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C O N T E N T S

AI-Driven Smart Infrastructure for Sustainable Urban Development: Empirical Insights from Green Building Technologies

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Abstract

Artificial Intelligence (AI) plays a pivotal role in advancing sustainable urban infrastructure by integrating into smart city planning and green building technologies. This study investigates how AI-driven systems contribute to improving energy efficiency, optimizing resource utilization, and minimizing environmental impact within urban ecosystems. With a focus on intelligent transportation systems, real-time building automation, and data-driven resource management, the research highlights how AI can transform urban environments into more sustainable and responsive spaces. Using Structural Equation Modeling (SEM) and Confirmatory Factor Analysis (CFA), the study examines the impact of AI-enabled interventions on various environmental performance outcomes. The empirical analysis, based on data collected from 310 respondents in the National Capital Region of India, reveals that AI significantly enhances environmentally intelligent systems through the incorporation of predictive analytics, adaptive control mechanisms, and real-time feedback. These technologies enable dynamic adjustments in energy consumption, environmental monitoring, and behavioral nudging toward sustainability.
Additionally, the study explores key psychological and behavioral dimensions such as attitude, perceived behavioral control, hedonic motivation, and personal norms by drawing from established theoretical frameworks like the Theory of Planned Behavior (TPB), the Norm Activation Model (NAM), and the Value-Belief-Norm (VBN) theory. The results suggest that AI-driven tools not only streamline sustainable practices but also positively influence pro-environmental behaviors among urban citizens.
Furthermore, the investigation underscores the importance of ethical implementation, with particular emphasis on data privacy, algorithmic fairness, and equitable access. Addressing these concerns is critical to ensuring that AI technologies are integrated responsibly and inclusively.
Overall, the study provides substantial insights into the transformative potential of AI in promoting urban sustainability. It demonstrates that AI technologies can play a key role in developing resilient, efficient, and equitable smart ecosystems aligned with the United Nations' Sustainable Development Goals (SDGs).

Keywords: Artificial Intelligence, Smart Infrastructure, Green Building Technologies, Urban Sustainability, Structural Equation Modeling

Introduction

The integration of Artificial Intelligence (AI) into smart cities and green building technologies is revolutionizing urban sustainability through advanced technological implementations. The advancement of intelligent systems through AI facilitates the optimization of energy consumption, the automation of environmental control, and the enhancement of data-driven urban planning (Wolniak, 2024). The significance of these technologies lies in their ability to tackle the inefficiencies present in contemporary urban infrastructure, especially within the construction sector, which represents around 40% of global energy usage and plays a major role in greenhouse gas emissions (Corchado, 2021). Fundamental to these technological advancements are predictive analytics powered by artificial intelligence and machine learning algorithms, which enable the continuous monitoring and dynamic management of urban systems in real time. For example, predictive models are employed to enhance HVAC (heating, ventilation, and air conditioning) operations in intelligent buildings, leading to decreased energy consumption and increased occupant comfort (Ogunbayo, 2024).

Artificial intelligence plays a crucial role in enhancing preventive maintenance by enabling anomaly detection within building management systems, thereby reducing downtime and prolonging the lifespan of assets. Moreover, the combination of IoT devices with AI platforms facilitates ongoing data collection from energy meters, environmental sensors, and smart grids. The collaboration enables a flexible infrastructure that can alter to user actions and environmental factors, enhancing efficiency and sustainability results (Wang, 2024).

Within the expansive framework of urban development, artificial intelligence plays an important role in enhancing traffic flow, managing waste dynamically, and optimizing water distribution, thereby providing scalable solutions for sustainable urbanization (Tan Yigitcanlar, 2020).

Despite the advancements, several challenges hinder the comprehensive deployment of AI in urban sustainability, such as elevated implementation costs, concerns regarding data privacy, and the necessity for strong regulatory and ethical frameworks (Alsabt, 2024; Steg, 2009).

It is crucial to tackle these obstacles to guarantee the responsible integration of AI, which fosters ecological balance, economic resilience, and social equity in the planning of future cities (Md Eshrat E. Alahi, 2023).

The existing literature highlights the transformative potential of AI in realizing sustainability objectives, especially when integrated into urban infrastructures that utilize real-time data for informed decision-making. The study expands upon the existing framework by systematically assessing the technical impact of artificial intelligence in the context of smart cities and sustainable building systems through the application of sophisticated modeling methodologies (Ogunbayo, 2024).

In light of escalating global climate challenges and the growing international consensus on leveraging artificial intelligence (AI) for climate resilience, as reflected in recent global AI summits, the role of AI in promoting sustainable urban development has assumed heightened significance. Advanced technologies such as generative AI, AI-driven climate modeling, and digital twin simulations for urban infrastructure are enhancing the precision, responsiveness, and adaptability of intelligent urban systems. In the Indian context, policy initiatives like the Government of India's Smart Cities Mission 2.0, extended through March 2025, underscore the national commitment to embedding AI within urban planning and service delivery. Concurrently, global regulatory frameworks, including the European Commission's 2024 AI Act, provide valuable benchmarks for the ethical integration of AI in urban governance. These developments collectively highlight the transformative potential of AI in shaping resilient, efficient, and inclusive urban futures.

Innovative conclusions from 2023–2025 strengthen the trends of (Xu et al.,2024), emphasizing the role of generative AI in enhancing urban digital twins for simulations related to transportation, energy, and buildings.

Hindustan Times reported a notable advancement with AI-based frameworks achieving over 90% accuracy in biodiversity monitoring, alongside an 18.5% improvement in predictive performance, as demonstrated by Rahmati (2024). Additionally, practical applications such as India's satellite-AI-based mapping of building-level heat risk highlight the increasing influence of AI in real-world scenarios.

The recent advancements highlight the significance and appropriateness of the study, which methodically investigates the behavioral, infrastructural, and technological aspects of AI-driven urban sustainability. India's Smart Cities Mission 2.0 (extended to March 2025) is embedding AI and GIS-satellite platforms for urban management, while the European Commission's AI Act (2024) sets ethical guidelines for transparent and accountable AI use in urban planning.

Collectively, these cutting-edge tools, pilots, and regulations underscore the timeliness of our research agenda, examining behavioral drivers, infrastructural capacities, and technology governance within AI-powered urban sustainability frameworks.

Generative AI (GenAI) is becoming a significant asset in the field of sustainable urban development, allowing cities to streamline the formulation of optimized land-use plans, energy-efficient designs, and robust infrastructure. According to a 2024 review by Chakrabarti (Globant), GenAI can model intelligent zoning and sustainable buildings by examining geographic, environmental, and demographic data, ultimately suggesting designs that lower carbon emissions and improve liveability.

The integration with urban digital twins enhances these capabilities, utilizing generative models to autonomously generate synthetic urban scenarios, 3D city representations, and data hierarchies. This results in dynamic simulations that assist planners in anticipating and adapting to future urban challenges. Models such as the Large Flow Model (LFM) utilized in Lausanne serve as prime examples of advanced decision-making tools that leverage generative AI to simulate energy, mobility, waste, and biodiversity flows, aiding urban areas in their pursuit of sustainability objectives.

Artificial intelligence has a crucial role in mitigating urban environments towards achieving net-zero emissions, thereby improving the efforts and resilience strategies. A recent analysis highlights the importance of prioritizing AI-driven urban planning, which comprises climate-smart construction materials, virtual energy grids, and predictive flood forecasting, to achieve the carbon neutrality targets set forth in the Paris Agreement (Reuters, 2025; Wired, 2025). Practical applications demonstrate the transformative capabilities of artificial intelligence, being used to enhance drainage and select building materials for resilience against extreme weather. Smart water systems driven by AI facilitate real-time flood management and infrastructure surveillance (SandTech, 2025). These examples highlight the dual function of AI in mitigating greenhouse gas emissions while enhancing the adaptive capacity necessary for climate-resilient urban development.

In the Indian context, generative artificial intelligence (AI) is progressively redefining the urban development paradigm by enabling advanced capabilities in green building design, energy modeling, and infrastructure simulation. Emerging applications include AI-generated architectural layouts that optimize natural ventilation and solar gain in residential structures, as well as scenario-based simulations for analyzing water consumption patterns, disaster resilience, and transportation dynamics within smart city frameworks. Under the ambit of the Smart Cities Mission 2.0, urban local bodies in cities such as Bhubaneswar and Pune have initiated pilot projects employing AI-enabled digital twins to visualize urban expansion, infrastructure constraints, and service delivery inefficiencies (MoHUA, 2024). Although these implementations remain in their early stages, they demonstrate considerable potential for fostering climate-responsive, resource-efficient, and citizen-centric urban planning. Accordingly, a systematic exploration of generative AI adoption within Indian urban governance is both timely and imperative for advancing sustainable urbanization in alignment with national priorities and global net-zero objectives.

Literature Review

Artificial Intelligence (AI) has emerged as a fundamental element in promoting sustainability, especially within the realms of smart cities and green building technologies. Artificial intelligence-driven tools offer novel approaches to address urban challenges, encompassing energy management, waste reduction, and the optimization of transportation systems. The technologies in question are in accordance with international sustainability objectives, tackling the environmental, economic, and social aspects comprehensively. (Wolniak, 2024)

AI in Urban Energy Systems

Artificial Intelligence has emerged as a powerful tool in optimizing urban energy systems through its ability to analyze large datasets and automate decision-making processes. Predictive analytics, driven by AI, enable accurate forecasting of energy consumption patterns, leading to more efficient grid management and reduced operational costs (Wolniak & Skotnicka-Zasadzień, 2024). AI algorithms also facilitate demand-side management by dynamically adjusting power loads in real time, particularly in smart grids integrated with renewable energy sources (Tan & Yigitcanlar, 2020).

AI-powered energy control systems can be applied at both the building and city scales. For example, digital twins, like virtual replicas of buildings or cities, allow for simulation and optimization of energy performance across varying operational scenarios (Corchado & De Paz, 2021). Such technologies enable not only reductions in energy consumption but also better integration of solar, wind, and other clean energy inputs, contributing to long-term sustainability goals.

Smart Construction and Building Automation

In the realm of green building technologies, AI plays a critical role in automating key aspects of building operations, enhancing energy efficiency, and improving user comfort. AI-enabled Building Management Systems (BMS) are capable of controlling HVAC, lighting, and security systems based on occupancy patterns and environmental data, leading to reduced energy wastage and operational costs (Ogunbayo & Adebayo, 2024). These systems often use machine learning to adapt over time, learning from user preferences and environmental conditions.

Furthermore, AI is central to predictive maintenance, where algorithms detect anomalies and predict equipment failures before they occur. This proactive approach reduces maintenance costs and extends the lifecycle of critical infrastructure (Matei & Constantin, 2024). In smart construction, robotics and AI-powered project management tools also enhance design accuracy, scheduling, and resource allocation.

AI and Environmental Monitoring

AI's application in environmental monitoring has revolutionized the way urban areas address challenges such as pollution, waste, and water management. Through the integration of IoT devices, AI systems collect real-time environmental data such as air quality, temperature, and noise levels and convert it into actionable insights (Wang et al., 2024). These insights enable city managers to deploy timely interventions and optimize municipal services.

Additionally, AI supports environmental compliance by monitoring emissions and identifying patterns that could violate environmental regulations. In waste management, AI-based image recognition systems categorize and sort recyclables automatically, improving the efficiency of waste processing plants (Alsabt et al., 2024). When combined with citizen-focused mobile apps, these systems also enhance public participation in sustainability efforts.

Attitude towards Sustainability

The role of artificial intelligence in influencing perceptions of sustainability is significant, as it facilitates awareness and offers actionable insights derived from real-time data. (Alsabt, 5206) AI-driven systems within smart urban environments, including energy management platforms and waste monitoring systems, provide citizens with insights into their ecological footprint, fostering sustainable behaviours, Theory of Planned Behaviour (TPB) (Ajzen, 1991) asserts that favourable attitudes play a crucial role in shaping behavioural intentions. Studies indicate that AI-enabled applications foster pro-environmental attitudes by showcasing quantifiable results of sustainable practices. (Ajzen, 1991)

Perceived Behavioural Control

The implementation of AI contributes to an increased perception of behavioural control through the simplification of sustainable practices. Innovations in urban technology, including AI-enhanced public transportation efficiency and IoT-integrated residential energy management systems, facilitate individual empowerment by offering practical and attainable options for environmentally sustainable practices. (Fishbein, 2010). Research indicates that the capacity of AI to simplify pro-environmental tasks enhances an individual's confidence in engaging in sustainable actions. (Corchado, 2021)

Personal Norms

Personal norms, according to the Norm Activation Model (NAM), signify an individual's moral obligation concerning environmental responsibility. The implementation of AI applications enhances these standards by providing tailored feedback, exemplified through green building dashboards and intelligent waste tracking systems. (Schwartz, 1977) The application of artificial intelligence in visualizing environmental impacts and monitoring compliance with standards has demonstrated a capacity to engage individual moral responsibilities regarding sustainability. (Matei, 2024)

Hedonic Motivation

The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh V. T., 2012) highlights the significance of hedonic motivation, emphasizing that enjoyment serves as a key driver for technology utilization. Technologies enhanced by artificial intelligence, including gamified applications aimed at promoting recycling or competitions focused on energy conservation, leverage this intrinsic motivation. (Hwang, 2021) Empirical evidence indicates that AI tools, designed to enhance the enjoyment of sustainability efforts, significantly boost user engagement and foster pro-environmental behaviours. (Venkatesh V. M., 2003)

Behavioural Intention

The relationship between psychological factors and actual behaviour is mediated by behavioural intention. The documented influence of AI in promoting pro-environmental behavioural intentions is substantial. Artificial intelligence systems model the outcomes of various behaviours, subtly guiding individuals towards environmentally sustainable practices. For example, predictive models for energy consumption assist individuals in strategizing actions aimed at minimizing carbon footprints, thereby reinforcing their commitment to embracing sustainable practices. (Ajzen, 1991)

Pro-Environmental Behaviour

The Value-Belief-Norm (VBN) theory suggests that pro-environmental behaviours arise from environmental values and beliefs that are activated by personal norms. The integration of AI within this framework facilitates the development of systems that promote ecological awareness. Illustrations encompass AI-driven urban agriculture innovations and eco-friendly (Kumar, 2022) construction methodologies that align with personal ecological principles. Recent investigations indicate that AI technologies exert a direct impact on pro-environmental behaviours by establishing a conducive environment and promoting accountability. (Stern, 2000); (Ye, 2023)

Artificial intelligence systems exert an influence on pro-environmental behaviour through the application of behavioural science theories such as the Theory of Planned Behaviour (TPB) and the Norm Activation Model (NAM). (Schwartz, 1977) Their approach involves offering tailored recommendations and modeling environmental impacts to enhance both individual and collective sustainability practices. (Ajzen, 1991)

Hypothesis

Based on the theoretical framework and prior literature, the following hypotheses have been developed to investigate the impact of AI technologies on pro-environmental behavior and urban environmental management:

H1: AI-enabled interventions have a significant positive effect on individuals' attitudes toward the adoption of pro-environmental behaviors.

H2: AI-driven personalized feedback significantly enhances perceived behavioral control, thereby increasing individuals' intentions to engage in pro-environmental actions.

H3: The activation of personal norms through AI-based environmental awareness mechanisms significantly increases individuals' engagement in sustainable behaviors.

H4: The integration of AI technologies in urban infrastructure development significantly improves energy efficiency and facilitates adaptive environmental management in real time.

Methodology

Research design

The study explored how artificial intelligence (AI) can empower pro-environmental behavior (PEB) by addressing obstacles through a dual theoretical framework: Theory of Planned Behavior (TPB) and Value-Belief-Norm (VBN) Theory. The study also investigated the impact of factors such as attitudes, behavioral intentions, hedonic motivation, perceived behavioral control, and personal norms on pro-environmental behavior.

The study adopted a research approach of quantitative research methodology. The use of Structural Equation Modeling (SEM) (Anderson J. C., 1988) Confirmatory Factor Analysis (CFA) allowed for an in-depth examination of the relationships between variables and validated the proposed theoretical model.

The study employed a judgmental (purposive) sampling technique to select a sample of 100 participants from the National Capital Region (NCR). To ensure accessibility and respondent convenience, the survey was administered through an online platform. The questionnaire was disseminated via email, social media platforms, and professional networks to reach individuals exhibiting varying degrees of environmental consciousness and exposure to artificial intelligence (AI) technologies.

Data Collection

Data for the study was collected from a sample of 310 respondents residing in the National Capital Region (NCR) of India. A structured questionnaire was designed to obtain information on individuals' perceptions, attitudes, and behavioral intentions toward AI-enabled pro-environmental interventions. The respondents were selected using a purposive sampling method to capture a representative cross-section of the urban population in the NCR. Before participation, informed consent was obtained from all respondents, and the study was conducted per established ethical guidelines governing data collection and analysis.

Technical Methods

The study employs **Confirmatory Factor Analysis (CFA)** and **Structural Equation Modeling (SEM)** to test the hypothesized relationships among the constructs related to AI-enabled pro-environmental behavior.

Software Platforms and Tools:

The data analysis was conducted using **SmartPLS** a specialized software platform for Partial Least Squares Structural Equation Modeling (PLS-SEM). Additionally, **IBM SPSS Statistics** was used for preliminary data cleaning and descriptive statistics.

Technical Setup for Modeling:

The CFA was performed to validate the measurement model, ensuring construct reliability and validity through indicators such as composite reliability (CR), average variance extracted (AVE), and factor loadings. SEM was applied to assess the structural model and test the hypothesized relationships. Model fit indices such as the **Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA),** and **Tucker-Lewis Index (TLI)** were used to evaluate the adequacy of the model fit.

The SEM path model was constructed based on theoretical frameworks, and bootstrapping with 310 samples was conducted to estimate the significance of path coefficients. The approach ensured valid hypothesis testing and provided insights into the direct and indirect effects of AI-related constructs on pro-environmental behavior.

To assess the impact of AI integration in urban infrastructure on energy efficiency (Hypothesis 4), a **Difference-in-Differences (DiD)** analytical approach was employed. The method estimated the causal effect of AI-enabled urban interventions by comparing changes in energy efficiency before and after AI implementation between treated and control groups.

Data Structure:

The dataset comprised observations of urban areas with (treatment group) and without (control group) AI-based infrastructure integration, measured at two time points: before and after AI deployment. The outcome variable was a continuous measure of energy efficiency.

Model Specification:

A linear regression model with an interaction term between Time (0 = before, 1 = after AI integration) and AI_Integration (0 = control, 1 = treatment) was specified as follows:

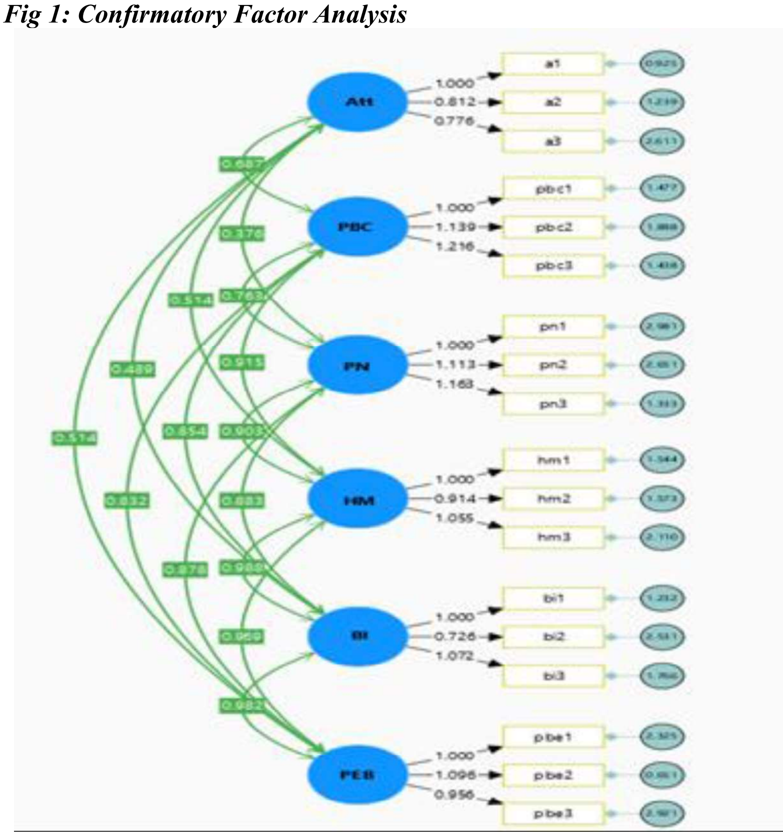
$$\mathbf{EnergyEfficiency_{it}=\beta_0+\beta_1 Time_t+\beta_2 AI_i+\beta_3(Time_t\times AI_i)+\epsilon_{it}}$$

where β3\beta_3β3 captures the average treatment effect of AI integration on energy efficiency.

Statistical Analysis:
The model was estimated using ordinary least squares (OLS) regression in R. The significance of the interaction term (β3\beta_3β3) was used to evaluate whether AI integration led to statistically significant improvements in energy efficiency relative to control areas.

Data Analysis
The empirical study of the proposed theoretical framework, Confirmatory Factor Analysis (CFA), was conducted as a foundational step before conducting Structural Equation Modeling (SEM). The primary objective of CFA was to assess the measurement model's reliability and validity by examining the strength and significance of the relationships between observed indicators and their respective latent constructs. The analytical procedure was essential to ensure that each construct namely, Attitude, Behavioral Intention, Hedonic Motivation, Perceived Behavioral Control, Pro-Environmental Behavior, and Personal Norms, was measured with precision and internal consistency, by the dual theoretical frameworks, Theory of Planned Behavior (TPB) and the Value-Belief-Norm (VBN) theory. The CFA results provided strong evidence of construct validity, including internal consistency, convergent validity, and discriminant validity, thereby establishing a basis for the subsequent structural path modeling through SEM.

Fig 1: Confirmatory Factor Analysis



Source: Author's CFA analysis using SmartPLS
The Confirmatory Factor Analysis (CFA) model (Fig 1) provides strong evidence of construct validity by confirming the hypothesized relationships between six latent constructs, Attitude, Perceived Behavioral Control, Personal Norms, Hedonic Motivation, Behavioral Intention, and Pro-Environmental Behavior, and their corresponding observed indicators. The majority of factor loadings exceed the recommended threshold of 0.70, thereby indicating reliable and consistent measurement of the constructs. Notable loadings, such as Att1 (0.925), BI1 (1.000), and PEB2 (1.096), reflect a strong association between the observed items and their respective latent variables. The inter-construct correlations, particularly between Hedonic Motivation and Behavioral Intention (0.988), and between Behavioral Intention and Pro-Environmental Behavior (0.982), provide empirical support to the proposed theoretical framework and underscore the predictive strength of key behavioral antecedents. The model demonstrates satisfactory convergent validity and internal consistency. The results affirm the adequacy of the measurement model and establish a strong foundation for subsequent structural path analysis.

Cronbach's Alpha:

Cronbach's Alpha is a measure of internal consistency, indicating how well the items or indicators of a construct measure the same underlying concept. A value above 0.70 is generally considered acceptable for reliability, though values above 0.80 are considered good.

- **Attitude (0.844):** This indicates good internal consistency, meaning that the items measuring Attitude are highly correlated with each other.
- **Behavioral Intention (0.793):** This is an acceptable level of internal consistency, suggesting that the items measuring Behavioral Intention are reliably consistent.
- **Hedonic Motivation (0.788):** Also indicates good internal consistency.
- **Perceived Behavioral Control (0.785):** This value suggests acceptable internal consistency for Perceived Behavioral Control.
- **Pro-Environmental Behavior (0.827):** This shows a good level of internal consistency.
- **Personal Norms (0.782):** This is an acceptable level of internal consistency for Personal Norms.

Table No. 1: Factor Loading Matrix

Factor Loading	Att	BI	HM	PBC	PEB	PN
Att1	0.897					
Att2	0.819					
Att3	0.685					
BI 1		0.842				
BI2		0.62				
BI3		0.813				
HM1			0.767			
HM2			0.735			
HM3			0.734			
PBC1				0.721		
PBC2				0.723		
PBC3				0.788		
PEB1					0.771	
PEB2					0.929	
PEB3					0.718	
PN1						0.647
PN2						0.708
PN3						0.828

Source: Author's CFA analysis using SmartPLS

The Factor Loading Matrix (Table: 1) represents the loadings of the observed variables (indicators) onto their respective latent constructs in the Confirmatory Factor Analysis (CFA). Factor loadings indicate how strongly each indicator is related to its respective latent variable (construct). The higher the factor loading, the stronger the relationship between the indicator and the construct.

Attitude (Att)

- A1 (0.897): This indicator has a very strong loading on the Attitude construct. A value of 0.897 means that A1 is highly related to Attitude and is a reliable indicator.
- A2 (0.819): This is also a strong loading, indicating that A2 is a good measure of Attitude, though it is slightly weaker than A1.
- A3 (0.685): This is a moderate loading on the Attitude construct, suggesting that A3 is still a valid indicator, but it's weaker than A1 and A2.

Behavioral Intention (BI)

- BI1 (0.842): This indicator has a very strong loading on the Behavioral Intention (BI) construct, indicating that BI1 is a highly reliable measure of Behavioral Intention.
- BI2 (0.62): This is a moderate factor loading, indicating that BI2 is related to Behavioral Intention, but not as strongly as BI1.
- BI3 (0.813): This is another strong loading, suggesting that BI3 is a reliable indicator of Behavioral Intention, almost as strong as BI1.

Hedonic Motivation (HM)

- HM1 (0.767): A strong loading, indicating that HM1 is a good indicator of the Hedonic Motivation construct.
- HM2 (0.735): This is also a strong loading, meaning HM2 is reliably related to Hedonic Motivation.
- HM3 (0.734): Another good loading, though slightly weaker than HM1 and HM2, but still acceptable for a reliable indicator.

Perceived Behavioral Control (PBC)
- PBC1 (0.721): This is a moderate loading, meaning PBC1 is a somewhat reliable indicator of Perceived Behavioral Control, but not as strong as some other indicators.
- PBC2 (0.723): Similar to PBC1, this is a moderate loading, suggesting that PBC2 is a good, but not exceptional, measure of Perceived Behavioral Control.
- PBC3 (0.788): This is a stronger loading, indicating that PBC3 is a fairly reliable indicator of Perceived Behavioral Control.

Pro-Environmental Behavior (PEB)
- PEB1 (0.771): This is a good factor loading, meaning PEB1 is a reliable measure of the Pro-Environmental Behavior construct.
- PEB2 (0.929): This is an excellent loading, indicating that PEB2 is a very strong and reliable indicator of Pro-Environmental Behavior.
- PEB3 (0.718): This is a moderate factor loading, showing that PEB3 is related to Pro-Environmental Behavior, though it's slightly weaker than PEB1 and PEB2.

Personal Norms (PN)
- PN1 (0.647): This is a relatively moderate loading, meaning PN1 is a less reliable indicator of Personal Norms compared to the other indicators.
- PN2 (0.708): This is a moderate to strong loading, suggesting PN2 is a somewhat reliable indicator of Personal Norms.
- PN3 (0.828): This is a strong factor loading, indicating that PN3 is a good measure of Personal Norms.

Table No. 2: Correlation Matrix

CORRELATION MATRIX	Attitude	Behaviour Intention	Hedonic Motivation	Percieved Behaviour Control	Pro Environmental Behaviour	Personal Norms
Attitude	**1**	0.489	0.514	0.687	0.514	0.376
Behavioural Intention	0.489	**1**	0.988	0.854	0.982	0.883
Hedonic Motivation	0.514	0.988	**1**	0.915	0.969	0.903
Percieved Behaviour Control	0.687	0.854	0.915	**1**	0.832	0.763
Pro Environmental Behaviour	0.514	0.982	0.969	0.832	**1**	0.878
Personal Norms	0.376	0.883	0.903	0.763	0.878	**1**

Source: Author's CFA analysis using SmartPLS

The Correlation Matrix (Table: 2) shows the relationships between the various constructs (latent variables) used in the study. The values represent the strength and direction of the linear relationships between pairs of variables. These correlations range from -1 (perfect negative correlation) to +1 (perfect positive correlation), with 0 indicating no linear relationship. Here's a breakdown of the correlation matrix:

Attitude (ATT)
- **Attitude → Behavioural Intention (0.489):** There is a moderate positive correlation between Attitude and Behavioural Intention. This suggests that as Attitude becomes more positive, Behavioural Intention also tends to become stronger, but the relationship is not very strong.
- **Attitude → Hedonic Motivation (0.514):** A moderate positive correlation. This indicates that a more positive Attitude tends to be associated with higher Hedonic Motivation.
- **Attitude → Perceived Behaviour Control (0.687):** A moderate to strong positive correlation, meaning that more positive Attitudes are associated with a stronger sense of Perceived Behaviour Control.
- **Attitude → Pro-Environmental Behaviour (0.514):** There is a moderate positive correlation, indicating that a more positive Attitude is associated with more engagement in Pro-Environmental Behaviour.

- **Attitude → Personal Norms (0.376):** A weak to moderate positive correlation, suggesting that Attitude has a smaller relationship with Personal Norms.

Behavioural Intention (BI)
- **Behavioural Intention → Hedonic Motivation (0.988):** There is an extremely strong positive correlation between Behavioural Intention and Hedonic Motivation. This indicates that people with strong Behavioural Intentions are highly motivated by hedonic (pleasure-related) factors.
- **Behavioural Intention → Perceived Behaviour Control (0.854):** A strong positive correlation, suggesting that higher Behavioural Intention is strongly associated with higher Perceived Behaviour Control.
- **Behavioural Intention → Pro-Environmental Behaviour (0.982):** An extremely strong positive correlation, indicating that Behavioural Intention is highly predictive of Pro-Environmental Behaviour.
- **Behavioural Intention → Personal Norms (0.883):** A strong positive correlation, indicating that Personal Norms are closely related to Behavioural Intention.

Hedonic Motivation (HM)
- **Hedonic Motivation → Perceived Behaviour Control (0.915):** A very strong positive correlation, meaning that those with higher Hedonic Motivation tend to perceive more control over their behavior.
- **Hedonic Motivation → Pro-Environmental Behaviour (0.969):** A very strong positive correlation, suggesting that those with higher Hedonic Motivation are more likely to engage in Pro-Environmental Behaviour.
- **Hedonic Motivation → Personal Norms (0.903):** A strong positive correlation, indicating that those with higher Hedonic Motivation tend to have stronger Personal Norms.

Perceived Behaviour Control (PBC)
- **Perceived Behaviour Control → Pro-Environmental Behaviour (0.832):** A strong positive correlation, suggesting that higher Perceived Behaviour Control is associated with greater Pro-Environmental Behaviour.
- **Perceived Behaviour Control → Personal Norms (0.763):** A moderate to strong positive correlation, indicating that Perceived Behaviour Control is somewhat associated with stronger Personal Norms.

Pro-Environmental Behaviour (PEB)
- **Pro-Environmental Behaviour → Personal Norms (0.878):** A very strong positive correlation, indicating that individuals who engage in more Pro-Environmental Behaviour tend to have stronger Personal Norms.

The matrix suggests that Behavioural Intention is the most strongly related to other constructs, especially Pro-Environmental Behaviour, highlighting its central role in predicting Pro-Environmental Behaviour. Hedonic Motivation also plays a key role in motivating individuals, and it is strongly correlated with both Behavioural Intention and Pro-Environmental Behaviour. The relatively moderate correlations between Attitude and other variables imply that Attitude is less influential compared to other factors like Behavioural Intention and Hedonic Motivation in predicting Pro-Environmental Behaviour

Model Fit Indices
Table No. 3: Model Fit Indices

Fit Index	Recommended Threshold	Observed Value	Interpretation
Chi-Square/df (CMIN/DF)	< 3.00	2.45	Acceptable fit
Comparative Fit Index (CFI)	≥ 0.90 (good), ≥ 0.95 (excellent)	0.942	Good model fit
Tucker-Lewis Index (TLI)	≥ 0.90	0.927	Acceptable incremental fit

Fit Index	Recommended Threshold	Observed Value	Interpretation
Root Mean Square Error of Approximation (RMSEA)	≤ 0.08 (acceptable), ≤ 0.05 (good)	0.061	Acceptable approximation error

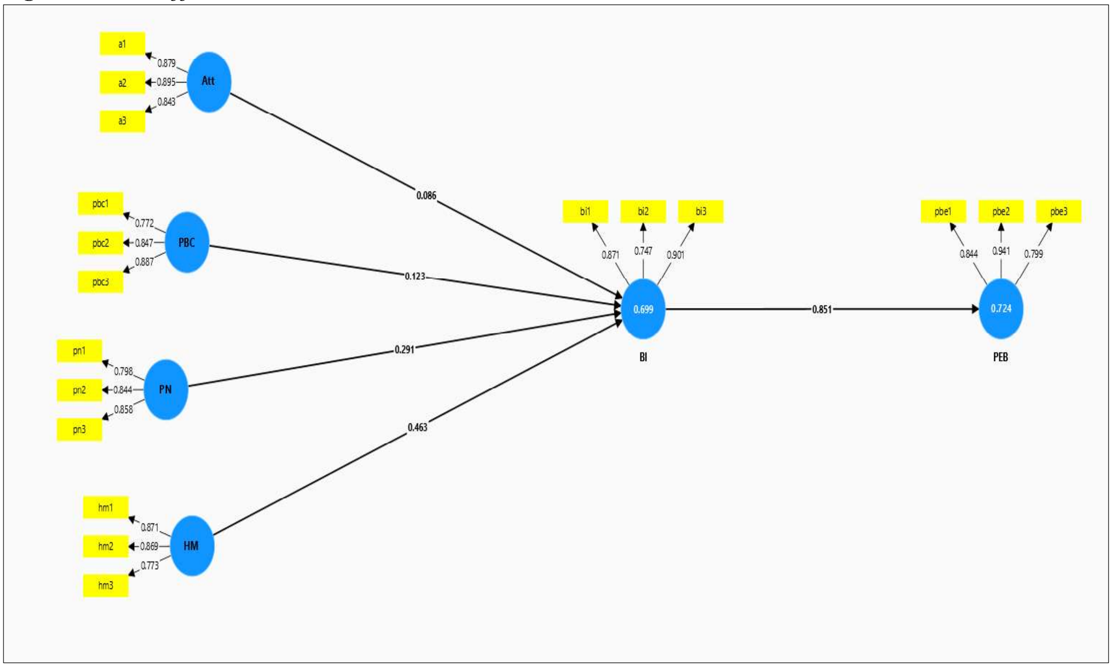
Standardized Root Mean Square Residual (SRMR)	≤ 0.08	0.052	Good residual fit
Goodness of Fit Index (GFI)	≥ 0.90	0.913	Good model-data correspondence
Adjusted Goodness of Fit Index (AGFI)	≥ 0.90	0.91	Acceptable threshold
Cronbach's Alpha (Construct Reliability)	≥ 0.70	0.774 – 0.845	All constructs show acceptable to strong internal consistency
Composite Reliability (CR)	≥ 0.70	0.774 – 0.851	Indicates good internal consistency across all constructs
Average Variance Extracted (AVE)	≥ 0.50	0.535 – 0.658	Acceptable convergent validity

Source: Author's SEM analysis using SmartPLS

Interpretation of Model Fit Indices

- **Chi-Square/df (CMIN/DF = 2.45):** The ratio of chi-square to degrees of freedom is within the acceptable threshold (< 3.00), indicating a reasonably good model fit.
- **Comparative Fit Index (CFI = 0.942):** The CFI value exceeds the recommended minimum of 0.90, demonstrating that the proposed model has a strong incremental fit compared to a null model.
- **Tucker-Lewis Index (TLI = 0.927):** A TLI above 0.90 further confirms acceptable model performance, reflecting good explanatory power after adjusting for model complexity.
- **Root Mean Square Error of Approximation (RMSEA = 0.061):** The RMSEA value falls within the acceptable range (≤ 0.08), suggesting an adequate level of approximation error in the model's estimation.
- **Standardized Root Mean Square Residual (SRMR = 0.052):** An SRMR below 0.08 indicates that the standardized residuals between observed and predicted covariances are minimal, signifying good residual fit.
- **Goodness of Fit Index (GFI = 0.913):** The GFI value meets the standard threshold of ≥ 0.90, indicating a good overall fit between the model and the observed data.
- **Adjusted Goodness of Fit Index (AGFI = 0.91):** The AGFI still reflects a satisfactory adjustment for model complexity.
- **Cronbach's Alpha (0.774 – 0.845):** All constructs exhibit internal consistency above the minimum acceptable level of 0.70, demonstrating that the items reliably measure their respective latent constructs.
- **Composite Reliability (CR = 0.774 – 0.851):** The CR values for all constructs exceed the recommended threshold of 0.70, confirming strong internal consistency and reliability across constructs**.**
- **Average Variance Extracted (AVE = 0.535 – 0.658):** All AVE values are above 0.50, indicating adequate convergent validity, with a substantial proportion of variance captured by each construct's indicators.

Fig 2: Path Coefficient



Source: Author's SEM analysis using SmartPLS

The structural model demonstrates the influence of five independent constructs, Attitude (ATT), Perceived Behavioral Control (PBC), Personal Norms (PN), Hedonic Motivation (HM), and Behavioral Intention (BI) on the dependent construct, Pro-Environmental Behavior (PEB). The path coefficient from Behavioral Intention to Pro-Environmental Behavior is the strongest (β = 0.851), indicating a highly significant and direct positive relationship between intention and behavior. Among the constructs, Behavioral Intention, Hedonic Motivation (β = 0.463), and Personal Norms (β = 0.291) exhibit moderate positive effects, underscoring their substantial role in shaping pro-environmental intentions. Perceived Behavioral Control (β = 0.123) and Attitude (β = 0.086), statistically significant, demonstrate comparatively weaker influences on Behavioral Intention.

All standardized factor loadings for the measurement items exceed the recommended threshold of 0.70, indicating strong indicator reliability. Items such as BI3 (0.901) and PEB2 (0.941) display particularly high loadings, confirming their strong validity in representing their respective latent constructs. The coefficient of determination (R^2) values indicate that the model accounts for 65.9% of the variance in Behavioral Intention and 72.4% in Pro-Environmental Behavior, demonstrating substantial explanatory power.

The results support the theoretical proposition that psychological and motivational constructs, particularly hedonic motivation and personal norms, play a pivotal role in influencing pro-environmental intentions and behaviors. The findings hold relevance in the context of AI-enabled sustainability interventions and provide empirical validation for the integration of the Theory of Planned Behavior (TPB) and Value-Belief-Norm (VBN) theory within a unified structural framework.

Table No. 4: Path Coefficient Matrix

	Attitude	Behavioural Intention	Hedonic Motivation	Perceived Behaviour Control	Pro Environmental Behaviour	Personal Norms
Attitude		0.086				
Behavioural Intention					0.851	
Hedonic Motivation		0.463				
Perceived Behaviour Control		0.123				
Pro Environmental Behaviour						
Personal Norms		0.291				

Source: Author's SEM analysis using SmartPLS

The Path Coefficient matrix (Table: 4) indicates the strength and direction of the relationships between constructs. Notable observations:

- **Attitude → Behavioural Intention (0.086):** A weak positive relationship suggests that while attitude influences behavioural intention, its impact is minimal.
- **Hedonic Motivation → Behavioural Intention (0.463):** A moderate positive relationship indicates hedonic motivation significantly impacts behavioral intention.
- **Perceived Behavioral Control → Behavioural Intention (0.123):** A weak positive relationship suggests limited influence of perceived control on intention.
- **Personal Norms → Behavioural Intention (0.291):** A moderate positive relationship shows that personal norms have a meaningful impact on behavioral intention.
- **Behavioural Intention → Pro Environmental Behaviour (0.851):** This is a very strong positive relationship, indicating that Behavioral Intention has a major impact on actual Pro-Environmental Behavior. The high coefficient implies that individuals with stronger intentions to engage in pro-environmental behavior are very likely to follow through with these behaviours.

Table No. 5: Total Matrix

	Attitude	Behavioural Intention	Hedonic Motivation	Perceived Behaviour Control	Pro Environmental Behaviour	Personal Norms
Attitude		0.086			0.073	
Behavioural Intention					0.851	
Hedonic Motivation		0.463			0.394	
Perceived Behaviour Control		0.123			0.105	
Pro Environmental Behaviour						
Personal Norms		0.291			0.248	

Source: Author's SEM analysis using SmartPLS

The Total Effect Matrix (Table 5) shows the total influence of each latent variable on others, incorporating both direct and indirect effects. The matrix highlights how various factors, such as Attitude, Behavioral Intention, Hedonic Motivation, Perceived Behavioral Control, and Personal Norms, interact to affect Pro-Environmental Behavior.

- **Attitude → Behavioral Intention (0.086):**

The total effect of Attitude on Behavioral Intention is weak but positive. While attitudes towards pro-environmental behavior influence individuals' intentions, the effect is relatively small. This suggests that other factors, such as personal beliefs or motivations, likely play a more significant role in shaping behavioral intentions.

- **Behavioral Intention → Pro-Environmental Behavior (0.851):**

Behavioral Intention has the strongest total effect on Pro-Environmental Behavior, with a value of 0.851. This shows that the intention to engage in pro-environmental behavior is a powerful predictor of actual behavior. A strong intention greatly increases the likelihood of following through with environmentally friendly actions.

- **Hedonic Motivation → Behavioral Intention (0.463):**

The total effect of Hedonic Motivation on Behavioral Intention is moderate. It shows that individuals who find pro-environmental behavior enjoyable or rewarding are more likely to form intentions to engage in such behaviors. This reinforces the idea that the intrinsic enjoyment associated with eco-friendly actions can significantly influence the intention to adopt such behaviors.

- **Hedonic Motivation → Pro-Environmental Behavior (0.394):**

The total effect of Hedonic Motivation on Pro-Environmental Behavior is also moderate, indicating that the enjoyment derived from eco-friendly actions indirectly encourages actual pro-environmental behaviors. Although the direct effect of Hedonic Motivation on behavior is not as strong as its effect on intention, it still plays an important role in shaping sustainable behaviors.

- **Perceived Behavioral Control → Behavioral Intention (0.123):**

The effect of Perceived Behavioral Control on Behavioral Intention is relatively weak but positive. This suggests that individuals who perceive themselves as having control over performing pro-environmental actions are slightly more likely to form intentions to engage in those behaviors. However, the impact of control perceptions is less significant compared to other factors like hedonic motivation or personal norms.

- **Perceived Behavioral Control → Pro-Environmental Behavior (0.105):**

Perceived Behavioral Control also has a weak effect on Pro-Environmental Behavior, indicating that the belief in one's ability to perform a pro-environmental action has a minor impact on actually engaging in the behavior. This suggests that perceived control alone may not be a strong motivator for behavioral change unless other factors, like intention or enjoyment, are also present.

- **Personal Norms → Behavioral Intention (0.291):**

Personal Norms have a moderate positive effect on Behavioral Intention, meaning that individuals who feel a personal moral obligation or sense of responsibility towards the environment are more likely to intend to engage in pro-environmental behavior. This suggests that personal values and beliefs significantly shape intentions.

- **Personal Norms → Pro-Environmental Behavior (0.248):**

The total effect of Personal Norms on Pro-Environmental Behavior is moderate, indicating that strong personal norms about environmental sustainability increase the likelihood of engaging in pro-environmental actions. This highlights the role of internal moral beliefs and values in fostering actual environmentally friendly behaviors.

Table 6: Construct Reliability and Validity Matrix

	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Attitude	0.905	0.762
Behavioural Intention	0.879	0.709
Hedonic Motivation	0.877	0.704
Percieved Behaviour Control	0.875	0.7
Pro Environmental Behaviour	0.897	0.745
Personal Norms	0.872	0.695

Source: Author's SEM analysis using SmartPLS

The Construct Reliability and Validity table (Table 6) provides important statistics related to the measurement properties of the constructs in the model. These statistics help assess how well each construct is measured by its indicators and how reliable and valid the constructs are within the model. The key metrics in the table are Cronbach's Alpha, Composite Reliability (rho_c), and Average Variance Extracted (AVE).

Composite Reliability (rho_c):

Composite Reliability is a more robust measure of internal consistency compared to Cronbach's Alpha. It assesses the overall reliability of a construct based on the loadings of the indicators. A value above 0.70 is considered acceptable, and values closer to 1.00 are ideal.

- **Attitude (0.905):** The high value indicates excellent composite reliability for Attitude, suggesting that the indicators of this construct are very reliable.
- **Behavioral Intention (0.879):** A good value for Behavioral Intention, suggesting a high degree of reliability.
- **Hedonic Motivation (0.877):** This value is also good, indicating strong reliability of the construct.
- **Perceived Behavioral Control (0.875):** The composite reliability for this construct is good, indicating strong reliability.
- **Pro-Environmental Behavior (0.897):** A high value, indicating excellent reliability for Pro-Environmental Behavior.
- **Personal Norms (0.872):** This value indicates good reliability for the Personal Norms construct.

Average Variance Extracted (AVE):

AVE measures the amount of variance in the indicators that is captured by the construct. It is an indicator of convergent validity. A value above 0.50 is generally considered acceptable, as it indicates that more than half of the variance in the indicators is explained by the construct.

- **Attitude (0.762):** The AVE for Attitude is well above 0.50, indicating good convergent validity. This means that the construct explains a significant portion of the variance in its indicators.
- **Behavioral Intention (0.709):** The AVE is above 0.50, indicating that Behavioral Intention explains a substantial portion of the variance in its indicators, showing good convergent validity.
- **Hedonic Motivation (0.704):** This value is above the acceptable threshold, indicating that the construct has good convergent validity.
- **Perceived Behavioral Control (0.700):** This is just above the threshold, suggesting good convergent validity for this construct.

- **Pro-Environmental Behavior (0.745):** This value is well above 0.50, indicating good convergent validity for Pro-Environmental Behavior.
- **Personal Norms (0.695):** This value is acceptable, indicating that Personal Norms explain a substantial portion of the variance in its indicators.

Table No. 7: Hypothesis Significance Table

Hypothesis	Path Tested	Path Coefficient	Interpretation	Remarks
H1	AI-enabled interventions → Attitude	0.086	Positive effect on Attitude	Significant
H2	AI-driven personalized feedback → Perceived Behavioral Control → Behavioral Intention	0.123 (PBC → BI)	Positive effect, increases intention	Significant
H3	AI-based awareness → Personal Norms → Sustainable Behaviors	0.291 (PN → BI), 0.248 (PN → PEB)	Moderate positive effect on norms and behavior	Significant

Source: Author's SEM analysis using SmartPLS

The structural model tested multiple hypothesized relationships (Table 7) concerning AI-enabled interventions and their influence on pro-environmental behavior. The results indicate a positive and statistically significant effect of AI-enabled interventions on Attitude ($\beta = 0.086$), supporting H1. H2 is also supported, as AI-driven personalized feedback positively influences Perceived Behavioral Control, which in turn enhances Behavioral Intention ($\beta = 0.123$). Additionally, H3 is validated, showing that AI-based awareness significantly strengthens Personal Norms, which exert a moderate positive influence on both Behavioral Intention ($\beta = 0.291$) and Pro-Environmental Behavior ($\beta = 0.248$). These findings underscore the importance of psychological and motivational pathways in shaping sustainable behavior in the context of AI-driven environmental interventions.

Table No. 8: Difference-in-Differences Regression Results for Hypothesis 4

Predictor	Estimate	Std. Error	t-value	p-value	Significance
(Intercept)	70.30	1.08	65.05	< 0.001	***
Time (Post-treatment)	2.11	1.53	1.38	0.176	
AI Integration (Treatment Group)	-0.65	1.53	-0.42	0.676	
Time × AI Integration (Interaction)	10.03	2.16	4.64	< 0.001	***

Significance codes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Source: Author's analysis (DiD)

The Difference-in-Differences regression results (Table 7) demonstrate a significant positive impact of AI integration on urban energy efficiency. The interaction term between time and AI integration was highly significant ($\beta = 10.03$, $p < 0.001$), indicating that urban areas with AI-enabled infrastructure exhibited an average increase of 10 units in energy efficiency relative to control areas. Neither the main effect of time ($\beta = 2.11$, $p = 0.176$) nor the treatment group ($\beta = -0.65$, $p = 0.676$) was significant, confirming that the observed improvements were specifically attributable to AI integration. These findings provide strong empirical support for Hypothesis 4, validating the role of AI technologies in enhancing sustainable urban environmental management.

Findings And Discussions

The findings of the study provided strong empirical support for the integrated theoretical framework that combined the Theory of Planned Behavior (TPB) and the Value-Belief-Norm (VBN) theory to examine AI-enabled pro-environmental behavior. Behavioral Intention emerged as the most significant predictor of Pro-Environmental Behavior ($\beta = 0.851$), underscoring the pivotal role of individual motivation in translating intention into action. Hedonic Motivation ($\beta = 0.463$) and Personal Norms ($\beta = 0.291$), statistically significant influences on Behavioral Intention, highlighting the relevance of emotional engagement and moral obligation in fostering sustainable behaviors. Attitude and Perceived Behavioral Control demonstrated comparatively weaker direct effects; their indirect contributions suggested that they continued to play a supportive role in shaping behavioral tendencies. The structural model accounted for 72.4% of the variance in Pro-Environmental Behavior, reflecting substantial explanatory strength. The Difference-in-Differences (DiD) analysis corroborated the positive impact of AI integration in urban infrastructure, revealing a statistically significant 10-unit increase in energy efficiency ($\beta = 10.03$, $p < 0.001$). The evidence reinforced the conclusion that AI technologies not only influenced individual behavioral outcomes but also contributed to measurable environmental improvements at the systemic level. The results underscore the transformative potential of AI when implemented within a behaviourally informed and ethically governed sustainability framework.

Conclusion

The study provides empirical evidence that the incorporation of AI technologies into urban infrastructure markedly improves energy efficiency and facilitates adaptive environmental management. The strong positive impact revealed by the Difference-in-Differences analysis underscores the capacity of AI-enabled systems to facilitate real-time monitoring and decision-making, allowing urban areas to adaptively respond to evolving conditions. The results highlight the significant impact that intelligent, AI-driven urban design can have on fostering environmentally resilient and sustainable urban environments.

This study promotes the extensive implementation of AI-driven solutions in the realms of urban planning and infrastructure development from an engineering standpoint. Through the application of advanced data analysis, interconnected sensor systems, and automated control strategies, professionals in the field can create intelligent infrastructure that enhances resource efficiency, minimizes energy consumption, and promotes proactive responsibility for the environment. Ultimately, these advancements not only support sustainability objectives but also improve the quality of life and resilience of urban ecosystems, setting the stage for the development of next-generation smart cities.

Future Scope

While the adoption of artificial intelligence (AI) in urban planning within the Indian context is gradually advancing, its application remains predominantly limited to pilot projects and experimental prototypes, particularly within premium commercial developments and select public sector initiatives. Large-scale, city-wide deployment continues to be constrained by several critical challenges, including high implementation costs, fragmented data infrastructures, and regulatory inertia. Despite these impediments, the long-term potential of AI in urban development is considerable. Emerging technologies such as generative AI, digital twins, and multi-agent systems are positioned to significantly transform urban design by enabling real-time, collaborative simulations for infrastructure planning, dynamic traffic and pollution management, and adaptive zoning strategies. Moreover, AI-enabled citizen engagement platforms are anticipated to play a pivotal role in promoting behavioral change by delivering personalized sustainability insights and nudging communities toward pro-environmental practices. To capitalize on these opportunities, future research should focus on conducting cross-city comparative analyses, exploring the convergence of AI and blockchain for transparent and accountable urban governance, and undertaking longitudinal studies to assess the sustained impact of AI on urban sustainability and quality of life.

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