ISSN 0974-763X

SOUTH ASIAN JOURNAL OF MANAGEMENT RESEARCH (SAJMR)

Volume 16, Issue No. 1 January, 2026

ESTD : 1976
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CHHATRAPATI SHAHU INSTITUTE OF BUSINESS EDUCATION AND RESEARCH,(CSIBER), KOLHAPUR , MAHARASHTRA, INDIA .

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Published by
CSIBER Press, Central Library Building
Chhatrapati Shahu Institute of Business Education & Research (CSIBER)
(An Autonomous Institute)
University Road, Kolhapur - 416004, Maharashtra State, India
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Chhatrapati Shahu Institute of Business Education and Research (CSIBER)

South Asian Journal of Management Research (SAJMR)

Volume 16, Issue No. 1, January 2026

Editor: Dr. Pooja M. Patil

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Central Library
Chhatrapati Shahu Institute of
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South Asian Journal of Management Research
(SAJMR)

Volume 16, Issue No. 1 **January, 2026**

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

Instroduction

The integration of Artificial Intelligence (AI) into smart cities and green building technologies is revolutionizing urban sustainability via 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). Central to these advancements are predictive analytics driven by artificial intelligence and machine learning algorithms that enable real-time monitoring and adaptive management of urban systems. 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. This collaboration enables a flexible infrastructure that can adjust to user actions and environmental factors, enhancing efficiency and sustainability results (Wang, 2024).

Within the expansive framework of urban development, artificial intelligence plays a pivotal 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 impede 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. This 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).

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 analyse 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 building and city scales. For example, digital twins—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

This study aims to explore 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 investigates the impact of factors such as attitudes, behavioral intentions, hedonic motivation, perceived behavioral control, personal norms, on pro-environmental behavior.

This study adopts a mixed-methods research approach that combines both qualitative and quantitative research methodologies. The use of Structural Equation Modeling (SEM) (Anderson, 1988) and Confirmatory Factor Analysis (CFA) will allow for an in-depth examination of the relationships between variables and validate the proposed theoretical model.

The research applied a Judgemental sampling method to identify 100 participants from the National Capital Region (NCR), with the survey administered online to facilitate accessibility and convenience for the respondents. The online survey was disseminated through email, social media channels, and professional networks, aiming to reach individuals with diverse levels of environmental awareness and interaction with AI technologies.

Data Collection

The data for this study were collected from a sample of 310 respondents residing in the National Capital Region (NCR) of India. A structured questionnaire was administered to gather information related to individuals' perceptions, attitudes, and behavioral intentions concerning AI-enabled pro-environmental interventions.

The respondents were selected using convenience sampling, to ensure a representative cross-section of the urban population in NCR.

All participants provided informed consent, and the study adhered to ethical standards in 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** (or specify if using AMOS, LISREL, or another SEM software), a specialized software platform for Partial Least Squares Structural Equation Modeling (PLS-SEM). Additionally, **IBM SPSS Statistics** was utilized 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. Following this, SEM was applied to assess the structural model and test the hypothesized relationships. Model fit indices such as **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 500 resamples was conducted to estimate the significance of path coefficients. This approach ensures robust hypothesis testing and provides 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. This method estimates 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:

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

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

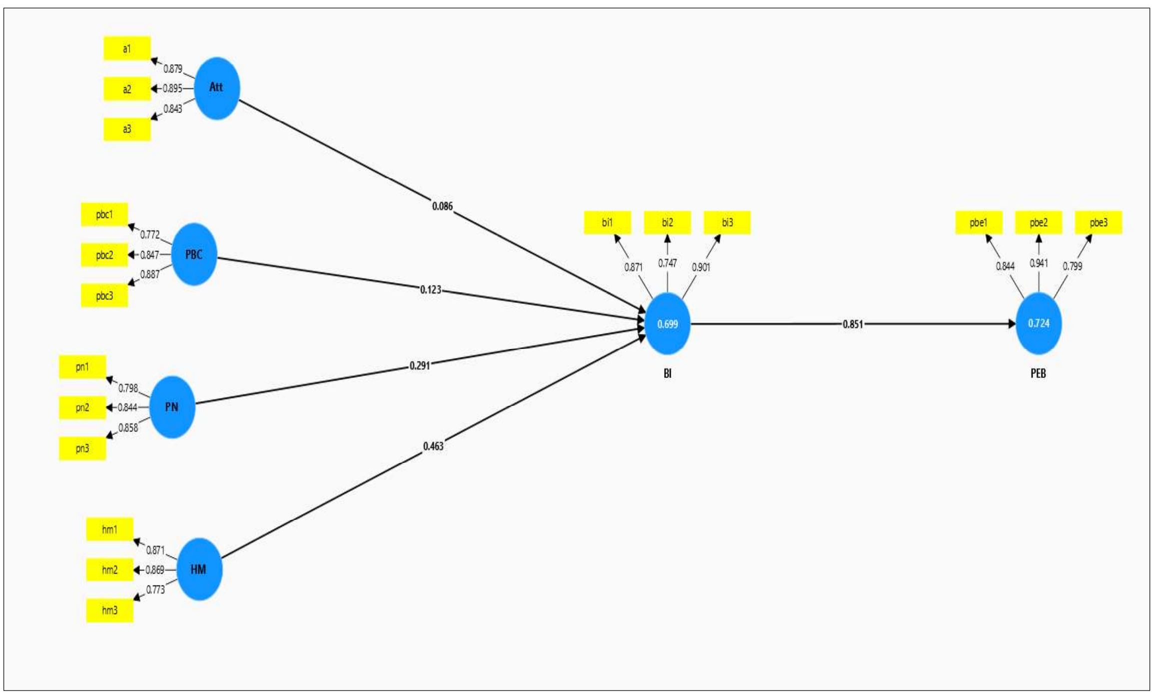

Fig 1: Path Coefficient

Table 1: 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				

The Path Coefficient matrix 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 2: 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	

The Total Effect Matrix 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 3: Construct Reliability and Validity Matrix

	Cronbach's Alpha	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Attitude	0.844	0.905	0.762
Behavioural Intention	0.793	0.879	0.709
Hedonic Motivation	0.788	0.877	0.704
Percieved Behaviour Control	0.785	0.875	0.7
Pro Enviornmental Behaviour	0.827	0.897	0.745
Personal Norms	0.782	0.872	0.695

The Construct Reliability and Validity table 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).

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.

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.

Confirmatory Factor Analysis

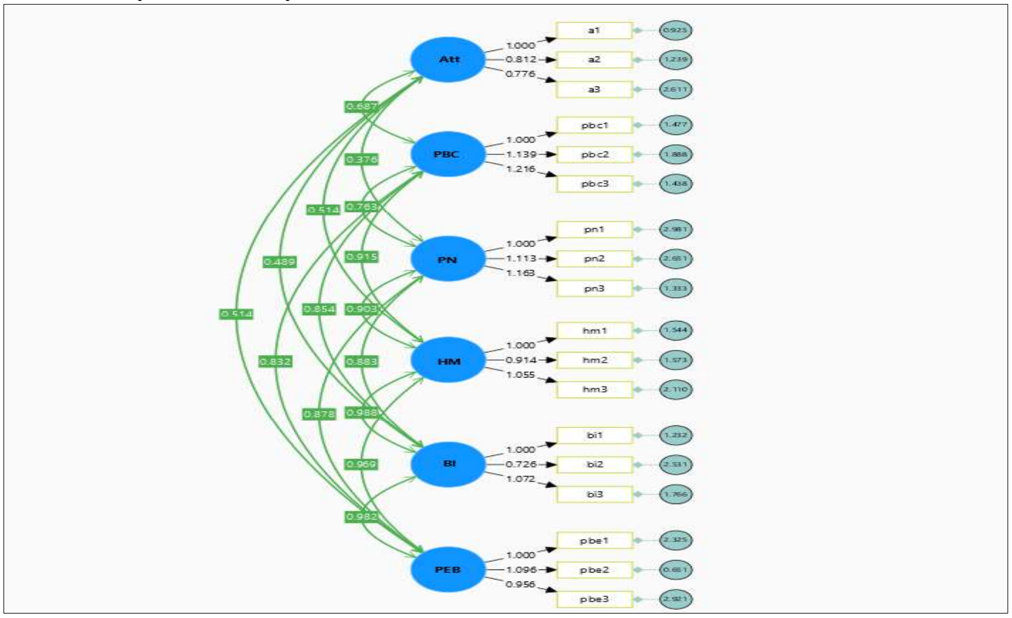

Fig 2: Confirmatory Factor Analysis

Table 4: 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

The Factor Loading Matrix 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 5: Correlation Matrix

CORRELATION MATRIX	Attitude	Behaviour Intention	Hedonic Motivation	Percieved Behaviour Control	Pro Enviornmental 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 Enviornmental 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

The Correlation Matrix 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.

Overall, 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

Table 6: Hypothesis Significance Table

Hypothesis	Path Tested	Path Coefficient	Interpretation	Supported? (Yes/No)
H1	AI-enabled interventions → Attitude	0.086	Positive effect on Attitude	Yes
H2	AI-driven personalized feedback → Perceived Behavioral Control → Behavioral Intention	0.123 (PBC → BI)	Positive effect, increases intention	Yes
H3	AI-based awareness → Personal Norms → Sustainable Behaviors	0.291 (PN → BI), 0.248 (PN → PEB)	Moderate positive effect on norms and behavior	Yes

Table 7: 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: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

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 ($\beta = -0.65$, $p = 0.676$) were 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.

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.

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