“Sustainable digital transformation in the energy sector: The role of artificial intelligence training in achieving Jordan’s green growth strategy”

AUTHORS	Azzam Abou-Moghli
ARTICLE INFO	Azzam Abou-Moghli (2026). Sustainable digital transformation in the energy sector: The role of artificial intelligence training in achieving Jordan’s green growth strategy. *Environmental Economics*, *17*(1), 1-11. doi:10.21511/ee.17(1).2026.01
DOI	http://dx.doi.org/10.21511/ee.17(1).2026.01
RELEASED ON	Friday, 19 December 2025
RECEIVED ON	Sunday, 21 September 2025
ACCEPTED ON	Tuesday, 02 December 2025
JOURNAL	"Environmental Economics"
ISSN PRINT	1998-6041
ISSN ONLINE	1998-605X
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
35	1	3

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Azzam Abou-Moghli (Jordan)

SUSTAINABLE DIGITAL TRANSFORMATION IN THE ENERGY SECTOR: THE ROLE OF ARTIFICIAL INTELLIGENCE TRAINING IN ACHIEVING JORDAN'S GREEN GROWTH STRATEGY

Type of the article: Research Article

Received on: 21st of September, 2025
Accepted on: 2nd of December, 2025
Published on: 19th of December, 2025

Azzam Abou-Moghli, Ph.D. in Management, Professor, Department of Business, Middle East University, Jordan.

Abstract

This paper aims to examine the role of artificial intelligence (AI) training effectiveness in achieving a green growth strategy in Jordan, particularly at the Jordanian Electric Power Company, which represents the Jordanian energy sector. The analysis is supported by the multifaceted program evaluation framework by Daniel Stufflebeam (CIPP). AI training is considered a strategic intangible asset that promotes the growth of rare and invaluable intangible human capital. Quantitative cross-sectional research design was applied, targeting employees of the Jordanian Electric Power Company. Using a simple random sampling, 178 valid responses were directly engaged. The assessment of the theoretical and structural models was done using SPSS and SmartPLS. The results indicated that AI training effectiveness is a significant predictor of the green growth strategy's outcomes ($\beta = 0.562$, $t = 8.990$, $p < 0.001$), explaining 31.6% of the variance. The strongest predictor among the CIPP dimensions was the dimension of input ($\beta = 0.556$, $R^2 = 0.310$), then the dimensions of context ($\beta = 0.532$, $R^2 = 0.283$), process ($\beta = 0.516$, $R^2 = 0.266$), and product ($\beta = 0.487$, $R^2 = 0.237$). These findings indicate that highly developed training programs, when designed according to the organizational context, resource-rich, and executed effectively, yield quantifiable skills development and play an influential role in meeting the goals of the national green growth strategy.

Keywords sustainable digital transformation, artificial intelligence, training, green growth strategy, renewable energy

JEL Classification O33, M15, I25, Q55, Q42

INTRODUCTION

The world energy systems are shifting in new directions to respond to the rising demands, climate stress, and shifts in politics. The critical issue is the pace at which it will change and what it will bring to developing countries. Jordan has strategically positioned itself by developing strong digital and green support systems, even when it has fewer natural resources, and is now almost at the head of the regional level. Jordan has been ranked 49th in the Oxford Insights AI Readiness Index 2024 and fifth in the Arab region as well, which confirms how competitive Jordan is (Petra, 2025). Jordan has a successful national strategy, committed investments in AI, and a constant interest in redesigning the whole economy into an AI-driven and digitalized one.

However, there is a major gap between the rapid rate of technology and the lack of qualified personnel to sustain it. The policies of Jordan are oriented toward the future; however, the nation has not trained

Conflict of interest statement:
Author(s) reported no conflict of interest

its people as quickly as AI is diffusing. Since the local talent pool is too small to handle, design, and maintain AI systems, Jordan is increasingly relying on foreign specialists. Trusting external sources is a source of concern regarding self-reliance in the long term, data manipulation, and strategic autonomy, particularly in energy, where national security and the green agenda are inseparable.

Therefore, the transition to clean energy is both an opportunity and a threat for Jordan. On the one hand, effective digital and green initiatives might introduce resilience and diversify the economy. On the other hand, the achievement of these is hindered by the skills gap. Lack of a competent workforce capable of exploiting AI and digital technologies will leave foreign actors to reap the rewards, slowing the pace of local value generation and endangering sustainability goals. The gap needs to be closed and requires specific AI training, collaboration between the industry and academia, and investment in people. The energy shift in Jordan can be considered progressive, inclusive, autonomous, and sustainable.

1. LITERATURE REVIEW AND HYPOTHESES

One of the key drivers that can make energy companies utilize resources more efficiently, run their business more efficiently, and reduce carbon emissions is the digital transformation. The Internet of Things (IoT), which enhances analytics, automation, and artificial intelligence (AI), is changing the energy industry by enabling real-time data control, predictive maintenance, and more intelligent decision-making (Rojek et al., 2025). This is not merely revamping their technology, but they must be able to strategically compel the formulation of integrated energy systems to achieve the national sustainability levels. Sustainable digital transformation has become a major concept in research over the past few years. It focuses on the use of digital tools to achieve not only performance purposes, but also environmental and social sustainability. Huang and Lin (2023) claim that digitalization supports decarbonization by spreading power in the optimal way through the use of renewable energy and controlling the demand for power. The key to this change lies in artificial intelligence, which has massive development potential. AI techniques such as machine learning, neural networks, and large language models can make accurate predictions, reduce energy usage, and process data robotically to restore higher degrees of reliability (Khan et al., 2023). AI can also enhance the principles of the environmental, social, and governance (ESG) implementation (Rane et al., 2024). Several companies have created national digital sustainability frameworks that combine AI and IoT in energy-related monitoring systems to streamline the distribution of renewable resources and increase the level of transparency in carbon reporting. An example is the introduction of smart grid systems in European countries that rely on AI-based predictions to harmonize energy generation and demand, reducing waste and grid instability (Kruse et al., 2021). Likewise, Asian economies put a lot of money into AI-based predictive analytics to identify inefficiencies in energy networks, so that green technologies can be both cost-effective and eco-friendly (Lin & Yang, 2025). Therefore, countries like Jordan are crucial because the digital work perfectly fits the green growth strategy.

However, green digital transformation depends on the firms that can attract, develop, and keep skilled staff to operate complex digital networks, enabling them to attain environmental and economic goals. Technology alone will not do, but the ability to supply, maintain, and upgrade digital systems with human capital will result in success (Al-Khatib, 2025). The increasing utilization of AI also results in a similar requirement for reskilling the workforce, as well as digital literacy. Empirical evidence shows that the adoption of AI requires hybrid expertise comprising both technical knowledge and critical thinking, as well as flexibility (Uren & Edwards, 2023). Further, AI supplements human labor, and not replaces it, boosting the need to hire human-focused skills, including teamwork, creativity, and solving complex problems (Mäkelä & Stephany, 2024). Digital transformation, therefore, demands a culture of continuous learning in which employees are pushed to enhance their digital capabilities in line with emerging technologies (Al Abdallah et al., 2018). To promote the ability of employees to use intelli-

http://dx.doi.org/10.21511/ee.17(1).2026.01

gent systems and interpret analytical reporting to make a decision, organizations are initiating programs and digital upskilling programs that are AI-oriented to a greater number (Gautam et al., 2025). Therefore, training and reskilling should be viewed as a strategic investment aimed at enhancing competitiveness and sustainability, but not as a secondary role.

However, successful digital transformation is built on a proper training program since employees get the skills required to use and adjust to the new technologies. Kılınç et al. (2025) noted that the workforce should use digital resources, including AI and data analytics, to make operations more efficient and make decisions. Evidence from the energy industry shows that employee training programs would help employees learn to operate predictive maintenance and real-time monitoring systems, leading to reduced operating costs and energy efficiency (Erhueh et al., 2024). The operators of hydropower and renewable energies have also focused on constant training to implement Industry 4.0 tools effectively, enhancing cooperation and sustainability in everyday processes (Onu et al., 2023). In the end, these programs will help close the divide between technology and the population, which would result in the digital transformation process in the energy industry being successful in the long run.

To ensure that training and reskilling programs deliver desired results in the energy industry, it is critical to be familiar with the training effectiveness theory. Training effectiveness is a metric that describes the extent to which training achieves its targeted objectives and improves organizational performance (Kim et al., 2025). In the context of digital transformation in energy companies, it not only assumes acquiring technical skills in AI and IoT systems but also the formation of adaptability capacity and innovation mindset, which should be promoted in the organization to ensure its sustainability in changes (Arcelay et al., 2021). Empirical studies show that training effectiveness is a multidimensional construct that depends on numerous interrelated factors such as the design of training, the properties of the trainees, organizational support systems, and the mechanisms of transfer that enable the transfer of skills learnt to the real work settings (Saputro & Syaebani, 2024). Within the energy industry, in particular, the success of the digital transformation training programs largely depends on the correspondence between the training material and its operational needs, which, as illustrated by renewable energy organizations, have raised the efficiency of equipment monitoring by a significant margin due to the well-organized technical training courses (Kuzmin et al., 2024). The human factor is also crucial; training effectiveness and long-term skills retention are observed in those organizations that integrate technical training programs with organizational development programs based on job satisfaction and psychological safety (Riyanto et al., 2023).

Stufflebeam CIPP model stands for Context, Input, Process, and Product framework for training program assessment (Stufflebeam & Zhang, 2017). This method of systematic evaluation can be useful when the energy sector organizations are interested in determining the effectiveness of their training programs on digital transformation. The context evaluation analyses the organizational context, defining the training requirements, getting to know stakeholder expectations, and outlining organizational objectives on the digital adoption (Stufflebeam & Zhang, 2017). Context evaluation in energy companies would include determining the existing skills gaps in the operations of AI and IoT, regulatory requirements on sustainability reporting, and the readiness of the departments to change technologies (Akyazi et al., 2023). The input assessment is concerned with the resources spent on the training programs, which can be budget allocation, qualification of trainers, technology infrastructure, and the quality of instructional design (Muralidharan, 2025). Process evaluation dimension evaluates the training activities implementation, tracking the program, participant involvement, and finding out obstacles to successful training implementation (Barbero et al., 2023). Process evaluation, as applied to digital transformation efforts in the energy industry, can be used to monitor attendance rates, the quality of instructor-trainee interactions, the topicality of case studies, which are based on energy operations, and to pinpoint technical problems that hinder learning. The product evaluation element compares training results and consequences, which go beyond immediate learning outcomes to cover improvements in job performance, organizational

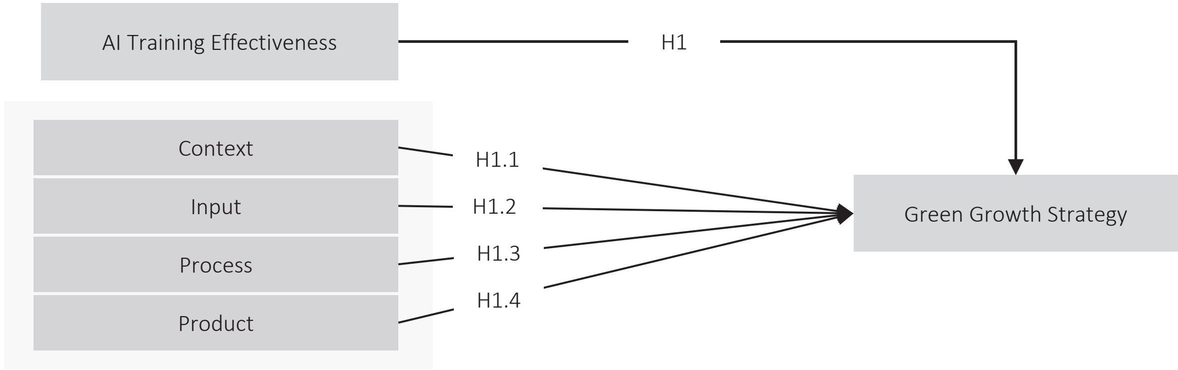

Figure 1. Structural model

productivity, and sustainability changes (Soni & Saraf, 2025). The product evaluation under the energy sector context can include quantitative measures, i.e., a reduction of the equipment downtime after the implementation of the predictive maintenance training, an increase in the quality of the demand forecasting with the help of the AI-based tools, and a decrease in carbon emissions due to the optimization of energy distribution. It also covers qualitative measures, i.e., the confidence of the employees in the application of the digital systems and the change in the organizational culture toward the use of data-driven decision-making.

Although the theoretical clarity of AI and digital technologies and the results of their role in creating sustainability outcomes are clearly documented, there is a lack of empirical studies to evaluate the role of AI-oriented training in delivering sustainability outcomes, especially in emerging economies like Jordan. Although the literature confirms that AI and digitalization will help companies optimize energy usage, lower the cost of operations, and enhance sustainability reporting, few studies examine how training interferes with the connections between technology adoption and green growth outcomes. These results emphasize the necessity of studying training as the main aspect of digital transformation strategies that connect technological potential with operational and environmental performance. Research can provide information on the role of workforce development in helping organizations realize the potential of digital systems and address broader questions about skill shortages, organizational preparedness, and sustainability goals by investigating the effectiveness of AI training programs.

Therefore, this paper aims to investigate the impact of AI training effectiveness, as measured by the CIPP evaluation model, on achieving a green growth strategy in the Jordanian energy sector. Figure 1 shows the conceptual model. The following hypotheses were formulated:

H_1: *AI training effectiveness has a positive impact on green growth strategy.*

$H_{1.1}$: *Context dimension of AI training has a positive impact on green growth strategy.*

$H_{1.2}$: *Input dimension of AI training has a positive impact on green growth strategy.*

$H_{1.3}$: *Process dimension of AI training has a positive impact on green growth strategy.*

$H_{1.4}$: *Product dimension of AI training has a positive impact on green growth strategy.*

2. METHODS

The study embraced the positivist paradigm, which emphasized objectivity, empirical measurement, and testing of hypotheses by quantifiable evidence. It utilized a quantitative, single-method design with a cross-sectional time plan, considered suitable for analyzing the causal relationship between AI training effectiveness and achieving green growth strategies within the Jordanian Electric Power Company (JEPCO).

JEPCO was chosen since it is a highly strategic, assets-intensive utility that takes a proactive stance toward its digital transformation programs and sustainable efforts in accordance with the National

http://dx.doi.org/10.21511/ee.17(1).2026.01

Green Growth Strategy in Jordan. JEPCO Annual Report (2024) notes that the firm had approximately 2,170 full-time workers in the operational, technical, and administrative divisions. The study population included employees directly engaged in significant operations and enrolled in AI training programs, such as technicians, administrative staff, engineers, and those from the computer department.

Simple random sampling was chosen to give every member of the target population the same, independent probability of selection, thereby minimizing sampling biases and increasing representativeness. N = 178 valid responses were obtained, which is more than a 5-to-1 ratio of respondents to indicators necessary to employ structural equation modeling (Hair et al., 2017).

The data were gathered using a structured, self-administered questionnaire distributed electronically. The instrument had 22 items that were rated on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). All measurement items were adopted and modified according to the existing tools in the related literature to guarantee content validity and conceptual clarity.

The demographic profile of the respondents is summarized in Table 1, thereby increasing transparency and providing contextual understanding of the sample's representativeness (Bryman, 2016; Saunders et al., 2019).

The demographic profile reveals that the great majority of the respondents were male (96%), which highlights the male-dominated workforce. Next, 69% were between 30 and 39 years old, with 14% being under 30 years, 14% being between 40 and 49 years, and 5% being above 50 years, thus representing a population that is mostly in the early to mid-career stages. Three-quarters of the respondents indicated moderate experience in the organization by reporting six to ten years of professional experience. Educational attainment in the sample was homogeneous, with all respondents holding a bachelor's degree. In terms of occupational groupings, technicians constituted 78% of the employees, engineers 12%, computer staff 8%, and administrative or financial staff 2%. The sample, as a whole, was typified by an overrepresentation of mid-career, technically trained male employees with a bachelor's degree.

Table 1. Demographics

Demographic Variable	Category	Frequency	Percent
Gender	Male	170	96%
	Female	8	4%
	Total	178	100%
Age	Under 30 years	24	14%
	30 to less than 40 years	122	69%
	40 to less than 50 years	24	14%
	50 years and above	8	5%
	Total	178	100%
Years of Experience	5 years or less	19	11%
	6 to less than 10 years	133	75%
	11 to less than 15 years	21	12%
	16 years or more	5	3%
	Total	178	100%
Educational Qualification	Bachelor	178	100%
	Master	0	0%
	Doctorate	0	0%
	Total	178	100%
Job Level	Technicians	139	78%
	Administrative Staff	3	2%
	Engineers	22	12%
	Computer Department	14	8%
	Total	178	100%

3. RESULTS

Data analysis was conducted using a two-stage approach with SmartPLS v4 and SPSS v30. The measurement model was evaluated using SmartPLS according to item loadings (> 0.70), Cronbach's alpha (α > 0.70), composite reliability (CR > 0.90), and average variance extracted (AVE > 0.50). These metrics and values represent the minimum common thresholds to establish convergent validity (Hair et al., 2017; Fornell & Larcker, 1981; Nunnally & Bernstein, 1994). The structural model was tested through SPSS using regression.

Table 2 presents the measurement model evaluation outcomes. The values show high reliability and validity of all dimensions. For the independent construct, AI training effectiveness, four dimensions (context, input, process, and product) were scored using three items each. The loading of all factors was higher than the suggested value of 0.70, with the values of 0.832 to 0.888 proving that all items were indicative of their dimensions. A mean score of 3.0 indicated moderate agreement by respondents, and standard deviations ranged between 1.17 and 1.24, which indicated reasonable changes in responses. The Cronbach's alpha of all four dimensions was greater than 0.80 and exceeded the level of reliability (0.70), and confirmed strong consistency internally. The composite reliability values ranged from 0.88 to 0.92, which exceeded the recommended cut-off, further supporting construct reliability. The levels of the average variance extracted averaged between 0.728 and 0.751 were above the 0.50 thresholds, which affirmed convergent validity. These results prove the reliability and the validity of the AI training effectiveness multidimensional construct and its training outcomes in the context of the CIPP framework.

Regarding the dependent construct, green growth strategy, the scale was operationalized with 10 items, and all exhibited satisfactory loadings ranging from 0.760 to 0.890, with the lowest still exceeding 0.70. The mean values were between 3.22 and 3.54, with a high level of agreement among the respondents on the statements. Standard deviations of 1.22 and 1.39 were decent. Reliability of the construct was also revealed to be high, with Cronbach's alpha of 0.94 and composite reliability of 0.96, which is well above the mark. The convergent validity AVE of 0.650 indicated sufficient capture of the underlying construct variance. These

Table 2. Mean, standard deviation, loading, Cronbach's alpha, CR, and AVE

Construct	Dimension	Items	Loadings	M	SD	α (> 0.7)	CR (> 0.7)	AVE (> 0.5)
AI Training Effectiveness (IV)	Context	IV1	0.888	2.97	1.236	0.518	0.92	0.728
		IV2	0.838	3.03	1.189			
		IV3	0.832	3.01	1.177			
	Input	IV4	0.833	3.02	1.208	0.618	0.88	0.730
		IV5	0.874	2.98	1.243			
		IV6	0.856	3.01	1.215			
	Process	IV7	0.851	3.01	1.177	0.518	0.89	0.730
		IV8	0.856	3.01	1.187			
		IV9	0.856	2.96	1.212			
	Product	IV10	0.852	3.00	1.206	0.835	0.90	0.751
		IV11	0.865	3.04	1.231			
		IV12	0.883	2.95	1.210			
Green Growth Strategy (DV)		DV1	0.785	3.38	1.285	0.940	0.96	0.650
		DV2	0.844	3.22	1.262			
		DV3	0.760	3.36	1.285			
		DV4	0.815	3.50	1.379			
		DV5	0.823	3.27	1.389			
		DV6	0.889	3.27	1.3			
		DV7	0.890	3.41	1.325			
		DV8	0.832	3.41	1.223			
		DV9	0.803	3.45	1.263			
		DV10	0.801	3.54	1.283			

Note: M = Mean; SD = Standard deviation; a = Cronbach's alpha; CR = Composite reliability; AVE = Average variance extracted.

http://dx.doi.org/10.21511/ee.17(1).2026.01

Table 3. Regression analysis results

Hypotheses	R^2	SD	B	SE	β	t	p	Durbin Watson	VIF	Decision
AI Training Effectiveness → Green Growth Strategy	0.316	0.79907	0.563	0.063	0.562	8.990	< .001	2.000	1.000	Supported
Context → Green Growth Strategy	0.283	0.87159	0.568	0.068	0.532	8.304	< .001	2.114	1.000	Supported
Input → Green Growth Strategy	0.310	0.87063	0.605	0.068	0.556	8.857	< .001	2.340	1.000	Supported
Process → Green Growth Strategy	0.266	0.87541	0.547	0.069	0.516	7.968	< .001	2.261	1.000	Supported
Product → Green Growth Strategy	0.237	0.92299	0.534	0.072	0.487	7.377	< .001	2.221	1.000	Supported

findings confirm that the constructs are indeed reliable and valid, and they offer a solid foundation to be used in the analysis through the structural model.

Table 3 presents the findings of the structural model analysis, which measured the effectiveness of the AI training as a predictor to the green growth strategy in Jordan.

On the construct level, the efficiency of AI training showed a significant increase to the green growth strategy ($\beta = 0.562$, $t = 8.990$, $p < 0.001$), explaining its 31.6% variance ($R^2 = 0.316$). The Durbin-Watson statistic of 2.000 indicates no autocorrelation, and a VIF of 1.000 indicates no multicollinearity.

At the dimensional level, all four components of AI training effectiveness (context, input, process, and product) were also found to significantly predict green growth strategy. The input dimension emerged as the strongest predictor ($\beta = 0.556$, $t = 8.857$, $R^2 = 0.310$), followed by the context ($\beta = 0.532$, $t = 8.304$, $R^2 = 0.283$) and process ($\beta = 0.516$, $t = 7.968$, $R^2 = 0.266$), and finally, the product dimension also showed a significant effect ($\beta = 0.487$, $t = 7.377$, $R^2 = 0.237$).

Taken together, the structural model results confirm that AI training effectiveness, both as an overall construct and through its specific dimensions, exerts a significant positive impact on achieving Jordan's green growth strategy. The consistently high t-values and low p-values (< 0.001) across all hypotheses provide strong evidence in support of the proposed model, while diagnostic tests (Durbin–Watson ≈ 2, VIF = 1.000) affirm the robustness of the regression analysis.

Consequently, the results of the regression analysis suggest that each of the proposed hypotheses was confirmed and that all had considerable and positive influences.

4. DISCUSSION

The results provide empirical evidence that effective training in artificial intelligence (AI) is a key factor in the development of the energy industry's green growth strategy in Jordan. The findings indicate that in cases where the employees are well-trained on AI, the utility is more progressive in the goal of green growth. This builds upon technology-focused research by explaining how the people element can be used to achieve sustainability. Further, there is a gap in the current research on the sustainable energy transitions: very little emphasis has been put on the role of AI training of employees in terms of the national green growth objectives.

The achievement of the green growth strategy has a strong correlation with the effectiveness of AI training ($\beta = 0.562$, $R^2 = 0.316$). This demonstrates that training is not a side effect but a driver that will enable digital technologies to deliver better environmental and operational outcomes. It aligns with earlier findings that emphasize digital transformation incorporates the human-capital efficiency (Kuzmin et al., 2024). Further, in the view of the CIPP model (Stufflebeam & Zhang, 2017), the findings show that well-designed training programs supported by the context and reinforced on a continuous basis have a facilitative role in enabling the energy utilities to achieve national goals on green growth more effectively. Of the CIPP dimensions, the input factor, which encompasses curriculum design, learning resources, and the quality of the instructional process, is most influential on green growth outcomes ($\beta = 0.556$, $R^2 = 0.310$). The results show that the most effective training programs are those whose content focuses on employees' operational activities, whose practical examples reflect the conditions of the location, and whose trainers have technical and industry-specific competencies. This aligns with the previous literature showing that digitally prepared training with a strategic focus and task relevance promotes a better outcome in the adoption process (Okuh et al., 2024). The context dimension also has a strong positive effect (β = 0.532, R^2 = 0.283), which means that the organizational preparedness and alignment of the policy are critical factors influencing the success of AI-based training. Employees will be more likely to apply the skills they gain on the job when leadership sets clear goals, provides the necessary institutional backing, and incorporates training into the overall sustainability goals. This observation can be aligned with Chwiłkowska-Kubala et al. (2023), who state that institutional readiness is a prerequisite to successful digital transformation. The process dimension, the quality of the delivery, the practice opportunities, and the access to the feedback also have a significant positive influence (β = 0.516, R^2 = 0.266). Based on the findings, interactive and experiential learning techniques such as hands-on practice, feedback through iterations, and mentorship provide the ability to retain the skills and apply them more practically. These findings align with the findings of studies that have highlighted participatory learning environments to enhance the adoption of AI and long-term commitment (Park, 2025). The product dimension, which features short-term learning outcomes that include the acquisition of skills and behavior change, is statistically significant though less significant (β = 0.487, R^2 = 0.237). It means that although employees show the first positive changes, the effectiveness of training in the long term depends on the reinforcing opportunities (periodical coaching, constant access to the data tools, and constant monitoring of the performance). The result is in line with Lucas et al. (2018), who have emphasized the fact that the effectiveness of training decays in the absence of structured follow-up and company support.

The results also differ from those of previous research because they focus on the human and training aspects of digital transformation, rather than on the technological improvements that have been the sole focus earlier. Although the concept of AI boosting operational efficiency and automation has been extensively studied in the past, the current study identifies the effectiveness of AI training as a key factor in achieving sustainability and green energy in the sector. It has shown, using the CIPP evaluation model, that such factors as contextual alignment, curriculum quality, and training delivery are more critical than technology. Besides, the study offers an emerging-country perspective by presenting evidence from the Jordanian energy industry, suggesting a link between workforce development and the national sustainability agenda, which adds to the existing literature on workforce development, which has been predominantly technology-focused.

Some practical implications can be suggested to JEPCO, preoccupied with developing their green growth plans using the AI-driven programs. AI training programs ought to be based on real operational issues, rather than purely theoretical ones. Further, the simulation training, which is similar to a real-world working environment, promotes active learning and allows staff to use their learning right away. Second, AI-related assignments are to be included in the routines of employees. As an example, allocate tasks such as checking AI model outputs, validating automated warnings, and recording system benefits. This way, employees will continue to apply their acquired knowledge and skills during training. By incorporating these activities into the daily business, short-term learning becomes long-term organizational capabilities. Also, it is interesting to measure AI training outcomes by employing measurable organizational outcomes, connecting training performance to measures like system dependability, energy consumption, and the cost of maintenance. This assists the companies in knowing whether training is contributing to strategic directions. Lastly, continuous follow-up after the training intake is critical for maintaining skill levels and outcomes. Companies should provide continuous learning such as mentorship, refresher, and professional peer groups. The activities are useful in avoiding skill degradation and encouraging continuous operational performance enhancement.

However, this study has several limitations. It only concentrates on one company, the Jordanian Electric Power Company (JEPCO), which represents the energy sector. Although

http://dx.doi.org/10.21511/ee.17(1).2026.01

this sector will be the key component of the application of the national green growth strategy, the outcomes might not comprehensively reflect the experiences or dynamics of the other industries that will also play a role in sustainable development, like water, manufacturing, transportation, construction, and waste management. These industries also play a critical role in advancing the broader environmental and economic objectives of Jordan. Thus, future research could widen the scope to other sectors to present a more in-depth insight into how AI training promotes green growth in various organizational and technological settings.

CONCLUSION

The study aimed to examine the impact of artificial intelligence (AI) training on meeting the goals of the green growth strategy at the Jordanian Electric Power Company (JEPCO) as part of the context-input-process-product (CIPP) assessment. The findings revealed a positive impact of AI training on the realization of green growth results. The input dimension of AI training was the strongest predictor among the four dimensions of analysis, compared with the other three: context, process, and product.

Based on these results, it is possible to draw a conclusion that human capital, not only technology, should be at the center of the successful digital and environmental transformation. The institutionalization of AI training as a strategic investment in the national sustainability programs in Jordan should be acknowledged and accepted. It is recommended that energy institutions reorganize training resources, tailor programs to the sector's needs, and create long-term feedback mechanisms to assess the program's effectiveness.

Future studies might examine the long-term effects of AI training across different fields in relation to the green-growth strategy. It might also question intermediate variables like institutional preparedness, digital preparedness, and policy structures in order to specify how the institution is motivated by AI training, which has encouraged sustainability.

AUTHOR CONTRIBUTIONS

Conceptualization: Azzam Abou-Moghli.
Data curation: Azzam Abou-Moghli.
Formal analysis: Azzam Abou-Moghli.
Funding acquisition: Azzam Abou-Moghli.
Investigation: Azzam Abou-Moghli.
Methodology: Azzam Abou-Moghli.
Project administration: Azzam Abou-Moghli.
Resources: Azzam Abou-Moghli.
Software: Azzam Abou-Moghli.
Supervision: Azzam Abou-Moghli.
Validation: Azzam Abou-Moghli.
Visualization: Azzam Abou-Moghli.
Writing – original draft: Azzam Abou-Moghli.
Writing – review & editing: Azzam Abou-Moghli.

ACKNOWLEDGMENT

Gratitude is expressed to the Middle East University, Amman, Jordan, for the financial support to cover this article's publishing fee.

REFERENCES

1. Akyazi, T., Goti, A., Bayón, F., Kohlgrüber, M., & Schröder, A. (2023). Identifying the skills requirements related to industrial symbiosis and energy efficiency for the European process industry. *Environmental Sciences Europe, 35,* Article 54. https://doi.org/10.1186/s12302-023-00762-z
2. Al Abdallah, G. M., Abou-Moghli, A. A., & Al-Thani, A. H. (2018). An examination of the e-commerce technology drivers in the real estate industry. *Problems and Perspectives in Management, 16*(4), 468-481. https://doi.org/10.21511/ppm.16(4).2018.39
3. Al-Khatib, A. W. (2025). Toward achieving the Sustainable Development Goals: The roles of digital human capital, circular supply chain practices, frugal innovation, and the moderating effect of relational capital. *Sustainable Development, 33*(6), 7974-7991. https://doi.org/10.1002/sd.70070
4. Arcelay, I., Goti, A., Oyarbide-Zubillaga, A., Akyazi, T., Alberdi, E., & García-Bringas, P. (2021). Definition of the future skills needs of job profiles in the renewable energy sector. *Energies, 14*(9), Article 2609. https://doi.org/10.3390/en14092609
5. Barbero, I., Rezgui, Y., & Petri, I. (2023). A European-wide exploratory study to analyse the relationship between training and energy efficiency in the construction sector. *Environment Systems & Decisions, 43,* 337-357. https://doi.org/10.1007/s10669-022-09891-x
6. Bryman, A. (2016). *Social research methods* (5th ed.). Oxford University Press.
7. Chwiłkowska-Kubala, A., Cyfert, S., Malewska, K., Mierzejewska, K., & Szumowski, W. (2023). The impact of resources on digital transformation in energy sector companies: The role of readiness for digital transformation. *Technology in Society, 74,* Article 102315. https://doi.org/10.1016/j.techsoc.2023.102315
8. Erhueh, O., Nwakile, C., Akano, O., Aderamo, A., & Hanson, E. (2024). Advanced maintenance strategies for energy infrastructure: Lessons for optimizing rotating machinery. *Global Journal of Research in Science and Technology, 2*(2), 65-93. https://doi.org/10.58175/gjrst.2024.2.2.0073
9. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50. https://doi.org/10.2307/3151312
10. Gautam, R., Saikia, A., Mishra, A., Rede, G., Patil, A., & Rastogi, S. (2025). Impact of reskilling initiatives on familiarity with AI. In *Proceedings of the 2025 International Conference on Computer Sciences, Engineering, and Technology Innovation (ICoCSETI)* (pp. 702-705). Jakarta, Indonesia. https://doi.org/10.1109/icocseti63724.2025.11019101
11. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). SAGE Publications. Retrieved from https://eli.johogo.com/Class/CCU/SEM/_A%20Primer%20on%20Partial%20Least%20Squares%20Structural%20Equation%20Modeling_Hair.pdf
12. Huang, C., & Lin, B. (2023). Promoting decarbonization in the power sector: How important is digital transformation? *Energy Policy, 182,* Article 113735. https://doi.org/10.1016/j.enpol.2023.113735
13. Jordan Electric Power Company (JEPCO). (2024). *Board of directors report and financial statements for the eighty-seventh year 2024.*
14. Jordan News Agency (Petra). (2025, March 5). *Jordan climbs in global AI readiness rankings, now 5th among Arab nations.* Petra News Agency. Retrieved from https://petra.gov.jo/Include/InnerPage.jsp?ID=69127&lang=en&name=en_news
15. Khan, S., Khan, N., Ullah, F., Kim, M., Lee, M., & Baik, S. (2023). Towards intelligent building energy management: AI-based framework for power consumption and generation forecasting. *Energy and Buildings, 279,* Article 112705. https://doi.org/10.1016/j.enbuild.2022.112705
16. Kılınç, E., Yücel, R., & Yücel, Ş. (2025). The effect of digitalization on human resources management training and development processes. *Pedagogy and Education Management Review, 2*(20), 25-32. https://doi.org/10.36690/2733-2039-2025-2-25-32
17. Kim, J., Chang, H., & Bell, B. (2025). Organizational-level training and performance: A meta-analytic investigation. *Journal of Management.* https://doi.org/10.1177/01492063251327588
18. Kruse, J., Schäfer, B., & Witthaut, D. (2021). Revealing drivers and risks for power grid frequency stability with explainable AI. *Patterns, 2*(11), Article 100365. https://doi.org/10.1016/j.patter.2021.100365
19. Kuzmin, E., Vlasov, M., Strielkowski, W., Faminskaya, M., & Kharchenko, K. (2024). Digitalization of the energy sector in its transition towards renewable energy: A role of ICT and human capital. *Energy Strategy Reviews, 53,* Article 101418. https://doi.org/10.1016/j.esr.2024.101418
20. Lin, B., & Yang, Y. (2025). Building efficiency: How the national AI innovation pilot zones enhance green energy utilization? Evidence from China. *Journal of Environmental Management, 387,* Article 125945. https://doi.org/10.1016/j.jenvman.2025.125945
21. Lucas, H., Pinnington, S., & Cabeza, L. (2018). Education and training gaps in the renewable energy sector. *Solar Energy, 173,* 449-455. https://doi.org/10.1016/j.solener.2018.07.061
22. Mäkelä, E., & Stephany, F. (2024). Complement or substitute? How AI increases the demand for human skills. *arXiv*, abs/2412.19754.

http://dx.doi.org/10.21511/ee.17(1).2026.01

https://doi.org/10.48550/arxiv.2412.19754

23. Muralidharan, P. (2025). Aligning HR training program with corporate strategy in the energy sector: Case study. *International Journal for Multidisciplinary Research, 7*(2). https://doi.org/10.36948/ijfmr.2025.v07i02.40507
24. Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.
25. Okuh, C., Nwulu, E., Ogu, E., Egbumokei, P., Dienagha, I., & Digitemie, W. (2024). Creating a workforce upskilling model to address emerging technologies in energy and oil and gas industries. *International Journal of Multidisciplinary Research and Growth Evaluation, 5*(1), 1327-1339. https://doi.org/10.54660/.IJMRGE.2024.5.1.1327-1339
26. Onu, P., Pradhan, A., & Mbohwa, C. (2023). The potential of Industry 4.0 for renewable energy and materials development – The case of multinational energy companies. *Heliyon, 9*(10), Article e20547. https://doi.org/10.1016/j.heliyon.2023.e20547
27. Park, C. (2025). Addressing challenges for the effective adoption of artificial intelligence in the energy sector. *Sustainability, 17*(13), Article 5764. https://doi.org/10.3390/su17135764
28. Rane, N., Choudhary, S., & Rane, J. (2024). Artificial intelligence driven approaches to strengthening environmental, social, and governance (ESG) criteria in sustainable business practices: A review. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4843215
29. Riyanto, S., Handiman, U., Gultom, M., Gunawan, A., Putra, J., & Budiyanto, H. (2023). Increasing job satisfaction, organizational commitment and the requirement for competence and training. *Emerging Science Journal, 7*(2), 520-537. https://doi.org/10.28991/esj-2023-07-02-016
30. Rojek, I., Mikołajewski, D., Mroziński, A., Macko, M., Bednarek, T., & Tyburek, K. (2025). Internet of Things applications for energy management in buildings using artificial intelligence – A case study. *Energies, 18*(7), Article 1706. https://doi.org/10.3390/en18071706
31. Saputro, K., & Syaebani, M. (2024). The influence of pre-training factors on training effectiveness mediated by motivation to learn, motivation to transfer, and self-efficacy – Case study on non-ministerial government institutions. *Quantitative Economics and Management Studies, 5*(3), 658-669. https://doi.org/10.35877/454ri.qems2646.
32. Saunders, M. N. K., Lewis, P., & Thornhill, A. (2019). *Research methods for business students* (8th ed.). Pearson.
33. Soni, P., & Saraf, V. (2025). Impact of training need analysis on employee performance and productivity in Madhya Pradesh power distribution companies. *International Journal for Multidisciplinary Research, 7*(3). https://doi.org/10.36948/ijfmr.2025.v07i03.48193.
34. Stufflebeam, D. L., & Zhang, G. (2017). *The CIPP Evaluation Model: How to Evaluate for Improvement and Accountability*. Guilford Press.
35. Uren, V., & Edwards, J. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management, 68,* Article 102588. https://doi.org/10.1016/j.ijinfomgt.2022.102588