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Causal Relationships among Artificial Intelligence Adoption, Environmental Technologies, Management Strategy, and Environmental Sustainability for Sustainable Urban Environmental Management (SDG 11)

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Abstract

This study examined the hypothesized structural relationships among Artificial Intelligence Adoption (AIA), Environmental Technologies (ET), Management Strategy (MS), and Environmental Sustainability (ES) in organizations involved in urban development and environmental management, with explicit relevance to Sustainable Development Goal 11 (SDG 11). Data were collected from 320 participant, and were analyzed through Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). The results of the study showed that standardized factor loadings ranged from .819 to .862, Average Variance Extracted (AVE) from .695 to .721, and Composite Reliability from .901 to .912. The structural model showed excellent reported fit with the observed covariance structure (χ^2 = 138.426, df = 126, χ^2/df = 1.099, p = 0.212, GFI = 0.958, NFI = 0.976, TLI = 0.991, CFI = 0.994, RMSEA = 0.016, RMR = 0.021). The results of the study showed that Artificial Intelligence Adoption (AIA) and Environmental Technologies (ET) had positive direct effect on Management Strategy (MS) (β = 0.468, $p < 0.001$ and 0.421, $p < 0.001$) respectively, while Management Strategy exerted positive effect direct on Environmental Sustainability (ES) (β = 0.493, $p < 0.001$). Artificial Intelligence Adoption (AIA) and Environmental Technologies had direct positive effect on Environmental Sustainability (ES) (β = 0.297, $p < 0.001$) and (0.276, $p < 0.001$) respectively. Management Strategy mediate the relationships between Artificial Intelligence Adoption (AIA) and Environmental Sustainability (ES) (β = 0.231, $p < 0.001$), and between Environmental Technologies (ET) and Environmental Sustainability (ES) (0.208, $p < 0.001$). The findings position Management Strategy as an organizational conversion mechanism linking technological capability with environmental sustainability outcomes relevant to sustainable urban environmental management (SDG 11).

Keywords:
Artificial Intelligence Adoption; Environmental Technologies; Environmental Sustainability; Sustainable Urban Environmental Management (SDG 11)

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Introduction

Sustainable urban environmental management increasingly depends on the capacity of organizations to integrate digital intelligence, environmental technologies, managerial coordination, and environmental objectives. Cities concentrate population, infrastructure demand, energy use, waste generation, pollution, and climate-related risks, while also creating opportunities for coordinated technological and institutional responses. Sustainable Development Goal 11 calls for cities and human settlements that are inclusive, safe, resilient, and sustainable. The present study focuses specifically on the environmental-management component of this agenda: the organizational capacity to conserve resources, reduce carbon emissions, protect ecological systems, and support environmentally sustainable urban development. This boundary is important because the study does not attempt to measure every target of SDG 11, such as housing, transport, heritage, public space, and participatory planning; instead, it examines organizational mechanisms that are directly relevant to environmental quality and urban sustainability.

Artificial Intelligence Adoption is increasingly relevant to urban environmental management because organizations rely on large and heterogeneous streams of operational, spatial, energy, waste, mobility, and environmental data. Artificial intelligence can support forecasting, anomaly detection, optimization, environmental monitoring, and evidence-based managerial decisions. Organizational adoption, however, depends on more than the availability of algorithms. Uren and Edwards (2023) showed that long-term AI adoption requires readiness across technology, people, processes, and data, while Neumann, Guirguis, and Steiner (2024) demonstrated that technological and organizational conditions shape AI adoption in public organizations at different stages of the adoption process. Yang, Blount, and Amrollahi (2024) similarly identified organizational readiness, innovation management, and environmental constraints as important determinants of AI adoption in professional service firms. These studies justify conceptualizing AIA as an organizational capability rather than as the mere possession of AI software.

In this study, Artificial Intelligence Adoption comprises Perceived Usefulness, Technological Readiness, Organizational Support, and AI Literacy. Perceived Usefulness captures whether personnel view AI as valuable for operational efficiency, data processing, environmental problem analysis, and managerial decision making. Technological Readiness concerns infrastructure, data availability, security, and technical capability. Organizational Support reflects managerial encouragement, training, resources, and implementation guidance, while AI Literacy captures the ability to understand AI principles, evaluate outputs, recognize ethical and data risks, and use AI responsibly. This multidimensional specification is consistent with the socio-technical nature of AI adoption and with UN-Habitat's (2024) emphasis on people-centered governance, institutional capacity, and responsible AI deployment in cities.

Environmental Technologies provide the second technological foundation of the model. They include Green Technology Adoption, Energy Efficiency Systems, Waste Management Technology, and Environmental Monitoring Systems. These technologies offer operational and monitoring capacity for reducing resource losses, improving energy efficiency, strengthening waste reduction and recovery, and detecting environmental risks. Alofaysan et al. (2024) reported a positive relationship between digitalization, green technology innovation, and energy efficiency, while Orazalin et al. (2025) stated that green technology innovation can contribute to waste reduction and recycling under different governance conditions. Sustainable smart-city research also increasingly links digital technologies, artificial intelligence, urban governance, resilience, and SDG 11 (Kaiser & Deb, 2025). Together, this evidence supports the view that environmental technologies should be conceptualized as an integrated portfolio rather than as a single technological category.

Artificial Intelligence Adoption and Environmental Technologies are therefore distinct but complementary organizational capabilities. AIA primarily strengthens analytical and decision-support capacity, whereas Environmental Technologies provide operational, physical, and monitoring systems through which environmental priorities can be implemented. Monitoring systems may generate data on pollution, energy use, or waste flows, while AI-enabled tools can analyze these data to detect anomalies, forecast risks, and prioritize interventions. Conversely, AI may identify opportunities for optimization, but environmental technologies are needed to translate analytical recommendations into operational change. The complementarity of the two capabilities suggests that sustainable urban environmental performance depends not on isolated technologies but on their coordinated use within an organizational management system.

Technology alone does not guarantee sustainability. Organizations require management arrangements that define environmental objectives, coordinate leadership, allocate resources, establish implementation priorities, and integrate environmental considerations into formal policy. This study therefore positions Management Strategy as a mediating organizational mechanism between technological antecedents and Environmental Sustainability. Tian, Siddik, and Sobhani (2024) showed that top-management commitment can influence environmental sustainability through green investment, corporate social responsibility, and environmental strategy. Kantabutra (2024) likewise emphasized the integration of sustainability strategy, organizational practices, and performance management. Sedovs, Volkova, and Ludviga (2025) identified strategic management as increasingly central to sustainable development under conditions of uncertainty and global disruption. These studies support the interpretation of Management Strategy as a conversion capability through which technological potential becomes coordinated organizational action.

Environmental Sustainability is defined through Resource Conservation, Carbon Emission Reduction, Ecological Balance, and Sustainable Urban Development. This multidimensional outcome captures an organization's environmental contribution to sustainable cities rather than the complete SDG 11 framework. The International Energy Agency (2025) illustrated the dual nature of AI in sustainability: AI can increase electricity demand through data centers while also supporting efficiency, innovation, resilience, and energy-system optimization. Al-Husain et al. (2025) found that digital dynamic capabilities can strengthen sustainable performance through green knowledge management and green technology innovation, while ul Haq et al. (2025) mentioned that Green AI adoption can contribute to SME sustainability through organizational investment and leadership mechanisms. These findings reinforce the proposition that sustainability value depends on how technological capability is governed, resourced, and embedded in strategic processes.

The four constructs therefore form an integrated technology-strategy-sustainability mechanism. Artificial Intelligence Adoption provides analytical and decision-support capability. Environmental Technologies provide operational and environmental-control capability. Management Strategy provides the organizational mechanism for planning, leadership, resource allocation, and policy integration. Environmental Sustainability represents the resulting contribution to resource conservation, carbon reduction, ecological protection, and sustainable urban development. This integrated perspective is particularly relevant to public agencies, local governments, state enterprises, private organizations, and educational or research institutions involved in urban and environmental governance because these organizations must coordinate digital transformation, environmental investment, strategic management, and sustainability policy rather than treat them as separate agendas.

Despite the growing literature, an important empirical gap remains. Research frequently examines AI adoption as a technology-acceptance or organizational-readiness issue, environmental technologies as domain-specific innovations, and sustainability strategy as a managerial or policy concern. Comparatively fewer studies integrate these domains within a single structural model that treats AIA and ET as parallel technological antecedents and Management Strategy as the organizational mechanism through which they are linked to environmental outcomes. The gap is especially relevant to sustainable urban environmental management because institutions operating in this context must coordinate digital intelligence, environmental infrastructure, strategy, and policy across organizational boundaries.

Accordingly, this study develops and tests a structural model in which AIA and ET are associated with Environmental Sustainability through both direct pathways and indirect pathways through Management Strategy. CFA is used to assess the dimension-level measurement model before SEM is applied to the structural relationships. The study aims to provide a coherent empirical framework for understanding how digital and environmental capabilities can be coordinated through management strategy to support resource conservation, carbon-emission reduction, ecological balance, and sustainable urban development within the environmental implementation context of SDG 11.

Research Objectives

1. To validate the dimension-level measurement structure of Artificial Intelligence Adoption (AIA), Environmental Technologies (ET), Management Strategy (MS), and Environmental Sustainability (ES) among organizations involved in urban and environmental management.
2. To examine the hypothesized direct structural relationships among AIA, ET, MS, and ES.
3. To examine the reported indirect relationship between AIA and ES through MS.
4. To examine the reported indirect relationship between ET and ES through MS.

Research Hypotheses

H1: Artificial Intelligence Adoption has a positive direct structural relationship with Management Strategy.

H2: Environmental Technologies have a positive direct structural relationship with Management Strategy.

H3: Management Strategy has a positive direct structural relationship with Environmental Sustainability.

H4: Artificial Intelligence Adoption has a positive direct structural relationship with Environmental Sustainability.

H5: Environmental Technologies have a positive direct structural relationship with Environmental Sustainability.

H6: Management Strategy mediates the relationship between Artificial Intelligence Adoption and Environmental Sustainability.

H7: Management Strategy mediates the relationship between Environmental Technologies and Environmental Sustainability.

Literature Review

Artificial Intelligence Adoption

Artificial Intelligence Adoption refers to an organization's readiness and capability to recognize the value of AI, establish the technological and institutional conditions required for use, support personnel in implementation, and develop sufficient literacy for responsible application. Perceived Usefulness captures the extent to which personnel believe AI can improve efficiency, forecasting, data processing, environmental problem analysis, and managerial decision quality. Technological Readiness concerns digital systems, data availability, infrastructure, security, and technical capability. Uren and Edwards (2023) demonstrated that successful AI adoption requires readiness across people, processes, technology, and data, while Neumann et al. (2024) stated that organizational and technological factors vary in importance across stages of AI adoption in public organizations.

Organizational Support refers to managerial encouragement, AI-related training, access to resources, clear guidelines, and opportunities for experimentation. AI Literacy concerns understanding basic AI principles, selecting appropriate tools, evaluating output reliability, recognizing ethical and data-related risks, and applying AI responsibly. UN-Habitat (2024) stressed that responsible urban AI requires governance safeguards and human capability rather than technology deployment alone. Yang et al. (2024) further presented that organizational readiness and innovation-management processes condition AI adoption in professional services. AIA in the present model therefore combines usefulness, readiness, support, and literacy to represent the organizational capacity to deploy AI in ways that can contribute to environmental decision making.

The environmental implications of AI adoption are not uniformly positive. The IEA (2025) reported that AI can increase electricity demand through data-center growth while also enabling energy optimization, innovation, resilience, and efficiency. This dual effect supports the proposition that AIA should be integrated with sustainability-oriented management. The model consequently predicts a structural relationship from AIA to Management Strategy because AI expands the information and analytical capacity available for planning and resource decisions. It also predicts a direct relationship from AIA to Environmental Sustainability because AI can strengthen monitoring, forecasting, optimization, and evidence-based environmental action.

Environmental Technologies

Environmental Technologies refer to technologies and systems used to reduce environmental impacts, improve resource efficiency, manage waste, and monitor environmental conditions. Green Technology Adoption includes cleaner and environmentally responsible technologies. Energy Efficiency Systems include energy-control technologies, energy-efficient equipment, monitoring of energy consumption, use of energy data, and measures to reduce energy loss. Waste Management Technology includes technological support for separation, reduction, recovery, reuse, recycling, and safe disposal. Environmental Monitoring Systems include continuous environmental measurement, pollution monitoring, risk identification, digital reporting, and the use of monitoring data for environmental management.

Empirical evidence supports the environmental value of these capabilities. Alofaysan et al. (2024) identified positive effects of digitalization and green technology innovation on energy efficiency in the European Union. Orazalin et al. (2025) and Youthao et al. (2026) found that green technology innovation can reduce waste generation and improve recycling, with national governance moderating these relationships. Kaiser and Deb (2025) further identified AI, big data, machine learning, urban governance, and resilience as emerging themes in sustainable smart-city research linked strongly with SDG 11. These studies support conceptualizing ET as an integrated portfolio of operational and monitoring technologies.

The model predicts that ET is associated with Management Strategy because monitoring data, energy systems, waste technologies, and green infrastructure provide operational options and environmental information for planning and policy implementation. ET is also expected to retain a direct relationship with Environmental Sustainability because these technologies can reduce resource losses, emissions, waste, and environmental risk. Yet technology cannot itself determine priorities or allocate organizational resources, which motivates the proposed indirect pathway through Management Strategy.

Management Strategy

Management Strategy is the organizational mechanism through which environmental objectives are translated into coordinated action. It consists of Strategic Planning, Leadership Commitment, Resource Allocation, and Policy Integration (Feng et al., 2025). Strategic Planning includes clear environmental objectives, action plans, performance indicators, environmental risk assessment, and adaptation to changing conditions. Leadership Commitment reflects the extent to which leaders prioritize environmental objectives, communicate policy, monitor performance, support sustainability initiatives, and accept responsibility for environmental impacts. Resource Allocation concerns budgets, personnel, technology, information, and prioritization of resources, while Policy Integration concerns the incorporation of environmental criteria into strategic plans, procurement, investment, evaluation, and institutional policy (Shao et al., (2025).

This construct is central to the mediation model because management strategy converts available technological capabilities into organizational routines and decisions. Tian et al. (2024) identified top-management commitment as a pathway toward environmental sustainability through green investment and environmental strategy. Kantabutra (2024) proposed that sustainability performance management requires alignment among sustainability culture, strategy, practices, outputs, and outcomes. Sedovs et al. (2025) highlighted the increasing integration of sustainable development into strategic management. These findings are consistent with a resource-to-strategy-to-outcome logic in which technologies provide information and operational possibilities but management determines objectives, leadership actions, resource commitments, and policy integration.

The mediating role of Management Strategy is also consistent with sustainable urban implementation. Urban environmental programs require cross-functional coordination, long-term planning, budgeting, monitoring, and alignment with public-policy goals. AI can improve analysis and forecasting while environmental technologies improve monitoring and resource efficiency. Without strategic planning and policy integration, however, these capabilities may remain fragmented projects. Management Strategy therefore represents the conversion mechanism through which AIA and ET can become coordinated sustainability action.

Environmental Sustainability and SDG 11

Environmental Sustainability refers to the capacity of organizations to reduce environmental pressures while protecting ecological systems and supporting long-term urban and community well-being. The construct consists of Resource Conservation, Carbon Emission Reduction, Ecological Balance, and Sustainable Urban Development. Resource Conservation concerns efficient use of natural resources, energy and materials, reuse practices, reduction of resource losses, and long-term conservation. Carbon Emission Reduction concerns greenhouse-gas reduction measures, cleaner energy choices, emissions monitoring, and explicit reduction targets. Ecological Balance captures protection of ecosystems, green areas, natural resources, environmental quality, and restoration of environmental damage. Sustainable Urban Development concerns environmentally responsible urban development, efficient urban resource use, resilience to environmental challenges, and environmental quality for communities.

SDG 11 provides the policy context for the outcome construct because sustainable cities depend on coordinated action across environmental quality, waste management, resource use, resilience, infrastructure, and institutional planning. The United Nations Goal 11 framework emphasizes inclusive and sustainable urbanization, while UN-Habitat (2024) argued that digital and AI-enabled urban transformation should remain people-centered and responsibly governed. Kaiser and Deb (2025) and Mohammad et al. (2025) stated that sustainable smart-city research is strongly connected with SDG 11 and increasingly incorporates AI, big data, resilience, and governance. The present study therefore treats

Environmental Sustainability as an organizational environmental contribution to SDG 11 rather than as a complete measure of the goal.

This distinction prevents level-of-analysis overreach. The full SDG 11 agenda includes housing, sustainable transport, cultural heritage, disaster resilience, public space, and participatory planning. The empirical ES construct captures only the environmental-management component represented by resource conservation, carbon reduction, ecological balance, and sustainable urban development. Sustainable Urban Environmental Management is therefore the application context of the model, not an additional latent variable.

Research Conceptual Framework

Based on the literature review and seven hypotheses, Artificial Intelligence Adoption (AIA) and Environmental Technologies (ET) are posited as exogenous latent variables, Management Strategy (MS) as the mediating latent variable, and Environmental Sustainability (ES) as the endogenous outcome. A covariance relationship is specified between AIA and ET because the two technological capabilities may coexist within the same organizations while remaining theoretically distinct. Figure 1 summarizes the dimension-level measurement architecture and the hypothesized structural paths.

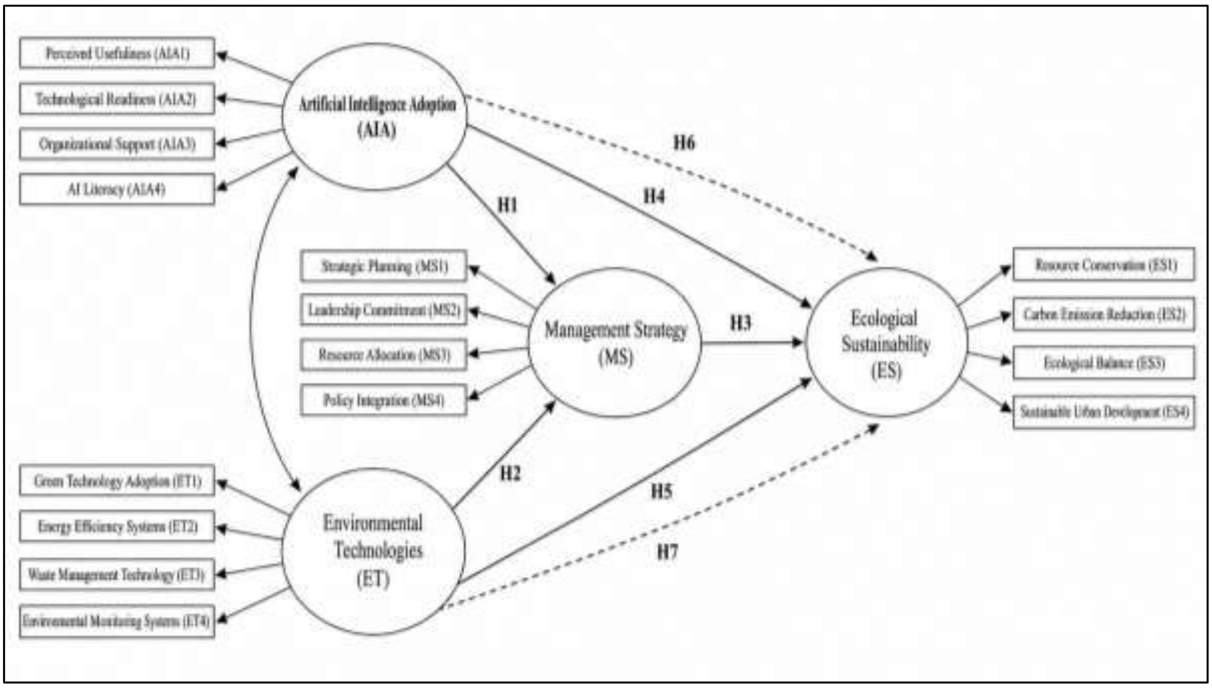

Figure 1 Proposed Structural Framework for Sustainable Urban Environmental Management under SDG 11

Methodology

Research Design

The study used a quantitative, cross-sectional explanatory survey design to evaluate the hypothesized structural relationships among AIA, ET, MS, and ES within the context of sustainable urban environmental management. CFA and SEM were applied in a two-step analytical sequence: the dimension-level measurement structure was evaluated first, followed by the structural model. Because the design is cross-sectional, directional coefficients are interpreted as model-implied structural relationships and should not be treated as proof of temporal causality. The source records supplied for this revision did not identify the SEM software, software version, or estimator; these details should be retained from the original analysis output in any final submission package rather than reconstructed retrospectively.

Population and Sample

The target population consisted of executives and personnel in organizations involved in urban development and environmental management in Thailand, including government agencies, local government organizations, state enterprises, private organizations, and educational and research institutions. Participants were purposively selected because their professional responsibilities involved technology adoption, environmental management, strategic management, urban planning, or related decision making. A total of 320 usable responses were analyzed. The sample exceeded a commonly used practical minimum for many SEM applications and provided 20 observations per dimension-level indicator for the reported model of four latent constructs and sixteen observed dimensions. Nevertheless, the study did not use probability sampling, and the available documentation did not provide a formal a priori power analysis, response rate, or final respondent distribution across organization types. Statistical adequacy should therefore be distinguished from population representativeness.

Research Instrument and Measurement

Data were collected through a structured bilingual Thai-English questionnaire developed from literature related to the four empirical constructs. Part 1 collected respondent and organizational information. Parts 2-5 measured AIA, ET, MS, and ES. Each construct was represented by four conceptual dimensions with five items per dimension, producing 80 substantive rating-scale items on a five-point Likert scale. The questionnaire was reviewed by experts and pilot tested according to the original study documentation; however, numerical content-validity coefficients, expert-panel characteristics, pilot-sample size, and pilot reliability statistics were not available in the source materials used for this revision and are therefore not reconstructed.

The reported SEM uses sixteen dimension-level observed indicators rather than the eighty individual items. AIA is represented by Perceived Usefulness, Technological Readiness, Organizational Support, and AI Literacy; ET by Green Technology Adoption, Energy Efficiency Systems, Waste Management Technology, and Environmental Monitoring Systems; MS by Strategic Planning, Leadership Commitment, Resource Allocation, and Policy Integration; and ES by Resource Conservation, Carbon Emission Reduction, Ecological Balance, and Sustainable Urban Development. The source material did not document the exact aggregation rule used to transform the five items in each dimension into the reported dimension-level composite. Accordingly, this article interprets the CFA as a dimension-composite measurement model and does not claim item-level CFA validation of all eighty questionnaire items.

Data Collection and Research Ethics

Data collection was conducted through online and institutional coordination channels. Potential respondents were informed of the academic purpose of the study, confidentiality and anonymity provisions, the voluntary nature of participation, and their right to decline participation without negative consequences. Returned questionnaires were screened for completeness and response consistency before analysis. The available records indicate that only complete questionnaires were retained but do not report the number initially received, exclusion counts, or an institutional ethics-approval identifier. The manuscript therefore avoids inventing an approval number. The authors should confirm the applicable institutional ethics statement in the final submission metadata.

Data Analysis

Confirmatory Factor Analysis (CFA) was used to evaluate the dimension-level measurement structure. Standardized factor loadings of .70 or higher were treated as strong indicator loadings, AVE values above .50 as evidence of convergent validity, and CR values above .70 as evidence of internal consistency. Discriminant validity was assessed using the Fornell-Larcker criterion by comparing the square root of each construct's AVE with its correlations with other constructs. The available analysis did not report HTMT, and no HTMT values are generated in this revision. Separate CFA model-fit indices were also not available in the supplied analysis output, so the measurement-model assessment reported below is based on factor loadings, AVE, CR, and Fornell-Larcker evidence.

The structural model was evaluated with χ^2, degrees of freedom, χ^2/df, GFI, NFI, CFI, TLI, RMSEA, and RMR. The source analysis used χ^2/df below 3.00, GFI/NFI/CFI/TLI at or above 0.90, and RMSEA/RMR at or below 0.08 as benchmarks.

Results

Measurement Model

The CFA results indicated satisfactory dimension-level measurement quality for all four latent constructs. Standardized factor loadings ranged from 0.819 to 0.862. AIA showed AVE = 0.704 and CR = 0.905. ET showed AVE = 0.695 and CR = 0.901. MS showed AVE = 0.713 and CR = 0.908, while ES showed AVE = 0.721 and CR = 0.912. These values exceeded the thresholds applied in the study for convergent validity and construct reliability. Because the CFA is reported at the dimension-composite level, the results validate the relationship between the sixteen-dimension indicators and the four latent constructs rather than the item-level psychometric properties of all eighty questionnaire items.

Table 1: Summary of construct, factor loading, average variance extracted (AVE), and composite reliability (CR)

Construct	Factor loading	AVE	CR
Artificial Intelligence Adoption (AIA)		0.704	0.905
AIA1 Perceived Usefulness	0.842		
AIA2 Technological Readiness	0.856		
AIA3 Organizational Support	0.821		
AIA4 AI Literacy	0.837		
Environmental Technologies (ET)		0.695	0.901
ET1 Green Technology Adoption	0.828		
ET2 Energy Efficiency Systems	0.846		
ET3 Waste Management Technology	0.819		
ET4 Environmental Monitoring Systems	0.841		
Management Strategy (MS)		0.713	0.908
MS1 Strategic Planning	0.839		
MS2 Leadership Commitment	0.861		
MS3 Resource Allocation	0.832		
MS4 Policy Integration	0.845		
Environmental Sustainability (ES)		0.721	0.912
ES1 Resource Conservation	0.846		
ES2 Carbon Emission Reduction	0.862		
ES3 Ecological Balance	0.833		
ES4 Sustainable Urban Development	0.854		

Note. Loadings, AVE, and CR are reported for the sixteen dimension-level indicators used in the supplied SEM analysis.

Discriminant Validity

The square roots of AVE were 0.839 for AIA, 0.834 for ET, 0.844 for MS, and 0.849 for ES. Each diagonal value exceeded the corresponding inter-construct correlations. The highest inter-construct correlation was 0.563 between MS and ES, remaining below the square roots of AVE for both constructs. The reported Fornell-Larcker criterion therefore supports discriminant validity among the four dimension-level latent constructs. Because HTMT was not available, the conclusion is restricted to the Fornell-Larcker evidence.

Table 2: Correlation Matrix of Latent Variables and Square Roots of AVE

Latent variables	AIA	ET	MS	ES
Artificial Intelligence Adoption (AIA)	**.839**			
Environmental Technologies (ET)	.486	**.834**		
Management Strategy (MS)	.542	.517	**.844**	
Environmental Sustainability (ES)	.498	.481	.563	**.849**

Note. Diagonal values are square roots of AVE; off-diagonal values are latent-construct correlations.

Structural Model Fit

The structural model showed very good correspondence with the observed covariance structure: χ^2 = 138.426, df = 126, p = 0.212, χ^2/df = 1.099, GFI = 0.958, NFI = 0.976, TLI = 0.991, CFI = 0.994, RMSEA = 0.016, and RMR = 0.021. These statistics indicate that the specified technology-strategy-sustainability model provides a highly satisfactory representation of the reported covariance structure. Close fit does not, however, establish temporal causality or substitute for missing details on estimator, data screening, item-level measurement properties, and model-modification history.

Table 3: Model Fit Indices of the Structural Model

Fit index	Criterion	Obtained value
χ^2	—	138.426
df	—	126
χ^2/df	< 3.00	1.099
p-value	> 0.05	0.212
GFI	> 0.90	0.958
NFI	> 0.90	0.976
TLI	> 0.90	0.991
CFI	> 0.90	0.994
RMSEA	< 0.08	0.016
RMR	< 0.08	0.021

Direct and Indirect Effect

The results of the study showed that Artificial Intelligence Adoption (AIA) and Environmental Technologies (ET) had positive direct effect on Management Strategy (MS) ($\beta = 0.468$, $p < 0.001$ and 0.421, $p < 0.001$) respectively, supporting hypothesis 1 and 2. Management Strategy exerted positive effect direct on Environmental Sustainability (ES) ($\beta = 0.493$, $p < 0.001$), supporting hypothesis 3. Artificial Intelligence Adoption (AIA) and Environmental Technologies had direct positive effect on Environmental Sustainability (ES) ($\beta = 0.297$, $p < 0.001$) and (0.276, $p < 0.001$) respectively, supporting hypothesis 4 and 5. Management Strategy mediate the relationships between Artificial Intelligence Adoption (AIA) and Environmental Sustainability (ES) ($\beta = 0.231$, $p < 0.001$), and between Environmental Technologies (ET) and Environmental Sustainability (ES) (0.208, $p < 0.001$), supporting hypothesis 6 and 7 respectively.

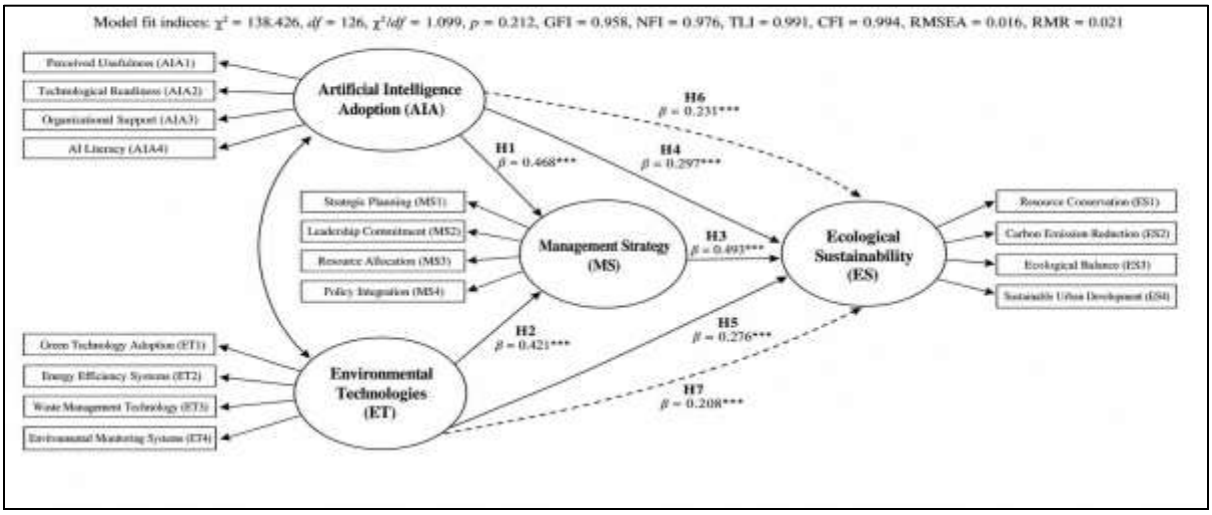

Fig. 2 Structural Equation Model of Artificial Intelligence Adoption, Environmental Technologies, Management Strategy, and Environmental Sustainability

Table 4: Standardized Path Coefficients of the Structural Model

Hypothesis	Path	Standardized β	p-value	Interpretation
H1	AIA → MS	0.468	< 0.001	Supported
H2	ET → MS	0.421	< 0.001	Supported
H3	MS → ES	0.493	< 0.001	Supported
H4	AIA → ES	0.297	< 0.001	Supported
H5	ET → ES	0.276	< 0.001	Supported
H6	AIA → MS → ES	0.231	< 0.001	Supported
H7	ET → MS → ES	0.208	< 0.001	Supported

Note. S.E. and t-values were omitted because the source table paired them with standardized β values without reporting the corresponding unstandardized coefficients. Indirect effects were significant in the reported analysis but were not accompanied by bootstrap confidence intervals.

Discussion

The findings support an integrated technology-strategy-sustainability perspective on sustainable urban environmental management. AIA and ET were structurally associated with ES through both direct and indirect pathways, while MS showed the strongest direct relationship with ES. This pattern suggests that digital intelligence and environmental technologies create analytical, operational, and monitoring opportunities, but their sustainability value depends substantially on whether those capabilities are translated into strategic planning, leadership commitment, resource allocation, and policy integration. The model therefore challenges technological determinism by identifying management as the organizational mechanism that coordinates technological resources and embeds them in sustained environmental action.

The positive AIA → MS relationship suggests that organizations with stronger perceptions of AI usefulness, technological readiness, organizational support, and AI literacy also report stronger environmental strategic management. This result is theoretically consistent with Uren and Edwards (2023), who emphasize readiness across technology, people, processes, and data, and with Neumann et al. (2024) and Ebekozien et al. (2025) who showed that organizational factors shape AI adoption in public organizations. The structural coefficient should nevertheless be interpreted as a cross-sectional association rather than proof that AIA temporally causes stronger strategy. Reverse ordering is plausible because organizations with stronger management systems may also be better positioned to adopt AI.

ET was also positively related to MS. Green technology, energy-efficiency systems, waste-management technology, and environmental monitoring can provide organizations with both operational tools and information that support planning, budgeting, target setting, and policy implementation. This is consistent with Alofaysan et al. (2024) who identified digitalization and green technology innovation as contributors to energy efficiency, and with Orazalin et al. (2025), who show that green technology innovation can improve waste outcomes under supportive governance conditions. Environmental technologies therefore function not only as technical assets but also as information-generating and decision-support infrastructures that can strengthen environmental management.

MS showed the strongest direct relationship with ES. This result identifies strategic planning, leadership commitment, resource allocation, and policy integration as the most proximal organizational capabilities in the model. The finding is consistent with Tian et al. (2024), whose results connect top-management commitment and environmental strategy with environmental sustainability, and with Kantabutra (2024), who emphasizes alignment among sustainability strategy, practices, and performance management. It also resonates with Sedovs et al. (2025), who highlight the increasing role of strategic management in sustainable development under uncertain conditions. Technological investments may create opportunities, but management is required to define priorities, mobilize budgets, assign responsibilities, establish performance indicators, and institutionalize environmental criteria.

AIA retained a direct structural relationship with ES after MS was included. AI can support environmental data processing, predictive monitoring, anomaly detection, resource optimization, and evidence-based decision making. The IEA (2025), however, documents a dual relationship between AI and sustainability because AI infrastructure itself consumes substantial electricity while AI applications may improve efficiency and system optimization. The positive coefficient should therefore not be interpreted to mean that all AI use is environmentally beneficial. Rather, organizations with stronger capacity to adopt and govern AI for environmental purposes tend to report stronger environmental outcomes within the study's cross-sectional model.

ET also retained a direct relationship with ES. Energy-efficiency systems can reduce unnecessary energy use, waste-management technologies can strengthen reduction and recovery, green technologies can reduce environmental burdens, and monitoring systems can identify environmental risks and provide evidence for corrective action. The smaller ET → ES coefficient relative to MS → ES suggests that operational technologies alone are not the dominant sustainability mechanism in the model. Their contribution appears stronger when combined with the organizational planning and policy processes represented by MS.

The indirect-effect pattern represents the central integrative contribution of the model. AIA and ET retained significant direct relationships with ES while the reported indirect coefficients through MS were also significant. The pattern is therefore consistent with complementary partial mediation. Al-Husain et al. (2025) similarly show that digital dynamic capabilities can support sustainable performance through green knowledge management and green technology innovation, while Ul Haq et al. (2025), Fei et al. (2026) and Channuwong et al. (2026) demonstrated that Green AI adoption can operate through organizational investment and leadership mechanisms. The present model extends this logic by positioning Management Strategy as a general organizational conversion mechanism linking both analytical AI capability and environmental technologies with environmental outcomes. Because bootstrap confidence intervals were unavailable, this interpretation remains provisional rather than fully bootstrap-validated.

The SDG 11 relevance should be interpreted at the environmental-management level. The study does not measure the full set of city-level SDG 11 targets. Instead, it explains an organizational mechanism relevant to resource efficiency, carbon reduction, ecological protection, and environmentally sustainable urban development. UN-Habitat (2024) emphasized the importance of responsible governance and institutional capacity in AI-enabled cities, while Kaiser and Deb (2025) identified AI, resilience, and governance as emerging themes in sustainable smart-city research. The contribution of the model is therefore an organizational explanation of how technology and strategy may support the environmental dimensions of sustainable cities, not a comprehensive measure of SDG 11 achievement.

The study also has practical relevance across heterogeneous organizational settings. Public agencies, local governments, state enterprises, private organizations, and educational or research institutions differ in resources, mandates, regulation, and digital maturity. The purposive, multi-sector sample therefore provides broad organizational variation but limits population representativeness. Future multi-group SEM should examine whether the structural relationships are stable across institutional sectors, while longitudinal designs should test whether changes in AIA, ET, and MS precede changes in objective environmental outcomes.

Conclusion

This study developed and tested a structural model for sustainable urban environmental management under SDG 11 linking Artificial Intelligence Adoption, Environmental Technologies, Management Strategy, and Environmental Sustainability. The reported SEM estimates were consistent with all five direct hypotheses and with two significant indirect-effect patterns through Management Strategy. AIA and ET were positively related to MS, MS showed the strongest direct relationship with ES, and both technological antecedents retained direct relationships with ES. The indirect coefficients through MS were statistically significant in the supplied analysis and numerically consistent with the products of the component paths. Because bootstrap confidence intervals were unavailable, the mediation pattern is interpreted as provisionally consistent with complementary partial mediation rather than as fully bootstrap-validated mediation.

The central theoretical implication is that sustainable urban environmental management should not be treated as a direct technology-to-outcome process. AIA provides analytical and decision-support capability; ET provides operational and environmental-control capability; and MS provides the strategic mechanism through which these resources are prioritized, funded, governed, and integrated into organizational policy. ES represents the organizational environmental outcome of this coordinated technology-strategy system. The dimension-level measurement results support the four-construct framework, but the study does not claim item-level validation of all eighty questionnaire items because the reported CFA used sixteen-dimension composites.

The study's relevance to SDG 11 lies primarily in the environmental-management dimensions of sustainable cities and communities, especially resource efficiency, emissions reduction, ecological protection, and environmentally sustainable urban development. The findings should not be generalized to the complete SDG 11 agenda or interpreted as proof of temporal causality. Future research should improve measurement transparency, report the full sampling and ethics record, include contemporary discriminant-validity and model-fit diagnostics, use bootstrap confidence intervals for indirect effects, compare organizational sectors, and validate the model longitudinally with objective environmental indicators.

Recommendations

1. The findings suggest that organizations may benefit from developing Artificial Intelligence Adoption as a managed capability rather than as isolated tool use. Digital infrastructure, data governance, AI literacy, training, and clear institutional guidelines should be linked to environmental analysis, resource optimization, risk forecasting, and planning.
2. Environmental Technologies should be managed as an integrated portfolio covering green technology, energy-efficiency systems, waste-management technology, and environmental monitoring.

Technology investments should be linked to measurable environmental objectives rather than treated as stand-alone procurement projects.
3. Management Strategy should receive explicit attention as the central implementation mechanism. Leaders should define environmental goals, establish indicators, allocate budgets and personnel, integrate environmental criteria into investment and procurement, and connect performance evaluation with sustainability priorities.
4. AI and environmental technologies should be integrated rather than managed as separate transformation agendas. Monitoring systems can supply data to AI-enabled analysis, while AI can improve forecasting, anomaly detection, optimization, and prioritization of environmental interventions.
5. Future research should validate the model in clearly defined populations and geographic settings, report complete sampling and instrument-development records, use bootstrap mediation analysis, and compare structural relationships across sectors. Longitudinal and multi-source designs should examine whether improvements in AIA, ET, and MS precede changes in objective environmental outcomes.

Limitations and Future Research

Several limitations guide interpretation. First, the cross-sectional design does not establish temporal precedence. Stronger Management Strategy may facilitate AIA and environmental-technology investment as well as be associated with them. Longitudinal or quasi-experimental designs are therefore needed before strong temporal-causal claims can be made. Second, purposive sampling across heterogeneous public, private, state-enterprise, local-government, and research organizations limits population representativeness and may conceal sector-specific relationships.

Third, all substantive constructs were measured through the same questionnaire, creating potential common-method bias and self-report inflation. Future research should combine survey perceptions with objective indicators such as energy consumption, emissions, waste recovery, technology-use logs, budget allocation, and verified sustainability performance. Fourth, the available study documentation reports expert review and pilot testing but does not provide numerical content-validity coefficients, pilot reliability results, or a documented aggregation rule for the dimension composites. Future studies should preserve complete instrument-development records and report item-level CFA where feasible.

Fifth, discriminant validity was evaluated using Fornell-Larcker, whereas contemporary SEM reporting often supplements this with HTMT. Separate measurement-model fit, SRMR, and an RMSEA confidence interval were not available in the supplied analysis. Sixth, the indirect-effect analysis lacks bootstrap confidence intervals, which limits the strength of the mediation inference. Finally, the source material used for this revision did not identify the SEM software, estimator, or full data-screening procedure. These omissions do not change the numerical results supplied for the study, but they limit reproducibility and should be addressed in the final archival analysis package.

Conflict of Interest

The authors declared that they have no conflict of interest in writing and publishing this article.

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