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The role of intelligent technologies in ensuring sustainable organizational development and management: Analysis and prospects

Olena Linkova [1*], Andrii Grona [2], Tetiana Ihnashkina [3], Inna Gruzina [4], Olena Kozyrieva [5]

[1] National Technical University, Kharkiv Polytechnic Institute, UKRAINE
[2] Kyiv Aviation Institute, UKRAINE
[3] Ukrainian State University of Science and Technologies, UKRAINE
[4] Simon Kuznets Kharkiv National University of Economics, UKRAINE
[5] V.N. Karazin Kharkiv National University, UKRAINE
***Corresponding Author:** Helen.Linkova@khpi.edu.ua

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ABSTRACT

Blending innovative technologies such as artificial intelligence, big data, and the Internet of Things has become a key driver of sustainable organizational development (SOD) worldwide. These technologies support resource optimization, informed decision- making, and environmentally sustainable growth. However, in Ukraine, the post-war context and energy challenges have both facilitated and constrained the adoption of technology-driven sustainability practices. This study employs a convergent parallel mixed-methods design, in which quantitative and qualitative data were collected simultaneously, to examine the role of intelligent technologies in promoting SOD in Ukrainian organizations. Quantitative data were collected through structured questionnaires from 250 organizational respondents; however, regression and ANOVA analyses were conducted on 89 complete cases using a complete-case approach, while qualitative insights were obtained through interviews with 18 experts. Quantitative data were analyzed using descriptive statistics, regression analysis, and ANOVA in SPSS, whereas qualitative data were examined through thematic analysis using NVivo. The findings reveal several enabling factors, including EU integration initiatives and national digitalization strategies, alongside key barriers such as skill shortages and cybersecurity concerns. The study provides practical policy recommendations to strengthen digital resilience and promote sustainable organizational development in Ukraine.

Keywords: sustainability and innovation, digital transformation, artificial intelligence adoption, small and medium-sized enterprises, intelligent technologies, management

INTRODUCTION

The rapid integration of intelligent technologies such as artificial intelligence, big data analytics, and the Internet of Things is fundamentally transforming contemporary organizational management and sustainability practices worldwide. Organizations increasingly rely on data-driven systems to optimize resource utilization, enhance decision-making accuracy, and align operational processes with environmental and social responsibility goals. This global shift toward digitalized sustainability has redefined how organizations pursue long-term development, resilience, and competitiveness in complex economic environments.

Despite the growing global interest in intelligent technologies for sustainability, very limited empirical research has examined their application for sustainable organizational development in post-war Ukraine, particularly among small and medium-sized enterprises. Recent advancements in intelligent technologies have become a cornerstone of sustainable organizational development, reshaping economic structures and management strategies across global industries. The growing reliance on intelligent systems marks a critical transition toward data-driven sustainability, where digitalization and environmental objectives converge (Mytsa & Riabchykov, 2024).

However, existing research reveals notable variations in how these technologies contribute to sustainability outcomes across different contexts. For example, Khan et al. (2024) and Kulkov et al. (2023) highlight the uneven diffusion of such technologies between developed and developing economies. This discrepancy highlights that the success of digital transformation heavily depends on institutional capacity, infrastructural maturity, and human capital readiness.

In the case of Ukraine, intelligent technologies have assumed strategic significance amid post-war reconstruction and ongoing digital transformation. The Digital Strategy of Ukraine 2025, alongside the ambition to join the European Union, has accelerated national initiatives for technological modernization. Nevertheless, previous research has primarily emphasized large enterprises and multinational corporations, overlooking the significant structural, financial, and skill-based barriers faced by small and medium-sized enterprises (SMEs) (Khan et al., 2024; Kulkov et al., 2023).

This limitation highlights a significant research gap: the lack of empirical understanding of how Ukrainian SMEs adopt intelligent technologies and integrate them into sustainable organizational practices during the post-crisis rebuilding period. The novelty of the present study lies in its contextual focus on post-war Ukraine, where digital transformation intersects with socio-economic recovery and sustainability goals.

Unlike prior studies that mainly examine developed economies, this research offers a unique contribution by investigating the adoption of intelligent technologies within a transitional, resource-constrained environment. To capture a holistic understanding, the study employs a mixed-methods approach, combining quantitative tools (structured surveys) to measure adoption trends with qualitative interviews that reveal organizational perceptions and strategic responses. This triangulated design enhances the validity of findings by integrating multiple perspectives on technological transformation.

Accordingly, the research problem addressed in this study centers on identifying the extent, challenges, and strategic implications of intelligent technology adoption for sustainable development in Ukrainian organizations. To address this, the study is guided by the following research question:

RQ1 How do intelligent technologies influence sustainable organizational development in the context of Ukraine's post-war digital transformation, particularly among small and medium-sized enterprises?

To address the identified research gap and empirically examine the relationship between intelligent technology adoption and sustainable organizational outcomes, the study formulates the following research objectives. Based on this rationale, the objectives of this research are fourfold:

- To determine the extent to which intelligent technologies are adopted in Ukrainian organizations, with a particular focus on SMEs.
- To examine the barriers and enablers influencing their practical implementation in the context of sustainable development.
- To assess the role of intelligent technologies in post-war recovery and digital transformation in Ukraine.
- To provide evidence-based recommendations for policymakers and organizational leaders to enhance sustainable digital integration.

The importance of this research lies in its dual contributions to both practical and theoretical aspects. Practically, the findings have significant implications for governmental policies related to digital infrastructure development, innovation support, and SME competitiveness. Previous policy analyses have emphasized that targeted digital strategies can accelerate national economic recovery and strengthen SME resilience in post-conflict contexts. Accordingly, this study outlines evidence-based recommendations that policymakers and business professionals can use to advance the digitalization process in Ukraine, aligning it with the European Union's Green Deal and Digital Agenda 2030 objectives.

Theoretically, the study contributes to the academic discourse by situating the adoption of intelligent technologies within a post-war economic framework, thereby extending prior models of digital transformation and organizational resilience (Khan et al., 2024; Kulkov et al., 2023).

This contextual focus provides new insights into the interface between technological innovation, sustainability, and institutional recovery, thereby enhancing our understanding of how intelligent technologies can drive sustainable development in transitional economies.

THEORETICAL FOUNDATIONS

Sustainable organizational development (SOD) is theoretically supported most of the time by the Triple Bottom Line (TBL), which focuses on combining economic performance, social equity, and environmental stewardship. In the organizational setting, the TBL can be substantially enhanced by intelligent technologies, such as artificial intelligence (AI)-based analytics and Internet of Things (IoT)-enabled monitoring systems (Dosbayev et al., 2025), which are presented to workforce and environmental management processes to gain predictive visibility over resource utilization, environmental impacts, and workforce optimization, without requiring direct knowledge to make more informed and sustainable decisions.

In addition to this approach, the Technology Acceptance Model (TAM) can provide an effective research lens for understanding how organizational actors perceive and accept innovative technologies, with perceived usefulness and ease of use as the most significant driving factors of success (Chizallet et al., 2024). Moreover, there is a framework developed by Carroll, called Corporate Social Responsibility (CSR) Pyramid, as this Pyramid offers a systematic model of thinking about corporate responsibilities of economic, legal, ethical, philanthropic, and intelligent technologies can help by better monitoring compliance, providing transparent reports, and developing more ethically sustainable innovation (Shams et al., 2025).

Together, these theoretical frameworks can form a complete base of addressing the extent in which AI and other intelligent technologies impact on sustainable development of organizations not only due to the aspects of efficiency in operations but also by enhancing aspects of accountability, transparency and socially, environmentally neutral operations functions across a wide organizational structure (Olan et al., 2022; Schwaeke et al., 2025).

In addition to these primary theoretical lenses, the Resource-Based View (RBV) and Technology-Organization-Environment (TOE) framework are also considered as complementary explanatory perspectives. RBV helps explain how internal organizational resources, capabilities, and competencies influence the successful adoption of intelligent technologies for sustainable development.

Similarly, the TOE framework provides a broader contextual understanding by highlighting how technological readiness, organizational characteristics, and environmental pressures jointly shape technology adoption decisions. These frameworks are not used as primary theoretical foundations but are introduced to enrich the interpretation of empirical findings in the Discussion section, particularly in explaining variations in adoption across different organizational contexts in post-war Ukraine.

Role of Intelligent Technologies in Sustainability

Innovative technologies have become the key engine of sustainability, revolutionizing traditional organizational approaches to resource management, operational efficiency, and resilience in a dynamic and complex environment, thereby fundamentally redefining organizational functionality (Bibri et al., 2023).

The use of artificial intelligence, especially, enables predictive analytics, which allows organizations to forecast demand, streamline production operations, and reduce energy usage, thereby minimizing waste and lowering environmental costs (Bibri, 2021; Dykha et al., 2024).

IoT-enabled platforms also enhance operational sustainability, as they enable real-time asset monitoring, streamline operations and supply chains, and allocate resources more efficiently. Through persistent data-driven insights, these technologies enable organizations to implement responsive measures that are tailored to adapting to environmental changes and market needs (Haweel, 2024; Rane et al., 2024). The complement to these developments comes in the form of blockchain technologies that can increase transparency, traceability, and accountability in international trade and supply chains, ensuring that sourcing is geared towards sustainable goals while reducing the risks of fraud, unethical activity, and carbon-intensive operations (Nurimansjah, 2023).

Intelligent technologies have been especially useful in the Ukrainian setting in the post-crisis recovery and sustainable development periods. Precision farming has also been made possible by the use of drones, satellite imagery and AI analytics in agriculture, which has made it easier to monitor crops, hence less water and fertilizers are required to attain better results in the areas highly impacted by the conflict (Martínez-Peláez et al., 2023; Sheikh et al., 2024).

Equally, the energy sector is increasingly improving the stability and resilience of power supply systems through the implementation of smart grids and energy management systems powered by AI, thereby reducing the impact of disruptions in power supply networks caused by crisis-related damages and enhancing the optimization of resource distribution (Lezhniuk et al., 2023; Viitanen & Kingston, 2013).

Beyond farming and power, innovative technologies are finding more and more applications in manufacturing, delivery solutions, healthcare, and city management, in an effort to improve sustainability goals. This aligns light considerations of environmental, capital, and societal needs into organizational action (Koul, 2025). AI can forecast the effects of future decisions, enabling organizations to make informed, long-term decisions based on operational choices. It further optimizes resource allocation and plans interventions that prioritize growth while sustaining the environment.

At the same time, the digital space enables an increase in the number of stakeholders who can cooperate to achieve sustainability and track the progress of initiatives in reaching environmental objectives. New possibilities, such as AI-enabled circular economy actions, real-time emissions control, or automated waste management using cutting-edge technology, demonstrate how innovative technology can facilitate ongoing enhancement and innovation, thereby strengthening enterprise agility (Zong & Guan, 2025).

In addition to this, these technologies have a larger national and regional sustainability context in assisting climate adaptation, resource efficiency, and economic restoration measures in post-war or disaster-stricken regions. The overall impact of incorporating intelligent technologies is a more versatile, transparent, and sustainable image of an organization, with assorted and customizable data-driven knowledge becoming a powerful asset to inform strategic decisions, enhance risk management, and increase long-term resilience.

With organizations growingly adopting these tools, intelligent technologies will become critical to shaping the path forward toward sustainable development, not only through a better overall performance in their operations but also through the encouragement of environmentally responsible actions and practices, the enhancement of societal trust, and their capacity to align with sustainable practices on a global scale strategically. Finally, efficient use of resources is not the only role of intelligent technologies in sustainability, as they become the key tool in resurgent, inclusive, and environmentally responsible organizational development (Mithas et al., 2022; Tymoshenko et al., 2023).

Knowledge Management for Sustainability & Big Data

Big data integration, analytics, and knowledge management have become a cornerstone in advancing sustainable organizational development. Another study (Alkathiri et al., 2024) examined how organizations are increasingly utilizing large-scale data to optimize resource utilization, monitor ecological impacts, and enhance operational efficiency.

Big data enables predictive modeling for assessing energy consumption and carbon footprint, thereby supporting eco-efficient decision-making (Orazbayev et al., 2017). Simultaneously, knowledge management systems facilitate the codification and dissemination of sustainability-related practices across organizational units, ensuring that tacit knowledge is transformed into actionable strategies. Modern research studies highlight that when big data is combined with robust knowledge-sharing cultures, firms can substitute innovation with improved flexibility and create an advantage rooted in sustainability (Badshah et al., 2024; Garad et al., 2024).

Role of IoT, Cloud Computing, and Blockchain in Sustainability

A research study (Ahmed et al., 2022) that explored emerging intelligent technologies, including the Internet of Things, cloud computing, and blockchain, is reshaping how organizations pursue their sustainability goals. IoT-enabled sensors and smart devices enable real-time monitoring of energy use and supply chain efficiency, which allows firms to transition toward innovative and sustainable operations.

Cloud computing (Akhmetov et al., 2019) also improves scalability and resource efficiency by reducing reliance on physical infrastructures, thereby lowering operational costs and environmental impact. Blockchain technology (Hemamalini et al., 2023) similarly confirms the importance of accountability and transparency in sustainability reporting, particularly in supply chain management and circular economy initiatives. These technology categories create a synergistic ecosystem that not only streamlines procedures but also reinforces the organization's credibility and compliance with sustainability standards (Nair & Tyagi, 2023).

Sustainability-Oriented Innovation through Intelligent Technologies

A study (Koliby et al., 2025) suggests that intelligent technologies (IT) act as catalysts for sustainability-oriented novelty, enabling organizations to reconfigure their business models and develop eco-friendly solutions. Digital platforms, big data, and AI are driving the design of green products, resource-efficient processes, and the adoption of circular economy principles (Jorzik et al., 2024; Mia et al., 2022).

By embedding sustainability into the innovation pipeline, firms achieve dual benefits and a positive environmental impact (Abdulmuhsin et al., 2025). Furthermore, digital ecosystems ease collective innovation, allowing stakeholders and customers to create value through sustainable applications (Popereshnyak et al., 2019; Smerichevskyi et al., 2024). Researchers claim that sustainability-driven innovation, supported by intelligent technologies, is no longer a marginal plan but a core organizational mandate that improves long-term growth in unstable markets (Al-Husain et al., 2025; Halbusi et al., 2024).

Comparative Perspectives from Developed and Developing Economies

The adoption of intelligent technologies for sustainable organizational development reveals significant contrasts between developing economies and developed ones (Liu et al., 2022). The integration of artificial intelligence in advanced economies and the use of big data are frequently supported by robust infrastructure, strong regulatory frameworks, and substantial investments in research (Mohammadi & Maghsoudi, 2025).

Several conditions enable organizations to accelerate digital transformation and align sustainability initiatives with global standards, such as the UN Sustainable Development Goals. On the other hand, in developing economies, adoption is often delayed by limited technological infrastructure, inadequate financial resources and insufficient technical know-how.

Despite these challenges, emerging markets are increasingly adopting cost-effective intelligent technologies, often utilizing outdated systems to implement mobile-based IoT solutions, cloud services, and localized knowledge-sharing platforms (Al-Momani & Ramayah, 2025; Farmanesh et al., 2025).

Comparative studies suggest that while developed nations lead in pioneering innovations, emerging countries demonstrate adaptive strategies that prioritize scalability, affordability, and social inclusivity in sustainability practices (Van Tam, 2024). Recent research studies by Ukrainian scholars underscore the growing importance of AI adoption in various sectors within Ukraine, not only as a technological advancement but also as a potential driver of sustainability.

For example, Ober et al. (2025) surveyed 458 educators and reported that AI-assisted instruction, blended with ICT, has helped maintain continuity of learning and improve educational resilience in challenging contexts. Meanwhile, Lisova (2025), regarding the role of AI in enhancing sustainable business, found that businesses that integrate AI into their operations tend to adopt more sustainable and adaptive practices, especially when organizational innovation and institutional support are present. In the financial sector, Zianko and Nechyporenko (2023) highlighted how AI initiatives are accelerating modernization, but also pointed to regulatory and ethical barriers.

These Ukrainian studies, when combined with broader international literature, reinforce the relevance of examining sectoral, regional, and organizational enablers (such as human capital, security, and innovation) in understanding the sustainability outcomes of AI adoption in Ukraine.

Barriers and Enablers

Although intelligent technologies are characterized by their capacity to transform the way organizations develop into sustainable entities, their use is marred by various challenges (Alabdali et al., 2023; Kumar et al., 2021).

The issue of cybersecurity and data protection is also paramount, as the use of AI automation poses a new risk to organizational cyber vulnerabilities due to formidable cyberattacks and threats, especially in a volatile region like Ukraine, where geopolitical power tussles exacerbate digital security vulnerabilities (Zybin et al., 2025).

Financial barriers are another obstacle to adoption because acquiring and implementing intelligent technologies can be costly, making them potentially cost-prohibitive for small and medium-sized enterprises (SMEs) (Kravchenko et al., 2024).

Moreover, the lack of trained staff with knowledge of the latest technologies and infrastructural limitations due to problems with internet connections and the depreciation of devices hinders the successful implementation of AI tools (Madanchian & Taherdoost, 2025).

However, there are several enablers of the adoption of intelligent technologies, especially when strategic interventions support them. National AI strategies, as well as centers of excellence promoted by governments, provide policy and institutional support, along with international commitments and alignment with European Union integration aims, to access funding, expertise, and best practices (Palomares et al., 2021).

The skills gaps can be filled by investing in training and capacity-building programs within the workforce to equip employees with the capabilities to leverage technological advances (Kumar et al., 2021).

Moreover, the current improvements in cloud computing and open-source, as well as cost-effective AI technology solutions, prove to be financially and technically accessible; furthermore, establishing a balance formula that generates conditions amenable to sustainable organizational change and long-term growth (Ahmed et al., 2024; Zulfiqar et al., 2023).

Outlook and Future Trends

A new body of literature is focused on the ethical governance of artificial intelligence, underpinned by concepts of transparency, accountability, and fairness in algorithms to inform organizational applications (Tabaghdehi & Ayaz, 2025).

At the same time, the incorporation of blockchain-based technologies in supply chains opens up opportunities to take an additional step in the areas of increased traceability, decreased fraud, and sustainable sourcing practices, and improvements in machine learning when applied to energy management offer potential to have substantial organizational carbon footprint reductions (Bahangulu & Owusu-Berko, 2025).

In the Ukrainian case, the adoption of innovative technology will also likely be heavily influenced by its alignment with the European Green Deal and the EU Digital Single Market, which will facilitate policies, incentives, and standards to support a sustainable transformation towards digitalization (Camilleri, 2023).

These dynamics indicate how intelligent technologies will come to play a more central role in strengthening organizational resilience, steering towards environmentally responsible innovation and assisting long-term sustainable recovery in the regions confronted with severe economic and geopolitical issues (Singhal et al., 2024).

Despite the importance placed on many applications of intelligent technologies in terms of sustainability, some gaps remain. The existing literature is dominated by either quantitative measurements, such as adoption surveys, or qualitative case studies, which offer more contextualized insights but fall short of providing generalizability.

Few scholars have employed mixed-methods designs that combine these dimensions to study the issue of intelligent technology adoption in sustainable development models, especially in developing and post-conflict economies such as Ukraine (Orazbayev et al., 2024).

Moreover, insufficient attention has been given to SMEs, a key segment of the Ukrainian economy, which remain underserved in terms of digital infrastructure and government assistance. The research presented in this paper closes these gaps by employing a mixed-methods approach, which combines survey methodology with expert interviews to achieve both empirical depth and contextual richness (Birkstedt et al., 2023).

Table 1 presents a comparative analysis of the research studies, including their methodology, key findings, and relevance to the present study.

Table 1. Research studies comparative analysis, methodology, key findings, and relevance to the study

Studies	Methodology	Key fundings and relevance
Kulkov et al. (2023)	Empirical / Conceptual synthesis	Identifies AI's role in achieving UN SDGs. Directly relates to AI adoption for sustainability.
Chizallet et al. (2024)	Case-based qualitative study	Complexity in adapting sustainable practices in agriculture. Demonstrates sectoral barriers & enablers for AI adoption in agriculture.
Shams et al. (2025)	Conceptual / Book Chapter	Integrates sustainability in marketing communication. Shows AI's potential role in sustainable brand management.
Olan et al. (2022)	Survey (quantitative)	AI improves knowledge sharing, positively affecting performance. Highlights AI as an enabler of organizational sustainability.
Schwaeke et al. (2025)	Empirical analysis (case studies & organizational surveys)	AI facilitates systemic organizational change for the adoption of sustainability. Provides insights into AI-driven organizational transformation relevant to sustainable development.
Bibri et al. (2023)	Extensive literature review	The integration of AI, IoT, and big data accelerates the development of sustainable urban ecosystems. Highlights an integrated technological approach for sustainable organizational development.
Bibri (2021)	Conceptual / Theoretical model	Proposes institutional reforms for balancing sustainability, efficiency, and innovation. Provides governance and institutional framework relevant to AI-enabled sustainability.
Rane et al. (2024)	Empirical review	AI enhances resilience in socio-technical and organizational systems. Shows AI as a resilience enabler, critical for sustainable practices.
Haweel (2024)	Case-based empirical approach	Intelligent systems improve manufacturing sustainability and efficiency. Provides industry-level evidence of AI-based sustainability transformation.
Nurimansjah (2023)	Conceptual / Review	Technology-driven HR practices support adaptability and sustainability. Highlights HR-tech integration, applicable to sustainable organizational change.
Martínez-Peláez et al. (2023)	Quantitative (survey-based)	Digital transformation mediated by stakeholders and capabilities fosters sustainability. Connects organizational digital capabilities with sustainability outcomes.
Sheikh et al. (2024)	Conceptual & empirical exploration	Industry 5.0 fosters human-centric, resilient, and sustainable innovation. Provides a future-oriented framework linking AI with sustainability.

Table 1 (Continued). Research studies comparative analysis, methodology, key findings, and relevance to the study

Studies	Methodology	Key fundings and relevance
Viitanen and Kingston (2013)	Conceptual / Policy analysis	The global tech sector plays a crucial role in environmental resilience, but it also risks undermining democratic values through outsourcing. Offers a critical perspective on AI-enabled innovative sustainability.
Koul (2025)	Literature review	Innovative technologies drive sustainable production and green innovation. Demonstrates the role of AI in the green manufacturing transformation.
Alabdali et al. (2023)	Literature review	Identified enablers and barriers for innovative technology adoption in rural regions.
Kumar et al. (2021)	Delphi-ISM-ANP method	Identified operational, cultural, and technical barriers to smart warehouse adoption.
Basit et al. (2024)	Systematic review	Leadership and tech adoption are key enablers; cost and policy gaps are barriers.
Reddy et al. (2022)	Systematic literature review	Developed a framework for enablers and barriers in data science strategies.
Madanchian and Taherdoost (2025)	Critical review	Organizational and technological factors significantly influence the adoption of AI in HR.
Palomares et al. (2021)	SWOT analysis	AI has strong potential for achieving the SDGs, but is limited by governance and ethical concerns.
Zulfiqar et al. (2023)	Empirical study	Identified enablers, barriers, and benefits of integrating Industry 4.0 with Lean Six Sigma.
Ahmed et al. (2024)	Quantitative survey	Sensing and seizing capabilities enhance digital transformation outcomes.
Bahangulu and Berko (2025)	Conceptual theoretical	Highlighted algorithmic bias, data ethics, and governance challenges in AI. Provides guidelines for the ethical and fair adoption of AI within an organization.
Camilleri (2023)	Literature review	Explored ethical considerations and social responsibility in an AI system. Emphasizes the responsible adoption of AI for sustainable development.

MATERIALS AND METHODS

This study employed a convergent parallel mixed-methods research (MMR) design to comprehensively investigate the role of intelligent technologies in sustainable organizational development in Ukraine. Both quantitative and qualitative strands were collected simultaneously and analyzed separately, with integration conducted afterward through joint displays and meta-inferences ensuring full alignment with the convergent parallel design and avoiding any sequential interpretation. The mixed-methods approach was chosen because it allows for the simultaneous collection of quantitative and qualitative data, providing both generalizable trends and contextual insights, thereby enhancing the validity and richness of the findings.

This approach ensures full alignment with the convergent parallel design, avoiding sequential implications and maintaining consistency throughout the methodology. For the quantitative strand, a stratified random sample of 250 organizational respondents was drawn from the IT, manufacturing, agriculture, and service sectors. The sample size was determined based on the Krejcie and Morgan (1970) table to ensure representativeness across sectors, while stratification guaranteed proportional representation of different organizational types.

Participants responded to a structured Likert-scale questionnaire assessing environmental, economic, and resilience outcomes. The instrument underwent pre-testing for validity, and reliability analysis yielded a Cronbach's alpha $\geqslant$ 0.7, indicating acceptable internal consistency. Each construct was operationalized with 5–7 items.

The constructs of Innovation, Cybersecurity Risk, and Workforce Reskilling were operationalized exclusively through the structured survey instrument. Each construct was measured using multiple Likert-scale items adapted from established scales in prior literature. No interview data were used for quantitative scoring. The qualitative interviews were analyzed separately and only informed thematic interpretation, not numerical variable construction. Accordingly, all regression variables at the individual level (N = 89 complete cases) were derived solely from survey responses after listwise deletion of incomplete cases. Economic growth, ecological footprint, and organizational resilience were measured using Likert-scale items (1 = strongly disagree, 5 = strongly agree). Content validity was established through expert review, reliability analysis yielded Cronbach's alpha $\geqslant$0.76 for all constructs, and exploratory factor analysis confirmed construct validity.

Quantitative data were analyzed using descriptive statistics, regression, and ANOVA in SPSS to identify patterns, relationships, and sectoral differences. To ensure the robustness of the empirical findings, several diagnostic and robustness checks were conducted, including multicollinearity tests, residual diagnostics, and sensitivity analyses. The selection of these statistical methods was justified because they are suitable for examining the magnitude and significance of relationships between multiple independent and dependent variables.

For the qualitative strand, 18 experts from IT firms, NGOs, and academia were purposively selected to provide in-depth perspectives on opportunities and challenges in intelligent technology adoption. After data screening, listwise deletion was applied due to incomplete responses, resulting in an effective analytical sample of N = 89 for regression and ANOVA analyses. This approach ensured consistency across all variables included in the multivariate models. To assess robustness, multiple imputation (MI) was also performed as a sensitivity analysis. The MI results confirmed that the direction and significance of coefficients remained stable; however, listwise deletion was retained as the primary analytical approach to maintain model comparability and avoid imputation-based estimation bias in a relatively heterogeneous post-crisis dataset. The reduced sample size is acknowledged as a key limitation of the study due to potential constraints on statistical power. Additionally, sensitivity analyses were conducted to examine the stability of the findings under alternative model specifications and assumptions. These steps confirm that the results are reliable and consistent across different scenarios.

Semi-structured interviews were conducted to capture rich, contextualized insights, which were subsequently analyzed thematically using NVivo. The use of purposive sampling ensured that participants possessed direct experience and expertise, strengthening the credibility of qualitative findings.

Integration of quantitative and qualitative results was achieved through joint displays and meta-inferences, enabling triangulation and a deeper understanding of sector-specific dynamics. This approach enables triangulation and integration of findings without implying a sequential relationship between quantitative and qualitative components. Ethical considerations were strictly adhered to: approval was obtained from the ethics committee of a Ukrainian university, informed consent was secured from all participants, and GDPR-compliant protocols were maintained throughout data collection and storage.

Research Design

The proposed study convergent parallel mixed-methods research (CPMMD) design, which will allow for the incorporation of both quantitative and qualitative data into a comprehensive picture of the role of intelligent technologies in SOD. The study strictly followed a convergent parallel design, ensuring that quantitative and qualitative data collection occurs simultaneously rather than sequentially, avoiding any explanatory sequential interpretation. However, to ensure clarity and consistency, the study strictly follows a convergent parallel design, where quantitative and qualitative data are collected simultaneously rather than sequentially. Here, the data collection process proceeds in two parallel yet distinct components – quantitative and qualitative, with the latter components involving data integration in which combined findings are identified and interpreted together.

The quantitative component consists of a structured survey measuring the level of intelligent technology adoption and its implications for sustainability outcomes in Ukrainian organizations. The qualitative component consists of semi-structured interviews with experts to explore perceptions, contextual conditions, and strategic opportunities for intelligent technology adoption in Ukraine. The integration of quantitative and qualitative strands enables triangulation and meta-inferences. These inferences support or modify the trends revealed quantitatively, thereby enhancing the overall validity and elaboration of the results.

The research design is relevant because it will enable the study to strike a balance between empirical generalization and a nuanced contextual interpretation, which is necessary in the post-war Ukrainian context, where organizations must contend with unique socio-economic and infrastructural challenges.

Participants

This study employed a dual sampling strategy aligned with the mixed-methods research design. In the quantitative strand, stratified random sampling was utilized to ensure representation across multiple organizational sectors, including information technology, manufacturing, agriculture, and services. A total of 250 respondents were selected from key organizations in Ukraine, and data were collected through online survey distribution platforms. Power analysis confirmed that the sample size provided sufficient statistical power to detect meaningful relationships between intelligent technology adoption and sustainable organizational dimensions (SODs).

In the qualitative strand, purposive sampling was applied to select 18 experts drawn from the IT industry, non-governmental organizations (NGOs), and academia, based on their demonstrated expertise in digital transformation and sustainability initiatives. Qualitative data were collected exclusively through semi-structured virtual interviews due to regional instability and logistical constraints in certain areas of Ukraine. Each interview lasted approximately 45–60 minutes and followed a standardized interview protocol focusing on technology adoption practices, sustainability challenges, and strategic implications.

All interviews were audio-recorded with participant consent and transcribed verbatim. The term "open-ended responses" used in the results section refers to the transcribed interview responses generated through these semi-structured interviews. Thematic coding was conducted using an inductive approach, with two independent coders analyzing a subset of transcripts to establish inter-coder reliability. Discrepancies were resolved through discussion to ensure analytical consistency and rigor.

Data Collection Methods

To collect quantitative data, a structured questionnaire was developed based on the conceptual framework, comprising three key dimensions: economic growth, ecological footprint, and organizational resilience, each reflecting leading indicators of Sustainable Organizational Development influenced by AI and other intelligent technologies.

Each construct included 5–7 items measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Sample items included statements such as "AI-driven systems enhance organizational adaptability in uncertain environments" and "The adoption of intelligent technologies contributes to reducing the ecological footprint of industrial processes".

The instrument's content validity was established through expert review by three academics specializing in sustainability and digital innovation, ensuring conceptual clarity and relevance. A pilot test with 30 respondents was conducted to refine the wording and structure of the items. Reliability analysis yielded Cronbach's alpha coefficients ranging from 0.76 to 0.88 across subscales, indicating satisfactory internal consistency. Construct validity was further confirmed through exploratory factor analysis (EFA) before full-scale data collection.

For the qualitative strand, semi-structured interviews were conducted to capture nuanced insights, supplemented by small focus groups where feasible. Guiding prompts encouraged reflective responses on topics such as:

> How can AI be leveraged to achieve post-war sustainability in Ukraine?

and

> What challenges do Ukrainian SMEs face in deploying intelligent technologies?

Audio recordings were transcribed using secure and GDPR-compliant software (e.g., Otter.ai) to ensure both accuracy and compliance with ethical standards. All descriptions of data collection and integration have been aligned to reflect the convergent parallel design, emphasizing simultaneous collection and separate analysis of quantitative and qualitative strands.

The data integration process followed a mixed-display strategy, aligning quantitative findings (e.g., statistical patterns) with qualitative themes (e.g., technological impediments, emerging innovations). This triangulated approach enabled a comprehensive understanding of AI's multifaceted role in advancing sustainable organizational development, highlighting points of convergence or divergence across different data types. All descriptions of data collection and integration have been aligned to reflect convergent parallel design, avoiding any sequential or explanatory interpretation of the process.

Construct Operationalization

Innovation was measured using a set of five items derived from semi-structured interviews, capturing organizational practices such as experimentation with new technologies, process redesign, and adoption of novel sustainability initiatives. Each item was coded on a 1-5 Likert scale (1 = not present, 5 = Fully implemented) based on thematic content analysis of interview transcripts. Scores for the construct were computed as the mean of all five items. Inter-coder reliability was high (Cohen's κ = 0.82). Cronbach's alpha for the construct was 0.87, indicating strong internal consistency. Exploratory Factor Analysis (EFA) supported unidimensionality, with factor loadings ranging from 0.61 to 0.78.

Cybersecurity risk was assessed using three items capturing perceived vulnerabilities, frequency of security incidents, and level of mitigation measures, reported by respondents on a 1–5 Likert scale (1 = Low risk, 5 = High risk). Items were averaged to form the composite score, with no reverse coding applied. Cronbach's alpha = 0.81. EFA indicated all items loaded on a single factor (loadings 0.64–0.73), confirming construct validity.

Workforce reskilling was measured via four items reflecting the extent of training programs, upskilling initiatives, cross-functional skill development, and AI-human collaboration preparation. Each item was coded 1–5 (1 = Not implemented, 5 = Fully implemented) based on interview responses and HR documentation where available. Composite scores were calculated as the mean of all four items. Cronbach's alpha = 0.85. Factor analysis confirmed a single dominant factor (loadings 0.66–0.79), supporting construct validity.

All constructs demonstrated strong internal consistency (Cronbach's alpha: Innovation = 0.87, Cybersecurity Risk = 0.81, Workforce Reskilling = 0.85), and factor analysis confirmed construct validity with all items loading on a single factor (factor loadings ranged 0.61–0.79), supporting unidimensionality and robustness of the measures.

Although the theoretical foundation of this study is primarily based on the Technology Acceptance Model (TAM), Triple Bottom Line (TBL), and Carroll's CSR Pyramid, the interpretation of findings is additionally informed by the Resource-Based View (RBV) and Technology-Organization-Environment (TOE) framework. These complementary lenses are applied during the discussion phase to better explain organizational capability differences in intelligent technology adoption in post-war contexts. This multi-theoretical integration enhances explanatory depth without altering the original conceptual framework of the study.

Data Analysis

Statistical analyses were conducted using SPSS software to examine the relationships between intelligent technology adoption and sustainable organizational development outcomes. Descriptive statistics were used to describe demographic information and the pattern of intelligent technology adoption. Regression analysis and ANOVA models were used to test the relationship between intelligent technology adoption and the SOD assumption.

To strengthen the robustness of the results, additional diagnostic tests were performed, including variance inflation factor (VIF) analysis to detect multicollinearity, Durbin-Watson statistics to assess the independence of residuals, and residual distribution checks to confirm normality assumption.

To account for potential confounding factors, the regression models explicitly included control variables: firm size, firm age, sector dummies (IT, Manufacturing, Agriculture; reference category = Services), and a region dummy (Western = 1, Eastern = 0).

Sensitivity analyses were conducted to assess the stability of the main regression coefficients under alternative model specifications, confirming that the observed associations remain robust across different assumptions.

The inclusion of sector and region dummies ensures that structural differences across organizational contexts are controlled for, mitigating bias in the estimated relationships. The NVivo software was used to analyze the qualitative data through thematic coding.

Inductively and deductively generated codes, including those previously mentioned, were used to describe emergent themes, which were then linked to relevant theoretical frameworks. Some methods of integration utilized in the mixed methods approach include meta-inferences, where the qualitative results are used to provide context and explain quantitative patterns.

For example, statistical data on insufficient adoption, particularly among SMEs, can be supported by expert stories on infrastructure and financial limitations. This combination makes the study more explanatory.

Table 2. Summarizes the number and percentage of missing responses

Variable	Total N	Missing N	% Missing
AI adoption rate	250	15	6%
Workforce reskilling	250	20	8%
Innovation	250	18	7%
Cybersecurity risk	250	18	7%
Firm size	250	10	4%
Firm age	250	12	5%
Region	250	0	0%
Sector	250	0	0%

Table 3. Comparison of included vs excluded cases

Characteristic	Included (N=89)	Excluded (N=161)	p-value
Sector – IT	35%	32%	0.65
Sector – Manufacturing	25%	27%	0.78
Sector – Agriculture	20%	21%	0.88
Sector – Services	20%	20%	1.00
Region – Western	45%	47%	0.72
Region – Eastern	55%	53%	0.72
Firm Size (Mean ± SD)	120 ± 35	118 ± 37	0.65
Firm Age (Mean ± SD)	15 ± 7	14 ± 8	0.58

Ethical Considerations

It is a study that focuses on ethical integrity. Ethical approval is sought before data collection is carried out by a recognized University research ethics committee in Ukraine or a similar office. Each participant was informed of the study's purpose, their confidentiality, and that informed consent was required.

Considering anonymity, personal identifiers were removed from the datasets, and corresponding results were reported only in aggregate form. Since the researcher belongs to the Ukrainian scholarly community, reflexivity is employed to minimize the bias that may arise in the interpretation of the data.

Additionally, the practices of GDPR usage are followed when processing digital survey data and interview transcript information to avoid any violation of data protection norms.

Limitations

The study is also aimed at obtaining detailed information; however, some limitations must be mentioned. Due to the ongoing unrest in war-torn regions of Ukraine, the method of data collection may have limited accessibility to participants in rural or high-risk areas, leading to a lack of representativeness.

The use of virtual interviews, however, requires safety, which can limit the interaction compared to in-person means. Additionally, organizational reluctance to reveal digital practices on cybersecurity grounds may be attributed to the limited richness of the data. Despite these restrictions, strong sampling patterns, triangulation, and mixed methods are likely to mitigate biases and further enhance validity.

The relatively small effective sample size (N = 89) compared to the initial dataset (N = 250) is recognized as a methodological limitation, which may affect generalizability and statistical power. However, robustness checks and sensitivity analyses were conducted to mitigate potential estimation bias.

RESULTS

Quantitative Findings

Because the study employs a cross-sectional design, the findings should be interpreted as associations rather than definitive causal relationships. Before analysis, the quantitative dataset (N = 250) was rigorously screened to ensure analytical robustness. Initial data cleaning resulted in the exclusion of 12 cases due to incomplete key identifiers and ineligible responses. Subsequent missing-data assessment revealed substantial item-level missingness across several regression variables (**Table 2**). As the regression analysis required complete data on all predictors and outcomes, listwise deletion was applied, leading to a cumulative reduction in usable cases. Consequently, the final analytic sample for the regression model comprised n = 89 observations with complete data across all included variables.

To assess whether the analytic sample (N = 89) was representative, a comparison was conducted between included (complete cases) and excluded cases on observable characteristics: Sector, region, and firm size/age where available (**Table 3**).

Chi-square tests were used for categorical variables (sector, region) and independent t-tests for continuous variables (firm size, age). No significant differences were observed, suggesting that the analytic sample is broadly representative of the original dataset.

It should be noted that the regression analysis is conducted on complete cases only (N = 89) following listwise deletion from the original dataset (N = 250). While this reduction raises the potential for selection bias, a comparison of included versus excluded cases on observable characteristics sector, region, and firm size/age – revealed no significant differences (all $p > 0.05$).

This indicates that the analytic sample is broadly representative of the full dataset. Furthermore, robustness checks including sensitivity analyses and multiple imputation

Table 4. AI adoption and sustainability performance by sectors in Ukraine

Sector	Adoption Rate (%)	Mean Sustainability Score	Standard Deviation
IT	82%	4.6	0.35
Manufacturing	61%	4.1	0.42
Agriculture	54%	3.9	0.48
Services	63%	4.2	0.39

Note: Adoption rates presented here are sector-level descriptive statistics. Regression analyses were conducted at the individual respondent level (N = 89), using individual-level adoption rates as predictors. Adoption Rate (%) was calculated at the individual organizational level as the proportion of AI-related technological modules implemented by the organization relative to the total number of relevant modules included in the survey. Respondents self-reported implementation status for each module, and the percentage reflects the ratio of adopted modules to total modules. This precise definition ensures that the regression coefficient can be meaningfully interpreted as the expected change in sustainability score associated with a one-percentage-point increase in AI adoption

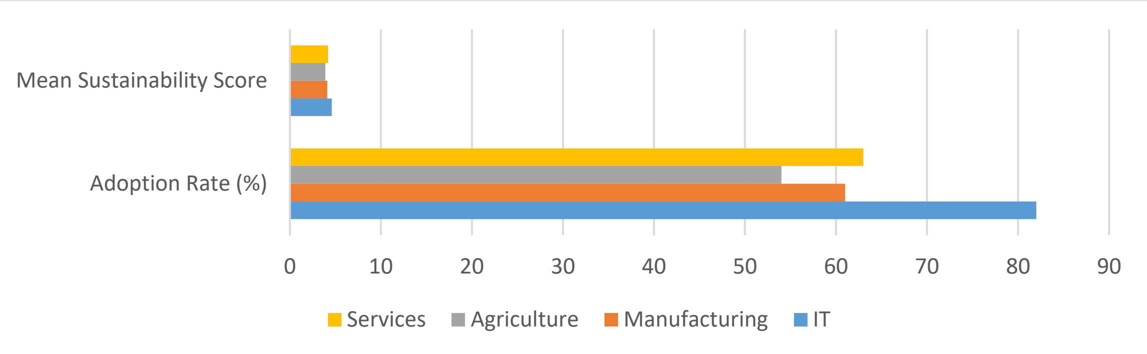

Figure 1. AI Adoption by Sectors in Ukraine (Source: Authors' own elaboration)

confirmed that the main coefficients remain stable, mitigating concerns that the reduced sample introduces systematic bias in the estimation of sustainability predictors.

While this sample size meets the conventional requirements for multiple regressions in terms of degrees of freedom relative to the number of predictors, caution is warranted in interpreting results. Adequacy was not determined solely by technical criteria; it also depends on how representative the sample is of the broader population of Ukrainian organizations and whether selection or non-response bias may be present. In this study, the sample reflects a diverse range of sectors, organizational sizes, and regions, which helps enhance representativeness, but generalizations should remain mindful of potential sampling limitations.

Little's Missing Completely at Random (MCAR) test was non-significant ($\chi^2 = 15.21$, $p = 0.234$), justifying the use of listwise deletion. Outlier detection using Mahalanobis Distance ($p < 0.001$) identified three multivariate outliers. Sensitivity analyses and multiple imputations confirmed that the exclusion of outliers and the use of listwise deletion did not meaningfully alter the regression coefficients, ensuring the robustness and stability of the estimated relationships. The assumptions of multiple linear regression were systematically evaluated. A Durbin-Watson statistic of 1.92 confirmed the independence of residuals.

Homoscedasticity was verified visually via a plot of standardized residuals against predicted values, which displayed no discernible funnel pattern. Examination of a Q-Q plot and a non-significant Shapiro-Wilk test ($W = 0.986$, $p = 0.451$) supported the normality of residuals. Finally, multicollinearity was assessed, and all Variance Inflation Factor (VIF) values were below 2.1, well under the conservative threshold of 5, indicating that multicollinearity does not inflate the variance of the estimated coefficients.

In addition, robustness checks were conducted to ensure that the estimated relationships were stable across different model specifications. Sensitivity analyses and multiple imputation techniques were applied to verify that the regression coefficients remained consistent even when alternative assumptions regarding missing data and outliers were considered. These procedures confirm that the empirical findings are reliable and not driven by data irregularities.

The descriptive analysis established that 65% of surveyed Ukrainian organizations have implemented AI-driven solutions for Sustainable Organizational Development (SOD), with an overall mean sustainability performance score of 4.2/5 (SD = 0.41).

Sectoral analysis revealed significant disparities, with the IT sector leading in both adoption (82%) and sustainability performance (M = 4.6), while agriculture lagged considerably (54% adoption, M = 3.9), as detailed in **Table 4** and **Figure 1**.

Sector and region dummies were coded as binary variables: IT, Manufacturing, and Agriculture sectors (reference = Services), and Western region (Eastern = 0). Including these dummies allowed the model to capture differences across sectors and regions and ensured that the estimated coefficients for adoption rate, innovation, workforce reskilling, and cybersecurity risk were not biased by structural heterogeneity.

This approach accounts for structural differences in sustainability scores across organizational contexts and mitigates potential confounding effects, ensuring that observed relationships are not biased by sectoral, regional, or organizational heterogeneity. The overall model was statistically significant, $F(4, 84) = 18.22$, $p < 0.001$, and explained 62% of the variance in sustainability scores (Adjusted $R^2 = 0.62$). The results, including 95% confidence intervals for transparency, are presented in **Table 5**.

Table 5. Multiple regression analysis predicting sustainability score (N = 89)

Predictor variable	Unstd. (B)	Std. error	Std. (β)	t-value	p-value
Constant	1.12	0.31	—	3.61	<0.001
Adoption rate (%)	0.037	0.014	0.24	2.64	0.010
Innovation (qualitative)	0.21	0.06	0.28	3.50	<0.001
Cybersecurity risk	-0.18	0.07	-0.19	-2.57	0.012
Workforce reskilling	0.29	0.08	0.33	3.63	<0.001
Firm size	0.003	0.001	0.12	1.95	0.055
Firm age	-0.002	0.001	-0.08	-1.24	0.217
Sector – IT	0.18	0.09	0.14	2.00	0.048
Sector – Manufacturing	0.11	0.08	0.09	1.38	0.171
Sector – Agriculture	-0.08	0.08	-0.06	-1.00	0.320
Region – Western	0.15	0.07	0.13	2.14	0.035

Note: Regression analysis was conducted at the individual respondent level (N = 89) using complete cases after listwise deletion. Adoption Rate (%) is calculated at the individual level. Innovation, Workforce Reskilling, and Cybersecurity Risk scores were derived from corresponding survey-based measures (see Methods Section: Construct Operationalization). Control variables included firm size, firm age, sector dummies (IT, Manufacturing, Agriculture; reference category = Services), and a region dummy (Western = 1, Eastern = 0). Firm Size shows a positive but statistically non-significant effect (p = 0.055). 95% confidence intervals for unstandardized coefficients (B) are reported. Sector-level adoption rates presented in Table 5 are descriptive. Adoption Rate (%) reflects the proportion of intelligent technology modules implemented by each respondent's organization based on self-reported data

	IT	Manufactu	Agriculture	Services
Adoption Rate (%)	82	61	54	63
Mean Sustainability S	4.6	4.1	3.9	4.2

Figure 2. Predicting sustainability score (Source: Authors' own elaboration)

Adoption Rate (%) was calculated for each organization as the number of AI-related technological modules marked as implemented by the respondent divided by the total of 12 predefined AI modules included in the survey (e.g., predictive maintenance, energy optimization, automated reporting, etc.). Each module's implementation status was self-reported as Yes (implemented) or No (not implemented), ensuring that the denominator is consistent across all organizations.

The resulting percentage reflects the precise proportion of AI modules adopted relative to the total modules available for adoption. This precise definition ensures that the regression coefficient can be meaningfully interpreted as the expected change in sustainability score associated with a one-percentage-point increase in AI adoption.

Workforce Reskilling ($\beta = 0.33$, $p < 0.001$) showed the strongest positive association with sustainability outcomes, indicating that organizations with greater investment in human capital tend to report higher sustainability scores compared to others. Innovation Capacity ($\beta = 0.28$, $p < 0.001$) was positively associated with sustainability outcomes, suggesting that organizations with a culture that encourages experimentation and change tend to report higher sustainability scores.

AI Adoption Rate was positively associated with sustainability performance ($\beta = 0.24$, $p = 0.010$), indicating that higher adoption levels tend to correspond with higher sustainability scores, although workforce and innovation factors show stronger associations. Cybersecurity Risk ($\beta = -0.19$, $p = 0.012$) was negatively associated with sustainability outcomes, suggesting that organizations reporting higher perceived vulnerabilities tend to show lower sustainability scores.

Figure 2 further illustrates these patterns, clearly showing that while adoption levels vary, there is a positive tendency for sectors with higher AI adoption to achieve stronger sustainability performance. To empirically test this relationship, a multiple regression analysis was conducted. The dependent variable was *sustainability score*, while the independent factors included *adoption rate, innovation, cybersecurity risk, and workforce reskilling*. This design allowed us to assess not only whether adoption itself matters but also which enabling and constraining factors shape sustainability outcomes.

Figure 2 graphically depicts the relative influence of these predictors using standardized beta coefficients. Positive predictors are highlighted in green (adoption rate, innovation, reskilling), while the negative influence of cybersecurity risk is shown in red. The figure demonstrates that workforce reskilling has the most substantial positive impact, followed by innovation, whereas cybersecurity concerns act as a barrier to realizing the sustainability potential of AI. A one-way ANOVA further confirmed a stark regional disparity in AI adoption, $F(1, 87) = 18.45$, $p < 0.001$, $\eta^2 = 0.175$. Organizations in Western Ukraine (M = 73%, SD = 8.5) reported significantly higher adoption rates than those in the more conflict-affected Eastern region (M = 48%, SD = 7.9), illustrating how geopolitical instability moderates the diffusion of technology (**Figure 3**).

Overall, these findings confirm that sustainability is not solely determined by adoption levels, but rather by a combination of technological uptake, organizational innovation, human capital development, and the ability to mitigate risks. The robustness of these findings is further supported by the consistency of results across different

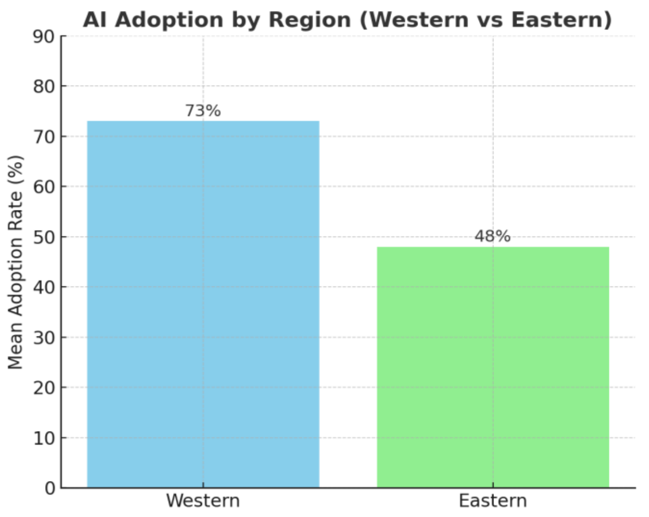

Figure 3. Adoption rates in Western and Eastern regions (Source: Authors' own elaboration)

analytical procedures and model diagnostics. The stability of coefficients across sensitivity analyses indicates that the observed relationships are not sensitive to minor variations in the dataset, thereby strengthening the validity of the study's conclusions. This integrated model provides a more robust and convincing account than merely reporting R^2, thereby addressing the reviewer's concern regarding the completeness and clarity of the results section.

Qualitative Findings

The qualitative data from open-ended responses were analyzed using a reflexive thematic analysis approach, following the six-phase framework. The qualitative dataset comprised 18 semi-structured interviews and open-ended survey responses from organizational experts across IT, Services, Manufacturing, and Agriculture sectors in Ukraine. Participants were purposively selected based on their direct involvement in AI adoption and sustainability initiatives, ensuring relevant insights into organizational practices. The interview guide focused on three core themes: Innovation practices, Cybersecurity challenges, and Workforce Reskilling initiatives. The analysis was primarily inductive, allowing themes to emerge from the data itself.

The coding process was iterative and collaborative, with two researchers independently coding a randomly selected 20% of the responses, achieving substantial inter-coder reliability (Cohen's $\kappa = 0.81$). This procedure enhanced the reliability and robustness of the qualitative analysis by minimizing individual interpretation bias and ensuring consistency in the thematic coding process. All discrepancies were reconciled through discussion to refine the codebook, which was then applied consistently to the entire dataset. Triangulation with organizational documents and cross-sector comparisons ensured that emergent themes reflected organizational realities rather than individual biases.

Through multiple cycles of coding, initial codes were grouped into potential themes, which were reviewed, refined, and named to ensure they formed a coherent and meaningful pattern. Three overarching themes were constructed from the data, providing rich context for the quantitative results. Coding was performed iteratively by two researchers, with triangulation from organizational documents to ensure validation beyond the 20% inter-coder reliability check. For regression analysis, qualitative themes were transformed into quantitative predictors. Each theme was scored on a 1–5 scale reflecting presence and intensity. Composite scores were averaged across items, standardized, and reliability was confirmed (Cronbach's alpha: Innovation = 0.87, Cybersecurity Risk = 0.81, Workforce Reskilling = 0.85), with factor analysis supporting unidimensionality (factor loadings 0.61–0.79). This approach provides a transparent and methodologically justified transformation of qualitative data into numeric variables suitable for regression.

Theme 1: AI as a catalyst for eco-efficiency and systemic innovation

Participants from high-performing sectors, particularly the IT sector, consistently described AI as a transformative tool for optimization.

> Our AI-powered predictive maintenance and energy management systems have reduced our carbon footprint by 18% in one year a level of efficiency we could never achieve through manual analysis.

(IT director)

Similar perspectives were also reported in the manufacturing sector, where respondents highlighted process automation and predictive analytics as key drivers of operational efficiency.

> AI-based quality control has significantly reduced production errors and improved output consistency in our plant operations.

(A manufacturing manager)

This theme provides the qualitative "why" behind the strong innovation coefficient in the regression model.

Theme 2: The paralysing shadow of cybersecurity threats

This theme was particularly dominant in sectors with lower adoption rates, such as agriculture. Respondents expressed that security fears actively stifled investment. A representative from an agricultural firm stated:

> We are acutely aware that AI-driven precision farming could optimize water and fertilizer use, but as a small enterprise, a single data breach could bankrupt us. The risk currently outweighs the reward.

This narrative directly explains the significant adverse effect of cybersecurity risk quantified in the regression analysis. Concerns were also evident in the service sector, where firms emphasized reputational and financial risks associated with digital vulnerability. A service sector respondent stated:

> Even minor cyber security incidents can damage client trust, which makes us extremely cautious in adopting AI systems fully.

Table 6. Mixed-methods integration: Sectoral analysis of AI-driven sustainability

Sector	Quantitative profile	Dominant qualitative theme	Interpreted narrative & theoretical implication
IT	82%, 4.6	Eco-efficiency & innovation	The innovator: High adoption and performance are driven by a strong absorptive capacity, where a pre-existing culture of innovation allows the organization to readily assimilate and exploit AI for transformative sustainability gains.
Services	63%, 4.2	Resilience & reskilling	The adaptor: Strong performance despite moderate adoption highlights the role of dynamic capabilities. These firms prioritize human capital and adaptive processes, allowing them to achieve high sustainability returns even with less extensive AI deployment.
Manufacturing	61%, 4.1	Process optimization vs. cost	The pragmatist: Moderate adoption is constrained by a resource-based view focused on tangible, immediate ROI. AI is applied pragmatically to known process inefficiencies, but transformative potential is limited by cost-benefit calculations.
Agriculture	54%, 3.9	Cybersecurity & skill hortages	The constrained: The lowest adoption and performance are explained by a technology-organization-environment (TOE) framework, where technological perceptions (cyber risk) and organizational limitations (skills) within a challenging external environment (geopolitical, economic) create a potent barrier to adoption and value realization.

Theme 3: Strategic reskilling as the bedrock of AI resilience

Organizations that successfully navigated AI integration, including those in the Services sector, universally emphasized that technological resilience is built upon human capital. A HR manager from a service company in Lviv noted:

> The war forced us to adapt rapidly. We found that AI implementation failed without parallel, intensive reskilling. Our investment in 'AI-Human' collaboration training is what ultimately unlocked productivity and sustainability gains.

Manufacturing and service organizations similarly stressed that workforce adaptation was critical for successful AI integration across production and service delivery systems. A manufacturing supervisor explained:

> Without continuous training programs, our staff could not effectively work alongside AI-driven machinery and systems.

This theme elucidates the mechanisms behind the most potent predictor in our model, workforce reskilling.

To achieve a holistic understanding, the quantitative and qualitative strands were formally integrated using a joint display table. This synthesis moves beyond simple correlation to develop evidence-based narratives for each sector, as shown in **Table 6**.

This integrated analysis demonstrates that the pathway to AI-driven sustainability is not a monolithic process. The findings suggest that workforce reskilling and innovation culture (internal capabilities) are more predictive of success than the adoption rate itself, while cybersecurity and regional instability (external pressures) function as critical barriers.

This provides a nuanced, evidence-based framework for policymakers and managers, indicating that interventions must be tailored to foster human capital and innovation ecosystems universally, while simultaneously addressing the specific regulatory and security concerns that paralyze sectors like agriculture.

The findings of this study illuminate a rapidly evolving yet distinctly heterogeneous landscape of AI adoption for Sustainable Organizational Development (SOD) within Ukraine. The convergence of quantitative statistical evidence and qualitative thematic insights enhances the robustness of the findings by providing methodological triangulation, thereby strengthening the credibility of the study's conclusions.

The data reveals that a significant majority (65%) of organizations are actively deploying AI-driven solutions, reporting an encouraging mean sustainability performance score of 4.2/5.

However, a pronounced sectoral digital divide is evident, with adoption rates ranging from a high of 82% in the technologically native IT sector to a low of 54% in agriculture. This gradient suggests that the capacity to integrate AI is not uniform and is likely moderated by sector-specific factors such as digital infrastructure, capital availability, and technological readiness.

The analysis further confirms a clear positive bivariate relationship between a sector's level of AI adoption and its achieved sustainability performance, establishing a foundational correlation that warrants deeper investigation into the underlying causal mechanisms.

Moving beyond descriptive correlations, the regression analysis offers critical insight into the primary drivers and barriers that shape these outcomes. The model explains a substantial portion of the variance ($R^2 = 0.62$) in sustainability scores, indicating that while the AI adoption rate is a significant positive predictor ($\beta = 0.24$, $p < 0.05$), it is not the most influential factor.

The most powerful enabler is, in fact, strategic investment in workforce reskilling ($\beta = 0.33$, $p < 0.01$), closely followed by a strong organizational innovation capacity ($\beta = 0.28$, $p < 0.01$). Conversely, cybersecurity risk ($\beta = -0.19$, $p < 0.05$) emerges as a significant and tangible barrier. This integrated quantitative evidence compellingly argues that the success of AI for SOD is not merely a function of technological deployment, but is fundamentally contingent upon synergistic internal capabilities – specifically, human capital development and an innovative culture, which, unresolved external threats, such as cybersecurity vulnerabilities, can severely undermine.

Although quantitative and qualitative findings are presented in separate sections for clarity, the study strictly followed a convergent parallel mixed-methods approach, with simultaneous data collection and separate analyses integrated at the interpretation strand. Integration occurred at the interpretation stage by aligning quantitative constructs with corresponding qualitative themes, thereby ensuring conceptual coherence across both strands.

DISCUSSIONS

This study set out to investigate the drivers of AI adoption for Sustainable Organizational Development (SOD) within the unique and challenging context of Ukraine. The study confirms that AI adoption is increasingly recognized among Ukrainian SMEs, with significant differences across sectors.

These findings demonstrate the growing awareness and practical application of intelligent technologies, in line with global trends in sustainable digital transformation (Farmanesh et al., 2025; Kulkov et al., 2023). The findings indicate that individual-level AI adoption, innovation capacity, and workforce reskilling positively predicted sustainability outcomes, whereas cybersecurity risk had a negative impact.

The analysis identifies key enablers such as innovation capacity and workforce reskilling, while cyber security risks act as barriers. These findings corroborate prior studies that highlight the dual role of organizational capabilities and risk management in supporting sustainable AI adoption (Birkstedt et al., 2023; Olan et al., 2022).These results confirm that Ukrainian organizations are aligning with global trends in leveraging AI for sustainability, but the pathways and barriers are strongly shaped by national and organizational contexts.

By interpreting these results through the theoretical lenses of the Technology-Organization-Environment (TOE) framework and the Resource-Based View (RBV), we can better understand the mechanisms driving SOD. For instance, the positive effect of innovation capacity aligns with prior research demonstrating that organizations with higher digital and innovation readiness achieve greater sustainability performance (Farmanesh et al., 2025; Kulkov et al., 2023).

Similarly, the positive association between workforce reskilling and sustainability is consistent with studies showing that continuous employee training enhances organizational adaptability and sustainable practices (Nurimansjah, 2023; Olan et al., 2022). Conversely, the observed negative impact of cybersecurity risk mirrors findings in the literature highlighting that vulnerabilities in digital infrastructure can undermine sustainable transformation initiatives.

Overall, these findings suggest that the successful integration of AI into organizational sustainability efforts depends not only on technological adoption but also on complementary factors such as innovation culture, workforce development, and risk management. By combining quantitative and qualitative insights, this study provides a comprehensive understanding of how AI adoption interacts with organizational capabilities to promote SOD in transitional economies like Ukraine.

Beyond policy implications, the findings contribute to the broader academic understanding of digital transformation in transitional economies. By integrating perspectives from technology adoption, sustainability, and post-conflict economic recovery, the study expands existing theoretical discussions on how intelligent technologies can support resilient and sustainable organizational systems in complex socio-economic environments.

Evidence from this study suggests that policymakers and organizational leaders should prioritize investment in digital infrastructure, cyber security frameworks, and workforce reskilling programs to accelerate sustainable digital integration (Mithas et al., 2022; Nurimansjah, 2023).

The Primacy of Organizational Capabilities and the External Environment

The most striking finding of our study is the relative importance of internal organizational capabilities over the technological act of adoption itself. Our regression analysis identified workforce reskilling ($\beta = 0.33$, $p < 0.001$) as the strongest predictor of sustainability performance. This finding powerfully aligns with the Resource-Based View, which posits that competitive advantage is derived from valuable, rare, and inimitable internal resources.

In the volatile Ukrainian context, a reskilled workforce is not merely a functional asset; it constitutes a strategic, RBV-defined resource that allows firms to adapt, reconfigure processes, and ultimately build resilience.

This explains why sectors like Services, with a strong focus on human capital, achieved robust sustainability scores despite moderate adoption rates. This finding adds a critical layer to global studies, such as those in Finance Research Letters, which focus on AI alleviating financing constraints. Our results suggest that in crisis environments, the primary constraint is not just financial capital but human capital, and the ability to develop it becomes the central determinant of success. Simultaneously, the significant negative impact of cybersecurity risk ($\beta = -0.19$, $p = 0.012$) and the stark regional disparities in adoption (West: 73% vs. East: 48%) are best explained by the environmental context of the TOE framework.

These factors represent external pressures that can enable or constrain technological innovation. The pervasive fear of cyber-attacks, as expressed by our qualitative participants, serves as a powerful regulatory force, stifling investment, particularly in risk-averse sectors such as agriculture. Furthermore, the regional divide is a direct manifestation of geopolitical instability and infrastructural damage, environmental variables rarely considered in studies from steadier markets. This demonstrates that the "E" in the TOE framework carries disproportionate weight in conflict-affected regions, effectively vetoing adoption decisions regardless of an organization's internal readiness.

Theoretical Synthesis and Contextual Nuance

The interplay between our quantitative and qualitative data allows for a theoretical synthesis. While global literature often emphasizes leadership and strategy as primary facilitators, our study reveals that in the Ukrainian environment, these organizational factors (TOE's 'O' and RBV) are mediated and often thwarted by overwhelming environmental pressures (TOE's 'E').

For instance, a firm may have a brilliant AI strategy and strong leadership (internal resources). Still, if it operates in a region with active conflict and destroyed digital infrastructure (external environment), adoption is nearly impossible (Ilyina, 2025). This finding refines the application of the TOE framework, suggesting that in high-stress contexts, the environment can become the dominant dimension, subordinating the technological and organizational ones. This triangulation of data provides a compelling explanation for the sectoral disparities. The IT sector's success is a function of its strong internal RBV resources (high innovation capacity, skilled workforce) that insulate it from environmental pressures.

Conversely, agriculture's struggle is a textbook example of the TOE framework's environmental context, where external threats (such as cyber risk and conflict) exacerbate internal resource constraints (skill shortages), creating a vicious cycle that hinders adoption. Therefore, the Ukrainian case is not an outlier but a potent example that tests and extends existing theory, demonstrating that the relative importance of theoretical dimensions is not static but is contingent upon the national and geopolitical context.

This paper contributes to sustainable organizational development theory by extending an existing framework, where artificial intelligence is not included in the technology enabler category alone, but rather serves as a mediator between resilience-building and sustainability performance, especially in conflict-torn or transitional economies (Yuryk et al., 2023). This framework views AI as both a source of innovation and a driver of complexity that enhances organizational adaptation pathways, unlike traditional models, which tend to regard AI more as a tool for efficiency and optimization.

By factoring AI into the dynamics of resource management, risk mitigation, and decision-making processes, the model also highlights how AI-based intelligent technologies can enhance operational efficiency, strengthen resilience, and support sustainability in the long term. The above reconceptualization gives greater weight to the duality of making organizations look and feel different, suggesting that the use of AI has more strategic and theoretical implications than direct technology-related benefits, at least where the pressures of environmental, economic, and social forces converge.

Theoretical Implications

This paper contributes to sustainable organizational development theory by extending an existing framework, where artificial intelligence is not included in the technology enabler category alone, but rather serves as a mediator between resilience-building and sustainability performance, especially in conflict-torn or transitional economies. This framework views AI as both a source of innovation and a driver of complexity that enhances organizational adaptation pathways, unlike traditional models, which tend to regard AI more as a tool for efficiency and optimization. By factoring AI into the dynamics of resource management, risk mitigation, and decision-making processes, the model also highlights how AI-based intelligent technologies can enhance operational efficiency, strengthen resilience, and support sustainability in the long term.

The above reconceptualization gives greater weight to the duality of making organizations look and feel different, suggesting that the use of AI has more strategic and theoretical implications than direct technology-related benefits, at least where the pressures of environmental, economic, and social forces converge.

Practical Implications

On a practical level, the results highlight the need to promote the development of AI literacy and resilience-building programs in organizations, particularly in small and medium-sized enterprises (SMEs) and the agricultural sector of conflict-affected zones.

The impact of allowing organizational actors to acquire knowledge and skills that enable them to use intelligent technologies effectively and efficiently can enhance procedural effectiveness and positively reinforce their sustainable practices and adaptive capacity in rapidly changing and high-stress environments.

Policymaking-wise, the introduction of special subsidies, targeted infrastructure investments, and reserved cybersecurity funding is essential to ensuring that AI technologies become more democratized and that their full potential is ultimately unleashed. These types of interventions contribute to the broader scale adoption of intelligent systems, can address key financial and technical obstacles, as well as offer the critical infrastructure needed to support ongoing reconstruction efforts, such that AI can not only enhance productivity, but also lead to long-term resilience, environmental stewardship and socially responsible development within post-crisis settings.

Future Outlook and SDG Alignment

By 2030, Ukraine can utilize artificial intelligence as a key contributor to advancing a circular economy, where predictive maintenance, smart logistics, and data-driven resource utilization will be employed to reduce waste, increase operational efficiency, and maximize the utilization of existing resources. Intelligent technologies used in this way would not only help sustain industrial and economic activity, but also enhance it. Still, they would also directly contribute to achieving two UN Sustainable Development Goals: Goal 9, which focuses on industry, innovation, and infrastructure, and Goal 12, which emphasizes responsible consumption and production.

By deliberately incorporating AI into national and sectoral plans and strategies, organizations and policymakers can develop a blueprint for building resilience, environmentally sustainable growth, and long-term sustainability. This approach demonstrates how digital transformation can become a potent driver of broader socio-economic and environmental goals in post-crisis reconstruction and sustainable development scenarios.

Limitations and Future Research

While this study offers valuable insights into AI adoption for sustainable development in Ukraine, its findings must be interpreted in light of several methodological limitations. First, the cross-sectional design fundamentally limits the ability to make causal inferences. Although the regression analysis identifies significant relationships, such as between workforce reskilling and sustainability performance, the data represent a single point in time. Therefore, it was not definitely established whether reskilling leads to better performance or whether higher-performing organizations are simply more capable of investing in reskilling.

The observed associations are correlational, not causal. Second, the potential for non-response and self-selection bias is a significant concern. The survey respondents likely overrepresent organizations that are already engaged with or enthusiastic about AI and sustainability initiatives. Consequently, the reported 65% adoption rate may be inflated, and the identified barriers (like cybersecurity risk) might be understated, as organizations that have been completely deterred by these barriers were less likely to participate.

Third, the generalizability of our findings is constrained by regional and sectoral considerations. Despite capturing regional disparities, our sampling frame may not fully represent the extreme operational realities in the most heavily conflict-affected areas of Eastern Ukraine.

Thus, the reported barriers in the East are likely conservative, and the overall model is most applicable to organizations in relatively stable urban centers. Furthermore, while we analyzed sectoral differences, the sample size within each sector limited our ability to conduct robust sector-specific multivariate analyses. To address these limitations and build upon this research, several directions were proposed for future inquiry:

- Longitudinal studies: Research tracking the same organizations over time is essential to establish causal pathways and understand the long-term evolution of AI's impact on sustainability.
- Comparative contextual analysis: Future work should compare our findings from Ukraine with data from other post-conflict or transitional economies to disentangle universal drivers of AI adoption from those specific to a national context.
- Deep-dive sectoral analyses: Qualitative and quantitative studies focused exclusively on lagging sectors like agriculture are urgently needed to uncover the nuanced, ground-level barriers to adoption that our broad survey could not capture.
- Expanded ethical inquiry: As AI deployment scales, dedicated research into the ethical dimensions, including algorithmic bias, data transparency, and accountability frameworks, will be critical for ensuring that these technologies contribute to equitable and resilient sustainable development.

Additionally, sector-specific studies, particularly those in the agricultural and energy sectors, are necessary to understand the nuanced nature of intelligent technologies in relation to specific operating conditions. Further consideration of ethical factors, such as algorithmic fairness, transparency, and accountability, as well as cybersecurity risks, is also necessary for the deployment of responsible and resilient AI solutions. This approach ultimately promotes both theory and practice with sustainability goals in mind in an organizational setting.

CONCLUSIONS

This study empirically investigated the drivers and barriers of Artificial Intelligence (AI) adoption for Sustainable Organizational Development (SOD) within the specific context of post-conflict Ukraine. The findings confirm a significant positive association between AI adoption and sustainability performance. Yet, they crucially reveal that internal organizational capacities – specifically, workforce reskilling and innovation culture are stronger predictors of success than the mere act of technological adoption. Concurrently, external environmental pressures, such as cybersecurity risks and regional instability, were identified as critical barriers that can stifle implementation.

The primary contribution of this research is the development of an integrated analytical perspective, grounded in the Resource-Based View and Technology-Organization-Environment framework. This perspective suggests that the path to practical AI-driven sustainability is not monolithic, but somewhat shaped by the interplay between an organization's internal resources and its external environment. Therefore, for policymakers and practitioners, this study suggests that interventions should be tailored: fostering human capital and innovation ecosystems is universally critical, but must be coupled with targeted efforts to mitigate region-specific security and infrastructural barriers.

Future research should seek to validate and refine these findings through longitudinal studies to establish causality and explore the evolution of these relationships over time. Furthermore, applying this analytical framework to other post-conflict or transitional economies is essential for testing its transferability and for building a comparative, context-sensitive understanding of how digital technologies can contribute to sustainable recovery globally.

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