed using multiple indicators, normalized to a 0–100 scale, where 0 represents no AI-driven smartization and 100 represents full smartization.

c) normalization of scores

To ensure comparability across enterprises, raw values for each indicator are *normalized* using min-max scaling:

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \times 100 \tag{3}$$

where:

X_{norm} is normalized score (0–100 scale);

X is actual value of the indicator;

$X_{\max}$, $X_{\min}$ are maximum and minimum observed values in the dataset.

Min-max scaling ensures that all indicators fall within a standardized 0–100 range, allowing for direct comparability across enterprises. Alternative normalization techniques, such as z-score standardization, were considered but not implemented due to potential distortion in non-normally distributed data.

In the normalization process, $X_{\min}$ and $X_{\max}$ represent the minimum and maximum observed values for each indicator. These values can be derived from different reference points, depending on the scope of analysis. If the study aims to compare enterprises across an industry, $X_{\min}$ and $X_{\max}$ should be sourced from industry-wide benchmarks or publicly available datasets. Alternatively, for an enterprise-level assessment, normalization can be performed using historical company data or a peer group of similar enterprises. This approach ensures that the AI-Enterprise Smartization Index (AIES-Index) reflects both industry positioning and internal progress over time, making the assessment more adaptable to different business contexts.

Each category score is computed as the *weighted sum* of its indicators:

$$M = \sum_{i=1}^{n} w_i X_i \tag{4}$$

$$D = \sum_{i=1}^{n} w_i X_i \tag{5}$$

$$B = \sum_{i=1}^{n} w_i X_i \tag{6}$$

$$I = \sum_{i=1}^{n} w_i X_i \tag{7}$$

$$S = \sum_{i=1}^{n} w_i X_i \tag{8}$$

d) adjusted weight distribution

To reflect the varying importance of each dimension in enterprise smartization, the following weights are assigned:

$$AESI = 0{,}3M + 0{,}25D + 0{,}2B + 0{,}15I + 0{,}1S \tag{9}$$

where:

M (AI adoption level) — 30%: evaluates enterprise AI maturity and integration.

D (decision-making autonomy & adaptability) — 25%: measures AI-driven decision automation and adaptability.

B (explainability & transparency) — 20%: assesses AI interpretability and compliance with ethical standards.

I (operational efficiency & business impact) — 15%: quantifies AI's contribution to business performance.

S (sustainability contributions) — 10%: evaluates AI's role in reducing resource consumption and emissions.

Each category score is computed using a set of measurable indicators and weighted according to its significance. The weights assigned to the five AIES-Index categories (M = 30%, D = 25%, B = 20%, I = 15%, S = 10%) were determined based on expert evaluation involving specialists in AI implementation, digital transformation, and business strategy, using the methodology based on the expert evaluation method using a priori ranking and the concordance coefficient [19]. A panel of industry experts and academic researchers was consulted to assess the relative importance of each category in the enterprise smartization process. Their insights emphasized that AI adoption and data utilization (M & D) contribute the most to enterprise smartization, followed by business process optimization (B), while innovation & adaptability (I) and sustainability & ethics (S) play supportive roles in long-term transformation.

e) indicator selection and measurement

To ensure a structured assessment of AI-driven enterprise smartization, the AI-Enterprise Smartization Index AIES-Index) utilizes a set of quantifiable indicators, each weighted according to its relative significance. The determination of these weights was based on expert evaluation, incorporating insights from specialists in AI implementation, digital transformation, and business strategy. The methodology follows the a priori ranking method and concordance coefficient

Table 2

AI-Enterprise Smartization Index (AIES-Index) categories, indicators, and weights

Category	Indicator	Weight in Category
AI adoption level (M) — 30%	AI maturity level (0–5 scale)	35%
	AI investment in corporate strategy (percentage of company budget allocated to AI, presence of an AI-driven corporate strategy)	25%
	Number of AI-driven processes (number of business processes automated by AI, such as AI-powered document processing, AI in HR recruitment)	15%
	Use of AI Maturity Models (e.g., Gartner, McKinsey) (use of corporate AI assessment models for planning digital transformation)	10%
	AI-driven decision support systems implemented (existence of AI systems for demand forecasting, automated reporting, AI in financial analysis)	15%
Decision-making autonomy & adaptability (D) — 25%	% AI-driven decisions (vs. human decisions) (percentage of decisions made by AI without human intervention, such as automated loan approvals)	30%
	AI adaptation speed to new conditions (time required for AI systems to adapt to changes, e.g., updating recommendation algorithms)	30%
	AI model update frequency (how often AI models are updated, e.g., the number of times per year AI is retrained with new data)	15%
	AI performance in dynamic environments (AI's ability to make decisions in volatile conditions, e.g., AI in algorithmic trading or supply chain forecasting)	10%
	AI-enabled risk management & anomaly detection (use of AI for predicting operational risks, fraud detection in banking, cybersecurity monitoring)	15%
Explainability & transparency (B) — 20%	SHAP/LIME-based AI interpretability score (how well AI decisions can be explained using methods like SHAP and LIME)	35%
	Number of explainable AI case studies published (number of published studies or reports on AI explainability, e.g., in corporate ESG reports)	35%
	User complaints about AI decision opacity (number of complaints from users regarding "unexplained" AI decisions, e.g., rejected applications without reasoning)	20%
	Compliance with DARPA XAI guidelines (alignment of AI systems with DARPA Explainable AI standards, e.g., use of interpretable machine learning techniques)	10%
Operational efficiency & business impact (I) — 15%	AI ROI (Return on Investment)	40%
	AI-driven workforce productivity improvement (increase in employee productivity due to AI, e.g., reducing time spent on task processing)	30%
	% of business processes automated by AI (e.g., AI chatbots in customer support)	20%
	AI's impact on financial performance (AI's effect on revenue growth, cost reduction, e.g., AI in inventory management)	10%
Sustainability contributions (S) — 10%	AI-driven reduction in resource consumption (reduction in water, electricity, and raw material usage through AI, e.g., AI optimizing energy consumption in factories)	35%
	AI's role in carbon footprint reduction (decrease in CO_2 emissions due to AI, e.g., AI in logistics to optimize vehicle routes and reduce mileage)	35%
	AI applications in circular economy strategies (use of AI for waste recycling, AI-driven waste management in industrial enterprises)	15%
	Sustainability reports mentioning AI-driven improvements (presence of AI initiatives in sustainability reports, e.g., AI for emissions monitoring in ESG disclosures)	15%

analysis, ensuring a balanced representation of critical AI-driven factors.

The detailed structure of AIES-Index categories, indicators, and assigned weights is presented in Table 2, outlining the key measurable dimensions that contribute to evaluating AI-driven enterprise smartization.

f) calculation methodology

Each category score is computed using a weighted sum of normalized indicators:

$$M = \left(0.35X_1 + 0.25X_2 + 0.15X_3 + 0.10X_4 + 0.15X_5\right) \quad (10)$$

$$M = \left(0.30X_1 + 0.30X_2 + 0.15X_3 + 0.10X_4 + 0.15X_5\right) \quad (11)$$

$$M = \left(0.35X_1 + 0.35X_2 + 0.20X_3 + 0.10X_4\right) \quad (12)$$

$$M = \left(0.40X_1 + 0.30X_2 + 0.20X_3 + 0.10X_4\right) \quad (13)$$

$$M = \left(0.35X_1 + 0.35X_2 + 0.15X_3 + 0.15X_4\right) \quad (14)$$

e) interpretation of AIES-Index scores

To ensure a clear understanding of how enterprises can be evaluated using the AIES-Index, the scoring system is structured into five levels based on the degree of AI-driven smartization. Each level reflects the extent to which AI is integrated into business processes, ranging from full AI adoption and autonomy to minimal or no implementation.

Table 3 presents the interpretation of AIES-Index scores, categorizing enterprises according to their AI integration level and describing the corresponding characteristics of each stage. This classification helps businesses, policymakers, and researchers assess the maturity of AI adoption and identify areas for further improvement.

3. Results and Discussion

3.1. Justification for the five categories in the AIES-Index model

The AI-Enterprise Smartization Index (AIES-Index) was developed to provide a comprehensive, multidimensional assessment of how AI contributes to enterprise smartization. The model is structured around five key categories, each selected based on its direct impact on AI-enabled business transformation:

1. AI adoption level *(30% weight)*

Why it was chosen: AI adoption is the foundational factor of smartization, determining how extensively AI is integrated into enterprise functions.

Key differentiator: unlike existing maturity models (e.g., Gartner AI Maturity Model, McKinsey AI Capability Model), AIES-Index quantifies AI adoption not only through organizational maturity but also through tangible investments and decision support system implementations.

2. Decision-making autonomy & adaptability *(25% weight)*

Why it was chosen: enterprises that successfully implement AI must demonstrate autonomous decision-making capabilities and adaptability to changing market conditions.

Key differentiator: most existing AI assessment models focus on task automation but overlook AI's self-learning adaptability — AIES-Index uniquely evaluates AI's ability to make independent, dynamic decisions and adjust in real time.

3. Explainability & transparency *(20% weight)*

Why it was chosen: as AI adoption increases, regulatory compliance and public trust depend on how explainable and interpretable AI-driven decisions are.

Key differentiator: unlike ISO/IEC AI governance frameworks that mainly focus on policy compliance, AIES-Index measures practical implementation of explainability techniques such as SHAP, LIME, and DARPA XAI compliance.

4. Operational efficiency & business impact *(15% weight)*

Why it was chosen: AI's primary business value lies in improving efficiency, cost savings, and overall performance.

Key differentiator: traditional AI impact assessments (e.g., AI ROI models from PwC, Accenture) focus solely on financial return — AIES-Index extends beyond ROI to include business process automation, productivity gains, and AI-driven supply chain optimizations.

5. Sustainability contributions *(10% weight)*

Why it was chosen: sustainability should be the fundamental principle of modern business, influencing long-term competitiveness, regulatory compliance, and corporate social responsibility. AI is increasingly leveraged to enhance sustainability by optimizing resource consumption, reducing environmental impact, and driving circular economy strategies..

Key differentiator: most AI assessment models overlook sustainability as a core business factor — AIES-Index uniquely integrates AI's role in energy efficiency, carbon footprint reduction, and sustainable innovation, ensuring alignment with ESG (Environmental, Social, and Governance) objectives and future-oriented business strategies.

Table 3

Interpretation of AIES-Index scores

AIES-Index score	Smartization level	Description
80–100	Fully smartized enterprise	AI is fully integrated, autonomous, and adaptive.
60–79	Advanced smartization	AI optimizes business processes with significant automation.
40–59	Intermediate smartization	AI adoption is moderate, digital transformation is ongoing.
20–39	Basic smartization	Early-stage AI adoption, limited business impact.
0–19	No smartization	No significant AI implementation in the enterprise.

Table 4

Comparison with existing AI assessment models

Model	Focus	Key Limitation	AIES-Index's Advantage
Gartner AI Maturity Model	AI adoption in business strategy	Lacks quantifiable impact metrics	AIES-Index incorporates measurable AI-driven decision-making and efficiency indicators
McKinsey AI Capability Model	AI maturity in organizations	Does not assess AI sustainability contributions	AIES-Index includes AI's role in carbon footprint reduction & circular economy
ISO/IEC 42001 AI Management System	AI governance & risk management	Does not evaluate business efficiency or decision autonomy	AIES-Index integrates AI-driven operational impact & adaptability
PwC AI ROI Framework	Financial return on AI investment	Limited to financial metrics, ignores business process automation	AIES-Index assesses *both financial and operational AI efficiencies*
OECD AI Policy Observatory	AI regulatory compliance & ethics	Does not measure AI adoption levels in enterprises	AIES-Index includes *AI investment levels & integration maturity*

3.2. Comparison with existing AI assessment models

To further validate the need for AIES-Index, a comparative analysis of existing AI assessment models was conducted. As shown in Table 4, each existing model focuses on a specific aspect of AI implementation, while AIES-Index integrates multiple dimensions to offer a holistic perspective on AI-driven enterprise smartization.

3.3. Discussion and key findings

The comparative analysis highlights the limitations of existing AI assessment models and demonstrates how AIES-Index provides a more holistic evaluation framework. Specifically:

1. Bridging the gap between AI maturity and business impact:
– while models like the Gartner AI Maturity Model focus on strategy, they fail to quantify AI's actual impact on business operations.
– AIES-Index addresses this gap by integrating measurable indicators of AI-driven efficiency, adaptability, and decision-making.

2. Incorporating sustainability as a key factor:
– unlike existing models that do not consider AI's environmental contributions, AIES-Index includes sustainability metrics, ensuring alignment with modern ESG requirements.

3. Enhancing AI transparency and governance:
– many existing models prioritize policy-level compliance, whereas AIES-Index provides practical, measurable indicators for AI explainability and fairness, making it more applicable to real-world AI deployments.

The findings suggest that AIES-Index provides a more comprehensive and future-oriented approach to AI-driven enterprise smartization. By integrating AI adoption, decision autonomy, explainability, business impact, and sustainability, the AIES-Index model enables enterprises to:
– quantify AI integration beyond traditional maturity scales;
– improve AI decision-making and adaptability;
– ensure transparency and regulatory compliance;
– maximize business efficiency and ROI;
– leverage AI for long-term sustainability and ESG goals.

This multi-dimensional approach makes AIES-Index a unique and practical tool for enterprises looking to evaluate and enhance their AI-driven transformation.

4. Conclusions

This study introduces the AI-Enterprise Smartization Index (AIES-Index) as a comprehensive framework for assessing the impact of AI on enterprise transformation. The AIES-Index model integrates five key dimensions — AI adoption, decision-making autonomy, explainability, operational efficiency, and sustainability — providing a holistic evaluation of AI-driven smartization.

Key findings:

1. AIES-Index offers a multi-dimensional assessment that surpasses traditional AI maturity models, which often focus only on strategy, financial returns, or governance.

2. The model quantifies AI adoption beyond theoretical frameworks, incorporating real business investments, automation levels, and AI-supported decision-making processes.

3. AI transparency and explainability are critical for trust and regulatory compliance, making AIES-Index valuable for enterprises navigating AI governance challenges.

4. Operational efficiency and business impact indicators enable enterprises to measure tangible benefits from AI implementation, such as productivity gains and process automation.

5. AIES-Index uniquely integrates sustainability metrics, emphasizing AI's role in resource optimization, carbon footprint reduction, and ESG compliance, a factor missing in many existing models.

Future research directions. While the AIES-Index model presents a structured methodology for evaluating AI-driven smartization, further research is required to validate its effectiveness in real-world applications.

1. Empirical validation. Future research will focus on testing and validating the AIES-Index model on

real enterprise data across various industries, ensuring its practical applicability.

2. Sensitivity analysis. A critical aspect of future work will be conducting a sensitivity analysis to assess how changes in individual indicators (e.g., AI adoption level, sustainability contributions) influence the overall AIES-Index score. This will help refine the model and improve its robustness.

3. Industry-specific adjustments. Different industries may require customized weighting of AIES-Index categories, as the role of AI varies across sectors such as manufacturing, finance, healthcare, and logistics.

Thus, the AIES-Index model provides a structured and quantifiable approach to evaluating enterprise smartization, offering a valuable tool for businesses, policymakers, and researchers seeking to understand and optimize AI-driven transformations. By integrating AI maturity, decision autonomy, transparency, efficiency, and sustainability, AIES-Index serves as a forward-looking assessment framework that aligns with modern technological, economic, and environmental challenges. Future empirical testing will further refine and validate its applicability in dynamic business environments.

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ВПЛИВ ШТУЧНОГО ІНТЕЛЕКТУ НА СМАРТИЗАЦІЮ ПІДПРИЄМСТВ

Анотація. *Зростаюча роль штучного інтелекту (ШІ) у трансформації підприємств потребує розробки комплексних моделей оцінювання, які охоплюють повний спектр впливу ШІ на процеси смартизації. У цьому дослідженні представлено індекс смартизації підприємств на основі ШІ (AIES-Index) — структуровану методику оцінки рівня впровадження ШІ за п’ятьма ключовими напрямами: рівень впровадження ШІ, автономність прийняття рішень, пояснюваність та прозорість, операційна ефективність та внесок у сталість. На відміну від існуючих моделей зрілості ШІ, які здебільшого зосереджені на стратегічних або фінансових аспектах, AIES-Index інтегрує кількісні метрики, що вимірюють реальний вплив ШІ на бізнес-операції, процеси ухвалення рішень та ініціативи сталого розвитку.*

Методологія дослідження базується на багатокритеріальному ваговому індексному підході, де кожна категорія отримує певну вагу залежно від її значущості у процесах смартизації. Використання методу нормалізації min-max забезпечує можливість порівняння між підприємствами, що дозволяє об’єктивно проводити бенчмаркінг. Для підтвердження унікальності моделі проведено порівняльний аналіз існуючих підходів до оцінки ШІ, який демонструє переваги AIES-Index у вимірюванні адаптивності ШІ, його прозорості та відповідності ESG-критеріям, що часто ігнорується в традиційних моделях оцінки ШІ.

Результати дослідження показують, що AIES-Index забезпечує більш комплексне та кількісно вимірюване оцінювання смартизації підприємств на основі ШІ, інтегруючи як фінансові, так і нефінансові показники. Модель підкреслює значущість ШІ у підвищенні операційної ефективності, оптимізації бізнес-процесів, покращенні пояснюваності та розвитку інновацій у сфері сталого розвитку. Одним із ключових висновків є те, що прозорість ШІ та його автономність у прийнятті рішень є критичними факторами, які впливають на масштабне впровадження ШІ на підприємствах та їх відповідність нормативним вимогам.

Подальші дослідження будуть спрямовані на апробацію моделі AIES-Index на реальних даних підприємств для перевірки її практичної застосовності у різних галузях. Крім того, буде проведено аналіз чутливості моделі, який дозволить оцінити вплив змін окремих показників на загальний індекс AIES-Index. Це сприятиме підвищенню точності та гнучкості моделі в умовах динамічного бізнес-середовища.

Запропонований індекс AIES-Index є цінним інструментом для підприємств, політиків та науковців, оскільки надає структурований підхід до оцінки впливу ШІ на бізнес-процеси та водночас забезпечує відповідність сучасним вимогам управління, етики та сталого розвитку.

Ключові слова: *Індекс смартизації підприємств на основі ШІ (AIES-Index), штучний інтелект (ШІ), смартизація, автономність прийняття рішень, пояснюваність та прозорість, операційна ефективність.*