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Smart Sustainable Architecture: Exploring the Role of Emerging Technologies in Creating Energy-Efficient and Climate-Responsive Buildings

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Abstract
Emerging digital technologies offer mechanisms for supporting energy-efficient and climate-responsive buildings, while architect reports need to be distinguished from measured operational performance. This paper analyses 189 records in a supplied Pune architect-response CSV and places the findings alongside verified literature and institutional secondary evidence. Digital adoption is represented by the arithmetic mean of Q1 to Q3, perceived energy reduction by the separate Q4 item, and climate responsiveness by the mean of Q6 to Q10. Each questionnaire statement is reported in its own frequency table with a separate interpretation. Pearson correlation indicates a positive association between the non-overlapping practice index and perception item, $r = 0.792$, with a one-sided $p < 0.001$. The revised second hypothesis concerns the mean climate-responsiveness score relative to the neutral benchmark of 3. Its mean is 3.430, and the one-sample test gives $t(188) = 7.420$, with a one-sided $p < 0.001$. The results indicate positive adoption-energy perceptions and above-neutral agreement with climate-responsive design statements. The hypotheses were adapted to the permitted procedures before interpreting the recalculated results. Collection dates, recruitment and respondent independence are not established by the CSVs, and arithmetic indices are not treated as validated constructs. The findings describe the supplied response records and support subsequent operational verification rather than causal or representative conclusions.

Keywords:smart sustainable architecture; digital adoption; perceived energy efficiency; climate-responsive design; Pune

1. Introduction

The building sector occupies a central position in contemporary debates on urban sustainability because buildings are among the principal consumers of energy in cities and therefore represent a strategic target for climate mitigation. Architectural practice sits at the origin of this problem, since decisions about form, orientation, envelope, materials and services are fixed early in design and condition energy performance for the whole life of a building. At the same time, a family of emerging technologies, including building information modelling, digital twins, the Internet of Things and artificial intelligence, is reshaping how buildings are designed, operated and evaluated. The central question for this paper is whether and how these digital tools support energy-efficient and climate-responsive architecture, or whether they remain aspirational instruments whose benefits depend on careful commissioning and verification against measured energy use and occupant comfort. The scope of digital approaches is mapped by Akbari et al. (2024) and Bortolini et al. (2022).

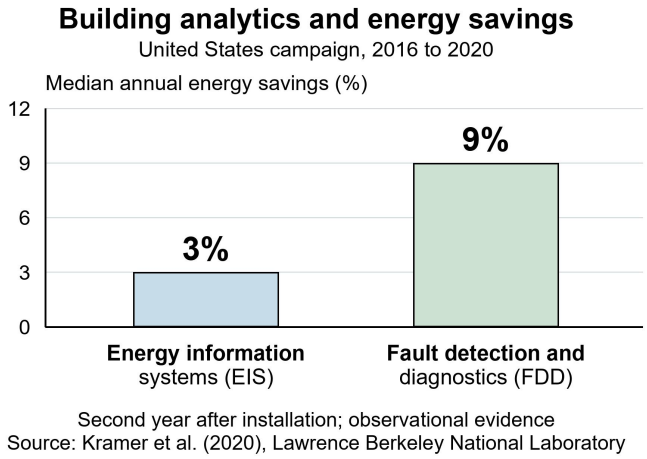

Figure 1. Median annual energy savings in the second year after installation: EIS 3% and FDD 9%. Source: Kramer et al. (2020), United States Smart Energy Analytics Campaign, 2016 to 2020. Technology-specific observational medians do not establish a randomized comparison or Pune outcomes.

Architecturally, climate-responsive design still rests on mechanisms that predate digital computation. Passive strategies such as orientation, shading, natural ventilation, thermal mass and daylighting remain foundational because they reduce demand before any mechanical system is engaged. Digital tools do not replace these mechanisms; at best they extend them. Building information modelling can carry performance information across design stages, simulation can test passive and active options before construction, and operational digital twins can compare predicted with actual behaviour. Yet each of these instruments must itself be commissioned, calibrated and judged against actual energy consumption and comfort outcomes. A model that is never reconciled with reality, or a monitoring system that is installed but not maintained, produces the appearance of responsiveness without its substance. The architectural profession therefore needs to understand both the capabilities and the conditions of use of these technologies.

Pune is the stated geographic setting of the supplied architect questionnaire. A local professional perspective can clarify how design choices, technological capabilities and passive strategies are understood, but it cannot substitute for energy records, comfort measurements or a verified climate analysis. This paper therefore examines coded response patterns alongside the international evidence rather than importing an external performance estimate into Pune. The firm categories provide an additional lens because project specialization may be related to both technological practice and the reported outcomes. Collection procedures and the meaning of the supplied category labels are not documented in the CSV.

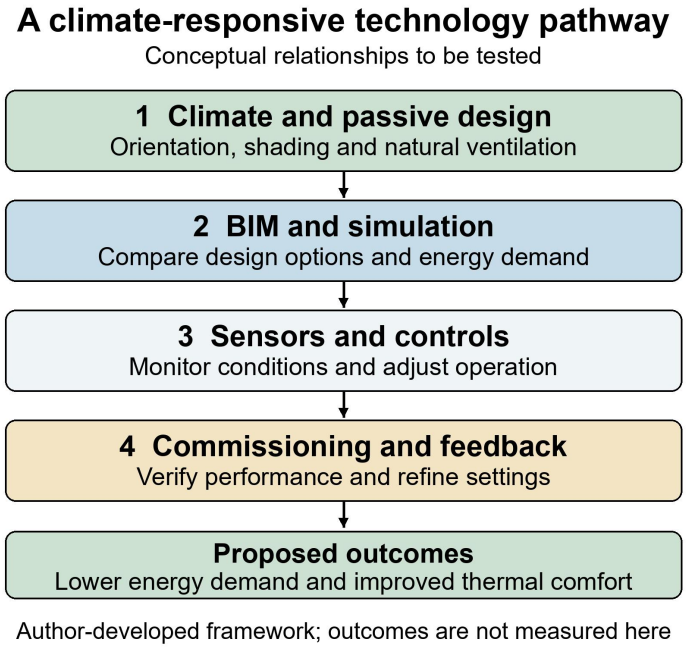

Figure 2. Proposed architectural process connecting climate and passive design, digital analysis, sensing and commissioning to energy and thermal-comfort outcomes. Source: Author-developed conceptual framework. Arrows represent conceptual relationships, not estimated causal effects.

The paper examines the correlation between reported digital adoption and perceived energy reduction, and whether mean climate-responsiveness agreement exceeds the neutral benchmark of 3. It analyses 189 records from the supplied CSV using non-overlapping predictor and outcome items. Figure 1 provides verified external evidence; Figure 2 organizes the conceptual pathway. The two hypotheses use Pearson correlation and a one-sample t test respectively. Firm categories are reported descriptively, without claims about differences between groups.

2. Literature Review

Akbari et al. (2024) examine the integration of Building Information Modelling and sustainability through a critical review of the literature. The authors selected journal articles and grouped them into major categories: BIM-based Life-Cycle Sustainability Assessment, BIM for green buildings, BIM-aided construction waste management, and state-of-the-art topics. By broadening keyword combinations and applying gap-spotting, the review offers a holistic understanding of previously dismissed issues and identifies research gaps and future opportunities. This critical framing of BIM-sustainability synergies is relevant to the present study because it situates digital tools within sustainable construction practice, although the review addresses the scholarly field rather than practitioner perceptions, and it provides no survey-based measures comparable to the architect responses analysed here.

Chang and Hsieh (2020) review Building Information Modelling research for green building design through building performance analysis. The authors systematically collected, analysed, and discussed publications, characterising them by research backgrounds, goals, methods, and outputs. The results show that among the building performance analysis types, energy and thermal analysis, green building rating analysis, and cost and benefit analysis are the most studied, while wind and ventilation, acoustic, and water efficiency analysis receive little attention. The review also notes limited examination of visualisation and documentation capabilities, reliance on single software packages, and limited use of information exchange formats. This highlights interoperability concerns relevant to practitioner tool adoption, although the evidence base is literature rather than architect survey data of the kind used in this study.

Bortolini et al. (2022) review Digital Twins applications for building energy efficiency in the Architecture, Engineering, Construction and Operation industry. Motivated by growing attention to energy efficiency and industry interest in Digital Twins for the Operation and Maintenance phase, the authors classify reviewed literature into application areas: optimisation design, occupants' comfort, building operation and maintenance, and energy consumption simulation. The review identifies research trends, gaps, and potential future directions, noting that Sustainability and Energy and Buildings are among the most frequently cited sources. This

overview of digital twin application domains is relevant to the present study's interest in digital technologies for sustainable architecture, but its findings derive from published literature rather than from practitioner responses, so it cannot substitute for primary survey measurement.

Cespedes-Cubides and Jradi (2024) review building digital twins for improving energy efficiency in the operational stage. The authors performed a systematic process to select pertinent use-case studies, complemented by analysis of enterprise-level digital twin solutions, followed by thematic classification, individual study analyses, and comparison with commercial tools. Main applications were identified: component monitoring, anomaly detection, operational optimisation, predictive maintenance, and simulation of alternative scenarios. The paper highlights challenges such as reliance on Building Information Modelling and the need for robust data acquisition systems, which hinder implementation in existing buildings without digital information. These implementation barriers are relevant to understanding practitioner constraints, although the review concerns documented use cases rather than architect-reported perceptions measured in this study.

Aguilar et al. (2021) present a systematic literature review on the use of artificial intelligence in energy self-management in smart buildings. Recognising that buildings are major energy consumers, the authors group research according to the concept of Autonomous Cycles of Data Analysis Tasks, which requires monitoring, analysis, and decision-making tasks to reach objectives such as improved energy efficiency. This organisation allows positioning of research and visualisation of challenges and opportunities in each domain. The review identifies that much research lies in the decision-making domain, largely on optimisation and control tasks, and defines potential projects on autonomous cycles, feature engineering, and multi-agent systems. This frames intelligent energy management relevant to the present study, though it reflects literature rather than survey evidence from architects.

Chen et al. (2023) explore the integration of Building Information Modelling and the Internet of Things for sustainable building. Noting limited macro-level knowledge of BIM-IoT integration and the predominance of literature review methods lacking objective quantitative analysis, the authors use topic searches in the Web of Science Core Collection and Citespace bibliometric analysis, supplemented by controlled and subject term statistics from Engineering Index results. The results show that BIM-IoT research focuses on building intelligence with BIM as the application basis, that sustainable building research concentrates on the first three life cycle phases, and that IoT enables occupant participation while BIM supports stakeholder information sharing. This macro perspective informs the present study's technology context, although it does not measure individual practitioner attitudes.

Sghiri et al. (2025) review the leveraging of digital twins for enhancing building energy efficiency. Employing a systematic literature review combined with bibliometric analysis, the study synthesises key contributions of digital twins in real-time monitoring, predictive modelling, renewable energy integration, and proactive maintenance, while addressing critical challenges such as interoperability, scalability, and privacy. The integrated approach identifies emerging trends, research gaps, and actionable insights for future adoption. This synthesis of applications, technologies, and challenges is relevant to the present study's focus on digitalisation and sustainability, but it is grounded in published literature and offers no architect-level survey measurements comparable to the response data analysed here.

Agostinelli et al. (2021) explore the potential of digital-twin-based methods and approaches aimed at achieving an intelligent optimization and automation system for energy management of a residential district through the use of a three-dimensional data model integrated with Internet of Things, artificial intelligence and machine learning. The case study is focused on Rinascimento III in Rome, an area consisting of 16 eight-floor buildings with 216 apartment units powered by 70% of self-renewable energy. The combined use of integrated dynamic analysis algorithms allowed the evaluation of different scenarios of energy efficiency intervention aimed at achieving a virtuous energy management of the complex, keeping the actual internal comfort and climate conditions. The objective is also to plan and deploy a cost-effective IT infrastructure able to provide reliable data using the edge-computing paradigm. The developed methodology led to the evaluation of the effectiveness and efficiency of integrative systems for renewable energy production from solar energy necessary to raise the threshold of self-produced energy, meeting the nZEB requirements. For the present study, this source stands as published evidence and cannot be read as a result from the Pune questionnaire.

Akbulut et al. (2025) present a systematic review of Building Energy Management Systems (BEMSs), focusing on the integration of sensors, the Internet of Things (IoT), and artificial intelligence (AI). The review synthesizes 89 peer-reviewed publications spanning from 2019 to 2025 and categorizes recent developments in HVAC optimization, occupancy-driven lighting control, predictive maintenance, and fault detection systems. It examines communication

protocols such as ZigBee and LoRaWAN, machine learning-based energy forecasting, and multi-agent control mechanisms within residential, commercial, and institutional building contexts. Findings across multiple case studies indicate that hybrid AI-IoT systems have achieved energy efficiency improvements ranging from 20% to 40%, depending on building typology and control granularity. The authors identify critical challenges, including data security vulnerabilities, lack of standardized interoperability frameworks, and the complexity of integrating heterogeneous legacy infrastructure, alongside gaps concerning real-time adaptive control strategies, trust-aware federated learning, and seamless interoperability with smart grid platforms. In contrast to the present study, which analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design, the reviewed work synthesizes published literature rather than measuring operational energy use.

Almadhor et al. (2025) present a digital twin based deep learning framework for personalized thermal comfort prediction and energy efficient operation in smart buildings. The authors note that traditional comfort models, such as Fanger's equation and adaptive approaches, often fall short in capturing individual occupant preferences and the dynamic nature of indoor environmental conditions. To address these limitations, they introduce a Digital Twin-driven framework integrated with an advanced attention-based Long Short-Term Memory model tailored for personalised thermal comfort prediction and intelligent HVAC control. The Digital Twin enables real-time simulation of indoor environments and occupant responses, facilitating proactive comfort management. Using a subset of the ASHRAE Global Thermal Comfort Database II, the model categorises Thermal Sensation Votes on a 7-point ASHRAE scale into three classes and achieves a test accuracy of 83.8%. Explainable AI techniques and scenario-based energy efficiency analyses are also integrated. This published evidence cannot be read as a result from the present study, which analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design and does not measure operational energy use.

Anjomshoa (2024) examines the application of building information modeling (BIM) systems in the smartification of green and sustainable buildings. The research aims to identify and rank the most influential factors in the application of BIM systems in the smartification of green and sustainable buildings. The present research is applied and descriptive. The most influential factors were identified through library studies and expert opinions, data were collected using a questionnaire, and a combination of the one-sample t-test method with a 95% confidence level and the fuzzy VIKOR method was employed for analysis. The results show that the most influential factors, in order, are energy saving and consumption reduction, increased productivity and efficiency, life-cycle assessment (LCA), eco-friendly design, and integration with IoT and other technologies. The most influential factors were ranked based on impact level, importance level, and availability of necessary tools for implementation in Kerman. This published evidence cannot be read as a result from the present study, which analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design.

Das (2025) examines the integration of IoT and AI in energy-efficient smart buildings, emphasising applications and challenges. The study adopts a qualitative methodology combining systematic literature review, case study analysis, and systems analysis. Findings indicate that IoT enables smart metering, real-time energy monitoring, automated lighting and HVAC, occupancy-based energy optimisation, and renewable energy integration, while AI complements these functions through predictive maintenance, energy forecasting, demand-side management, intelligent climate control, indoor air quality automation, and behaviour-driven analytics. Together, these technologies reduce carbon emissions, lower operational costs, and improve occupant well-being. Challenges remain, including data security and privacy risks, interoperability gaps, scalability and cost constraints, and retrofitting difficulties. The paper proposes a systems thinking-enabled conceptual framework structured around three pillars: adopting IoT and AI as enabling technologies, overcoming integration barriers, and identifying application areas that advance sustainability in smart buildings. The present study analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design, and does not measure operational energy use.

de Paula et al. (2025) developed a BIM-based machine learning framework to predict the energy performance of office buildings at the early design stage. The framework provides a reproducible and data-driven workflow that shortens simulation time while maintaining accuracy. Revit and Insight were integrated with statistical modeling in Weka to create an automated and regionally adaptable process derived from BIM-generated data. A reduced-factorial Design of Experiments guided the generation of 210 parametric simulations representing base, generalization, and stress-test models for Orlando, Florida. Each model combined

geometric, envelope, system, and operational variations, forming a dataset of 14 independent parameters and two dependent energy metrics: Energy Use Intensity and Operational Energy. Four regression algorithms were trained and validated through 10-fold cross-validation. All models achieved R2 values above 0.95, with the Random Forest model reaching the highest overall accuracy under default parameter settings, with R2 > 0.97 and mean absolute errors below 5% across both metrics. Feature-importance analysis identified HVAC system type, window-to-wall ratio, and operational schedule as the most influential variables. The present study instead examines architect-reported digital practice in Pune.

Elkhoukhi et al. (2025) present an overview of sensing and data processing technologies for smart building services and applications. The authors note that Internet of things (IoT) and big data technologies are increasingly gaining significance in the implementation of various services and applications, and that much research on energy efficiency and building management revolves around integrating these technologies for data collection and processing. They identify occupancy detection, comfort, and energy management as the most important services for optimizing building energy consumption in smart buildings, with environmental data playing a key role in improving these services. The paper discusses emerging technologies for designing novel IoT-based architectures, addressing interoperability, scalability, and real-time data processing, and reports comparative criteria between popular data processing techniques to select an appropriate framework for intelligent platforms managing building services and enhancing the deployment of digital twins for critical environment monitoring and anomaly detection. The present study analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design, and does not measure operational energy use.

Habibi (2026) presents a BIM-integrated life cycle analysis framework for climate-responsive urban energy performance assessment at district scale. The study addresses the need for consistent evaluation of operational energy demand under both design interventions and future climate conditions. A mixed-use district in Milan serves as the case study, where parametric BIM massing models at LOD 200-300 are coupled with building energy simulation to analyze three scenarios: a baseline configuration (S0), an envelope optimization scenario (S1), and a future climate scenario based on CMIP6 morphed weather data (S2). Results indicate that envelope optimization reduces energy use intensity by approximately 15-22% across building typologies, while under future climate conditions cooling demand increases significantly and reduced heating requirements yield a total district energy use intensity of 33.6 kWh/m2·year (1.60 GWh/year). The findings confirm the value of BIM-integrated, scenario-based workflows for supporting climate-responsive urban design decisions. The present study therefore draws on this work as background on BIM-integrated assessment while analysing architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design.

Khan et al. (2024) present a framework integrating building information modeling, explainable artificial intelligence, and multi-objective optimization for automated green building energy performance analysis. The authors state that sustainable green building design is essential to reducing environmental impact and enhancing energy efficiency, and that traditional methods often depend heavily on expert knowledge and subjective decisions. Their framework comprises data generation through DesignBuilder simulation, a BO-LGBM predictive model with LIME for energy prediction and interpretation, and the multi-objective optimization technique AGE-MOEA to address uncertainties. In a case study, the BO-LGBM model achieved high prediction accuracy (R-squared > 93.4%, MAPE < 2.13%), and LIME identified significant HVAC system features. The AGE-MOEA optimization resulted in a 13.43% improvement in energy consumption, CO2 emissions, and thermal comfort, with an additional 4.0% optimization gain when incorporating uncertainties. The authors note that future research should focus on validating real-world applicability, assessing generalizability across various building types, and integrating generative design capabilities. The present study analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design, and does not measure operational energy use.

Luo (2022) provides a critical review of advancements in artificial intelligence in recent applications in building environments, examining key research hotpots, important research institutes, researchers, and their contributions. The paper also discusses associated technologies, such as Internet of things (IOT) technologies, and advanced operational strategies for promoting building performance. Bibliometric analysis on the platform CiteSpace quantitatively summarizes the key characteristics of works in the literature and their applications. IOT based sensing networks are analyzed, discussed, and summarized since they play a pivotal role in securing the accuracy and efficiencies in data acquisition so as to facilitate building energy management systems. Additionally, the algorithms associated with machine learning and data-driven technologies are reviewed

in applications such as building energy prediction, building management optimization, and their maintenance. The paper explores emerging technologies and developing trends in the field to find potential routes for future studies. The present study analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design, and does not measure operational energy use.

Mehraban et al. (2025) develop an AI-driven workflow that integrates BIM-based residential models, automated EnergyPlus simulations, and supervised machine learning algorithms to predict indoor thermal trajectories and calculate thermal resilience against power failure events in hot seasons. The authors note that current building thermal resilience assessments rely mainly on physics-based simulations or IoT sensor data, which are computationally expensive and slow to scale. Four representative U.S. residential building typologies were simulated across fourteen ASHRAE climate zones to generate 16,856 scenarios over 45.8 h of runtime. The dataset included time-series of indoor thermal conditions and static thermal resilience metrics such as Passive Survivability Index (PSI) and Weighted Unmet Thermal Performance (WUMTP). Ensemble boosting models, notably XGBoost, achieved an average R2 of 0.9994 and nMAE of 1.10% across time-series recorded every 3 min for a 5-day simulation period with 72 h of outage. The present study analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design, and it does not measure operational energy use.

Patiño-Cambeiro et al. (2017) describe a multidisciplinary approach for the estimation of the energy performance of an educational building. The research involved data acquisition with advanced geomatic tools, the development of an optimized building information model, and energy assessment in Building Performance Simulation (BPS) software. Interoperability issues were observed in the different steps of the process. The inspection and diagnostic phases were conducted in a timely, accurate manner thanks to automated data acquisition and subsequent analysis using Building Information Modeling based tools (BIM-based tools). Energy simulation was performed using Design Builder, and the results obtained were compared with those yielded by the official software tool established by Spanish regulations for energy certification. The discrepancies between the results of both programs have proven that the official software program is conservative in this sense. The present study analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design, and does not measure operational energy use.

Petroşanu et al. (2019) review recent developments in integrating machine learning models with sensor devices in the smart buildings sector with a view to attaining enhanced sensing, energy efficiency, and optimal building management. The authors state that many scientists have focused their research on subjects such as smart buildings, sensor devices, virtual sensing, buildings management, the Internet of Things, artificial intelligence in the smart buildings sector, improving life quality within smart homes, assessing occupancy status information, detecting human behavior with a view to assisted living, maintaining environmental health, and preserving natural resources. The review surveys the current state of the art regarding the integration of supervised and unsupervised machine learning models with sensor devices in the smart building sector. The authors devised a research methodology to identify, filter, categorize, and analyze relevant scientific articles, using reliable sources of scientific information, and obtained a pool of 146 papers. The present study analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design, and thus connects to architect-reported digital practice rather than to any measured energy saving.

Shah et al. (2022) review the role of machine learning and the Internet of Things in smart buildings for energy efficiency. The abstract states that machine learning can be used to automate a wide range of tasks. Smart buildings, which use the Internet of Things to connect building operations, enable activities such as monitoring temperature, safety, and maintenance, for easier controlling via mobile devices and computers. Smart buildings are becoming core aspects in larger system integrations as the Internet of Things is becoming increasingly widespread. The review highlights the role of Internet of Things devices in smart buildings, including their platform and components, and provides security challenges regarding the Internet of Things and smart buildings. It also describes main factors pertaining to smart buildings and different methods of machine learning combined with Internet of Things technologies to improve the effectiveness of smart buildings to make them energy efficient. The present study analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design.

Tahmasebinia et al. (2023) provide a comprehensive review of the development and application of digital twin technology in building energy. The paper discusses the background of building information modeling and digital twin technology and their application in energy optimization in buildings. It reviews the application of digital twin technology in

building energy management, indoor environmental monitoring, and building energy efficiency evaluation. It also examines the benefits and challenges of implementing digital twin technology in building energy analysis and highlights recent case studies. Furthermore, the review emphasizes emerging trends and opportunities for future research, including integrating machine learning techniques with digital twin technology. The authors note that digital twin technology has enabled sustainable building energy management and cost reduction, and that its use in the energy sector is gaining momentum as efforts to optimize energy efficiency and reduce carbon emissions continue. The present study, by contrast, analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design, and does not measure operational energy use.

Villani et al. (2025) present an integrated approach for adapting building energy systems using Machine Learning (ML), the Internet of Things (IoT), and Building Information Modeling (BIM) in a hotel retrofit in Italy. In a concise multi-stage process, long-term climatic data and on-site technical documentation were analyzed to create a detailed BIM model. This model enabled energy simulations using the Carrier-Pizzetti method and supported the design of a hybrid HVAC system integrating VRF and hydronic circuits, further enhanced by a custom ML algorithm for adaptive, predictive energy management through BIM and IoT data fusion. The study also incorporated photovoltaic panels and solar collectors, reducing reliance on non-renewable energy sources. Results demonstrate the effectiveness of smart energy management, showcasing significant potential for scalability in similar building typologies. Future improvements include integrating a temporal evolution model, refining feature selection using advanced optimization techniques, and expanding validation across multiple case studies. The present study analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design, and does not measure operational energy use.

Xie and Xie (2024) examine Internet of things-based online monitoring for building equipment energy saving optimization control using building information modeling. The abstract states that smart building equipment monitoring is a well-established field focused on enhancing contemporary building comfort, and that the proliferation of Internet connectivity, facilitated by the internet of things, has transformed buildings from static structures into interactive environments. It notes growth across aspects of daily life, from monitoring environmental conditions to managing building systems and storing data in the cloud. The paper explores and analyzes IoT-based energy-saving optimization techniques for intelligent building equipment, integrating building information modeling technology, and delves into the energy conservation control algorithm for air-conditioning systems. The abstract reports control experiments over three sessions in August in two distinct areas, with Area 1 consuming 735 kWh compared to Area 2's 819 kWh, an 11.43% reduction. The present study analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design, and does not measure operational energy use.

Yitmen et al. (2025) assess the impact of AI-driven digital twins on enhancing indoor environmental quality and energy efficiency in smart building systems. The authors state that smart buildings equipped with diverse control systems serve the objectives of gathering data, optimizing energy efficiency, and detecting and diagnosing faults, particularly in the domain of indoor environmental quality. Digital twins offering an environmentally sustainable solution for managing facilities and incorporated with artificial intelligence create opportunities for maintaining indoor environmental quality and optimizing energy efficiency. The authors performed a scoping review, conducted semi-structured interviews with specialists in the industry, and gathered quantitative data via a computerized self-administered questionnaire survey. The results indicate that the AI-driven digital twin enhances occupants' comfort and energy-efficiency performance and enables decision-making on automatic fault detection and maintenance conditioning to improve buildings' serviceability and indoor environmental quality in real time. The integration of AI with digital twin presents a transformative approach to improving indoor environmental quality and energy efficiency in smart building systems. In relation to this work, the present study analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design.

Zocchi et al. (2024) explore the synergy of advanced lighting controls, Building Information Modelling and Internet of Things for sustainable and energy-efficient buildings through a systematic literature review. The abstract states that buildings are responsible for approximately 40% of global energy consumption, putting pressure on the construction industry to mitigate its environmental impact, and that there is an urgent need for innovative solutions to reduce power consumption, particularly in lighting systems. The review examined energy-saving actions, retrofitting practices and interventions across a range of multi-use buildings worldwide, focusing on research from 2019 to 2024, and after applying

eligibility criteria, 48 studies were included. The review indicates a lack of proper coordination between daylight and electrical lighting, resulting in energy inefficiency, and addresses the role of the Internet of Things in providing real-time data from sensor networks. A new parametric design framework is proposed, consisting of five iterative phases that cover all design stages, enhanced by integrating BIM and IoT. The present study analyses architect questionnaire responses in Pune on digital adoption, perceived energy reduction, and climate-responsive design, and does not measure operational energy use.

3. Research Objectives and Hypotheses

The objectives concern associations and mean agreement in the supplied responses. H1 evaluates a positive association using separate predictor and outcome items. H2 evaluates mean agreement against the neutral benchmark of 3. The hypotheses address the full supplied sample and do not compare independent firm categories. No preregistration information accompanies the dataset.

Objectives

Objective 1: To examine the relationship between digital adoption and perceived energy reduction.

Objective 2: To determine whether mean climate-responsiveness agreement exceeds the neutral score of 3.

Hypotheses

H1o: The population Pearson correlation between digital adoption and perceived energy reduction is zero or negative (rho <= 0).

H1a: The population Pearson correlation between these measures is positive (rho > 0).

H2o: The population mean climate-responsiveness index is no greater than the neutral value of 3 (mu <= 3).

H2a: The population mean climate-responsiveness index exceeds 3 (mu > 3).

4. Research Methodology

The primary analytical input is pune_smart_architecture_survey_n189.csv, containing 189 uniquely identified records with age group, years of experience, firm type and ten questionnaire responses. The analysis concerns architect responses in Pune. The file itself does not document recruitment, response rate, collection dates, eligibility verification or ethics approval. These procedures are therefore not asserted. The unit used in the calculations is one CSV row, with respondent independence required for population inference.

Every response is coded from 1, strongly disagree, to 5, strongly agree, with 3 denoting neither agree nor disagree. All ten item values are present and fall within this range. No rows are deleted, duplicated or generated. The original identifiers and categorical labels are retained. Frequencies, percentages, valid percentages and cumulative percentages are calculated for each statement; because item missingness is zero, percentage and valid percentage coincide. Standard deviations use the sample denominator n minus one.

The mean of Q1 to Q3 is the digital-adoption index. These questions concern BIM, IoT and AI practice. Q4 is the separate perceived-energy-reduction outcome and Q5 is a net-zero necessity belief, reported separately. The mean of Q6 to Q10 is the climate-responsiveness index. Each arithmetic mean gives equal weight to its included questions. The outcome is excluded from the predictor so that the correlation is not inflated by reusing the same item in both variables. These are descriptive indices rather than validated latent constructs.

H1 uses Pearson product-moment correlation, with a directional alternative of a positive relationship. The correlation treats the arithmetic index and the separate Likert outcome as approximately numeric measures. This is an analytical convention, and an individual ordinal item does not establish equal psychological distances between response categories. H2 uses a one-sample t test of the Q6 to Q10 mean index against 3, the scale's neutral midpoint, with the directional alternative of a mean greater than 3. Both tests report one-sided significance values and use alpha = 0.05 separately for each hypothesis. No family-wide error control is claimed. No reliability coefficients or additional inferential procedures are calculated.

Pearson inference assumes independently sampled observations and an adequate linear association for its interpretation; the exact conventional null significance calculation relies on distributional assumptions. The one-sample t statistic is the observed mean difference divided by its standard error, with n minus one degrees of freedom. The large number of rows supports an approximate sampling-distribution argument for the mean if records are independent, but it cannot establish that independence. The H2 table reports a two-sided 95% confidence interval for the mean difference as an uncertainty summary; this interval is distinct from the one-sided decision rule.

5. Data Analysis and Interpretation

Tables 1 to 3 describe the recorded demographic categories. Tables 4 to 13 each report one questionnaire statement and its own interpretation. Tables 14 and 15 address H1 and H2 respectively. The calculations describe all supplied records. Inferential conclusions remain conditional on

authentic independent observations and do not demonstrate causality, representativeness or measured environmental performance.

Table 1. Age Group

Valid category	Frequency	Percent	Valid Percent	Cumulative Percent
25-34	54	28.6	28.6	28.6
35-44	75	39.7	39.7	68.3
45-54	42	22.2	22.2	90.5
55+	18	9.5	9.5	100.0
Total	189	100.0	100.0	

Source: Authors' calculations from pune_smart_architecture_survey_n189.csv.

Table 1 records the age composition of the 189 Pune architect respondents. The 35-44 band is the largest with 75 respondents (39.7%), followed by 25-34 with 54 (28.6%), 45-54 with 42 (22.2%), and 55+ with 18 (9.5%). Cumulative percentages show that 68.3% of records fall at or below 44 years and 90.5% at or below 54 years, so the two younger age bands account for most records while the oldest band is a clear minority. These figures describe only the supplied records; no inference is drawn about age effects on responses, and the distribution is not evidence of the composition of the full Pune architect population. For analysis purposes, the composition documents the sample profile against which the statement responses in later tables should be read, and any subgroup comparison by age would require its own specified test.

Table 2. Experience Years

Valid category	Frequency	Percent	Valid Percent	Cumulative Percent
1-5	33	17.5	17.5	17.5
6-10	48	25.4	25.4	42.9
11-15	65	34.4	34.4	77.2
16-20	25	13.2	13.2	90.5
21+	18	9.5	9.5	100.0
Total	189	100.0	100.0	

Source: Authors' calculations from pune_smart_architecture_survey_n189.csv.

Table 2 reports years of professional experience for the 189 respondents. The 11-15 year band is the most frequent with 65 respondents (34.4%), followed by 6-10 years with 48 (25.4%), 1-5 years with 33 (17.5%), 16-20 years with 25 (13.2%), and 21+ years with 18 (9.5%). Cumulatively, 77.2% of records fall within 15 years or less of experience, and the two most senior bands together account for 22.8%. The distribution is therefore weighted toward early-to-mid career records with a smaller senior minority. These figures describe the supplied records only; no inference is made about how experience level relates to technology or climate responses, and the distribution is not evidence of the composition of the full Pune architect population. It serves as the documented sample profile for interpreting the statement tables that follow.

Table 3. Firm Type

Valid category	Frequency	Percent	Valid Percent	Cumulative Percent
Commercial	66	34.9	34.9	34.9
Mixed-Use	52	27.5	27.5	62.4
Residential	71	37.6	37.6	100.0
Total	189	100.0	100.0	

Source: Authors' calculations from pune_smart_architecture_survey_n189.csv.

Table 3 shows firm type across the 189 respondents. Residential firms are the largest group with 71 respondents (37.6%), followed by Commercial with 66 (34.9%) and Mixed-Use with 52 (27.5%). The three categories are fairly close in size, with a spread of about 10.1 percentage points between the largest and smallest, so no single practice type dominates the records. Each category contributes more than a quarter of the records, giving the pooled results a mixture of practice types. These figures describe the composition of the supplied records; they are not evidence of the distribution of firm types in the full Pune architect population, and no inference is drawn about how firm type affects technology or climate responses. The composition documents the practice mix underlying the statement responses, and any comparison across firm categories would require a separately specified test.

Table 4. Q1: Our firm regularly integrates BIM for energy modeling and optimization.

Valid response	Frequency	Percent	Valid Percent	Cumulative Percent
1 Strongly disagree	16	8.5	8.5	8.5
2 Disagree	22	11.6	11.6	20.1
3 Neither agree nor disagree	43	22.8	22.8	42.9
4 Agree	66	34.9	34.9	77.8
5 Strongly agree	42	22.2	22.2	100.0
Total	189	100.0	100.0	

Source: Authors' calculations from pune_smart_architecture_survey_n189.csv.

Agreement or strong agreement accounts for 108 responses (57.1%), neutrality for 43 (22.8%), and disagreement or strong disagreement for 38 (20.1%). The mean is 3.508, with a sample standard deviation of 1.201. A majority endorses routine BIM use for energy work, while the remaining responses leave a substantial gap between reported uptake and universal integration. The wording combines modeling and optimization, so endorsement does not reveal whether a firm merely evaluates energy demand or actually revises designs in response. The neutral group is especially relevant to this distinction because its answers provide no clear commitment to regular use. The architectural interpretation is therefore that BIM has a reported place in energy-related workflows across much of this sample, with incomplete agreement about its routine application. Project models and documented design revisions would be needed to establish how this reported integration changes design decisions.

Table 5. Q2: IoT sensors are actively used in our projects for post-occupancy monitoring.

Valid response	Frequency	Percent	Valid Percent	Cumulative Percent
1 Strongly disagree	11	5.8	5.8	5.8
2 Disagree	24	12.7	12.7	18.5
3 Neither agree nor disagree	51	27.0	27.0	45.5
4 Agree	60	31.7	31.7	77.2
5 Strongly agree	43	22.8	22.8	100.0
Total	189	100.0	100.0	

Source: Authors' calculations from pune_smart_architecture_survey_n189.csv.

Agreement or strong agreement accounts for 103 responses (54.5%), neutrality for 51 (27.0%), and disagreement or strong disagreement for 35 (18.5%). The mean is 3.529, with a sample standard deviation of 1.146. The balance favors reported sensor use, but more than a quarter of respondents take no definite position. Monitoring after occupancy is a specific activity, so this pattern concerns access to information about buildings in use rather than digital modeling during design. Agreement cannot establish whether sensors operate continuously, which variables they record, or whether their readings inform corrective action. This distinction matters because data collection and operational response are different stages of an energy-management process. The result supports describing post-occupancy monitoring as a reported practice for a majority of these respondents, while leaving the completeness and use of the monitoring records unresolved.

Table 6. Q3: AI-driven design tools influence our sustainability and orientation decisions.

Valid response	Frequency	Percent	Valid Percent	Cumulative Percent
1 Strongly disagree	2	1.1	1.1	1.1
2 Disagree	32	16.9	16.9	18.0
3 Neither agree nor disagree	64	33.9	33.9	51.9
4 Agree	63	33.3	33.3	85.2
5 Strongly agree	28	14.8	14.8	100.0
Total	189	100.0	100.0	

Source: Authors' calculations from pune_smart_architecture_survey_n189.csv.

Agreement or strong agreement accounts for 91 responses (48.1%), neutrality for 54 (28.6%), and disagreement or strong disagreement for 44 (23.3%). The mean is 3.354, with a sample standard deviation of 1.151. Positive responses form the largest combined group but remain below half of the sample. The statement asks whether AI influences sustainability and orientation decisions, making it more specific than a general endorsement of technology. A respondent can use an AI tool without allowing its outputs to shape those decisions; conversely, disagreement does not establish that all digital design work is absent. The sizeable neutral share means the extent of decision-making influence is uncertain for many records. Compared with the BIM and IoT items, the lower mean identifies a less strongly endorsed role for AI within the supplied responses. It does not demonstrate lower design quality among respondents who disagree.

Table 7. Q4: Buildings designed with smart tech show measurable energy reductions.

Valid response	Frequency	Percent	Valid Percent	Cumulative Percent
1 Strongly disagree	2	1.1	1.1	1.1
2 Disagree	32	16.9	16.9	18.0
3 Neither agree nor disagree	64	33.9	33.9	51.9
4 Agree	63	33.3	33.3	85.2
5 Strongly agree	28	14.8	14.8	100.0
Total	189	100.0	100.0	

Source: Authors' calculations from pune_smart_architecture_survey_n189.csv.

Agreement or strong agreement accounts for 91 responses (48.1%), neutrality for 64 (33.9%), and disagreement or strong disagreement for 34 (18.0%). The mean is 3.439, with a sample standard deviation of 0.975. Fewer than half endorse the claim, while roughly one third remain neutral. This is a more qualified pattern than a simple declaration that smart buildings save energy. The wording refers to measurable reductions, yet the dataset contains agreement ratings rather than meter readings, baselines, weather adjustments or occupancy information. The neutral responses consequently matter: they prevent the positive side from being interpreted as broad confirmation of demonstrated savings. This item provides the energy-perception outcome for H1, separate from the three adoption questions. Its architectural relevance lies in the degree of professional confidence in the claimed performance benefit, while the magnitude and verification of any energy reduction remain outside this table.

Table 8. Q5: Digital technology integration is essential for achieving net-zero targets.

Valid response	Frequency	Percent	Valid Percent	Cumulative Percent
1 Strongly disagree	10	5.3	5.3	5.3
2 Disagree	20	10.6	10.6	15.9
3 Neither agree nor disagree	59	31.2	31.2	47.1
4 Agree	73	38.6	38.6	85.7
5 Strongly agree	27	14.3	14.3	100.0
Total	189	100.0	100.0	

Source: Authors' calculations from pune_smart_architecture_survey_n189.csv.

Agreement or strong agreement accounts for 100 responses (52.9%), neutrality for 59 (31.2%), and disagreement or strong disagreement for 30 (15.9%). The mean is 3.460, with a sample standard deviation of 1.034. A majority agrees with the necessity of digital integration, but the substantial neutral share shows that this view is far from unanimous. The term essential is stronger than useful: respondents are judging whether digital tools are indispensable to net-zero goals, rather than simply whether they assist design. The result should therefore be read as a distribution of strategic beliefs. It cannot identify which technologies are necessary, how they interact with passive design, or whether any project reaches a net-zero balance. For the paper's argument, the table indicates support for a prominent role for digital workflows, alongside considerable uncertainty about the stronger proposition that those workflows are a prerequisite.

Table 9. Q6: Passive cooling techniques are prioritized over mechanical systems.

Valid response	Frequency	Percent	Valid Percent	Cumulative Percent
1 Strongly disagree	12	6.3	6.3	6.3
2 Disagree	24	12.7	12.7	19.0
3 Neither agree nor disagree	51	27.0	27.0	46.0
4 Agree	69	36.5	36.5	82.5
5 Strongly agree	33	17.5	17.5	100.0
Total	189	100.0	100.0	

Source: Authors' calculations from pune_smart_architecture_survey_n189.csv.

Agreement or strong agreement accounts for 102 responses (54.0%), neutrality for 51 (27.0%), and disagreement or strong disagreement for 36 (19.0%). The mean is 3.460, with a sample standard deviation of 1.113. The positive balance indicates that passive cooling receives stated priority for a majority, while the neutral and negative groups show that this hierarchy is not shared across the entire sample. Prioritized over mechanical systems concerns relative design emphasis; it does not imply that mechanical cooling is absent or unnecessary. That distinction is central to interpreting the question, because a building may incorporate passive measures and still use mechanical systems. The table offers a view of reported design priorities rather than cooling-load or comfort measurements. It contributes one specific aspect of climate responsiveness to H2, without showing whether the preferred strategies are adequate for particular spaces, occupants or operating periods.

Table 10. Q7: Sun-path analysis strictly dictates facade design and shading devices.

Valid response	Frequency	Percent	Valid Percent	Cumulative Percent
1 Strongly disagree	13	6.9	6.9	6.9
2 Disagree	33	17.5	17.5	24.3
3 Neither agree nor disagree	43	22.8	22.8	47.1
4 Agree	65	34.4	34.4	81.5
5 Strongly agree	35	18.5	18.5	100.0
Total	189	100.0	100.0	

Source: Authors' calculations from pune_smart_architecture_survey_n189.csv.

Agreement or strong agreement accounts for 100 responses (52.9%), neutrality for 43 (22.8%), and disagreement or strong disagreement for 46 (24.3%). The mean is 3.402, with a sample standard deviation of 1.175. The positive group exceeds the negative group, but almost a quarter disagree with the strict wording. Sun-path analysis can inform a facade without dictating every design decision, so rejection of this statement should not automatically be classified as rejection of solar-responsive design. Neutral answers likewise leave the strength of its influence unresolved. The question primarily distinguishes reported adherence to a demanding design rule, rather than the presence or absence of shading devices. Its contribution to climate responsiveness is consequently about stated control of facade decisions by solar analysis. Drawings, analysis records and shading-performance calculations would be required to determine whether this reported discipline produces effective solar protection.

Table 11. Q8: Materials are selected primarily based on thermal mass properties.

Valid response	Frequency	Percent	Valid Percent	Cumulative Percent
1 Strongly disagree	13	6.9	6.9	6.9
2 Disagree	35	18.5	18.5	25.4
3 Neither agree nor disagree	46	24.3	24.3	49.7
4 Agree	58	30.7	30.7	80.4
5 Strongly agree	37	19.6	19.6	100.0
Total	189	100.0	100.0	

Source: Authors' calculations from pune_smart_architecture_survey_n189.csv.

Agreement or strong agreement accounts for 95 responses (50.3%), neutrality for 46 (24.3%), and disagreement or strong disagreement for 48 (25.4%). The mean is 3.376, with a sample standard deviation of 1.190. Only a narrow majority agrees that thermal mass is the primary basis for material selection, and the negative group is slightly larger than the neutral group. This is the lowest mean among the five climate-response questions, identifying comparatively weaker endorsement of this particular priority. The word primarily limits the inference: disagreement could coexist with consideration of thermal mass alongside other criteria, although the responses do not identify those criteria. The result therefore concerns the rank given to a material property, rather than whether materials possess suitable thermal characteristics. It highlights a distinction between acknowledging thermal behavior and making it the dominant selection principle; neither actual specifications nor resulting indoor temperatures are measured here.

Table 12. Q9: Natural cross-ventilation is a core design driver for our layouts.

Valid response	Frequency	Percent	Valid Percent	Cumulative Percent
1 Strongly disagree	12	6.3	6.3	6.3
2 Disagree	32	16.9	16.9	23.3
3 Neither agree nor disagree	50	26.5	26.5	49.7
4 Agree	52	27.5	27.5	77.2
5 Strongly agree	43	22.8	22.8	100.0
Total	189	100.0	100.0	

Source: Authors' calculations from pune_smart_architecture_survey_n189.csv.

Agreement or strong agreement accounts for 95 responses (50.3%), neutrality for 50 (26.5%), and disagreement or strong disagreement for 44 (23.3%). The mean is 3.434, with a sample standard deviation of 1.195. The positive group represents just over half of respondents, making endorsement a narrow majority rather than a consensus. Cross-ventilation as a core driver refers to the organization of layouts around airflow, which is more demanding than including an operable window or another ventilation feature. The combined neutral and negative responses show that this design priority cannot be attributed to all records. The table also cannot distinguish between layouts intended to promote airflow and buildings that achieve effective ventilation in operation. Its architectural meaning is a reported emphasis on airflow during planning, with substantial variation in endorsement. Performance assessment would require information about openings, airflow paths and conditions of use beyond these ratings.

Table 13. Q10: Our designs highly adapt to Pune's local microclimate fluctuations.

Valid response	Frequency	Percent	Valid Percent	Cumulative Percent
1 Strongly disagree	13	6.9	6.9	6.9
2 Disagree	30	15.9	15.9	22.8
3 Neither agree nor disagree	43	22.8	22.8	45.5
4 Agree	60	31.7	31.7	77.2
5 Strongly agree	43	22.8	22.8	100.0
Total	189	100.0	100.0	

Source: Authors' calculations from pune_smart_architecture_survey_n189.csv.

Agreement or strong agreement accounts for 103 responses (54.5%), neutrality for 43 (22.8%), and disagreement or strong disagreement for 43 (22.8%). The mean is 3.476, with a sample standard deviation of 1.201. Agreement is the largest combined group, while neutrality and disagreement have identical counts. This symmetry is useful because it separates respondents who reject the broad adaptation claim from those who do not take a definite position. The statement covers whole-design responsiveness to local microclimate fluctuations, rather than one named technique, so the ratings summarize a general self-assessment. They do not reveal which fluctuations are addressed or how design adaptation is assessed. The mean is the highest within the climate-response set, suggesting that the broad adaptability claim receives somewhat stronger endorsement than several specific priorities. That pattern supports examining how respondents define adaptation before equating these ratings with verified climate performance.

Table 14. H1 Correlations

Variable	Statistic	Digital adoption	Energy perception
Digital adoption	Pearson Correlation	1	0.792
	Sig. (1-tailed)		<0.001
	N	189	189
Energy perception	Pearson Correlation	0.792	1
	Sig. (1-tailed)	<0.001	
	N	189	189

Source: Authors' calculations from pune_smart_architecture_survey_n189.csv.

Table 14 reports the H1 correlation between the digital adoption predictor, formed as the mean of Q1-Q3, and the energy-perception outcome Q4. The Pearson correlation is $r = 0.792$ with a one-sided $p < 0.001$ and $N = 189$. Under the stated assumptions, H1o is rejected at alpha = 0.05 and the directional H1a is supported by the supplied responses: architects reporting greater adoption of BIM, IoT, and AI tools also report greater agreement with the claim of measurable energy reductions. The predictor mean is 3.464 (SD 0.847) and the outcome mean is 3.439 (SD 0.975). The correlation is a pooled association between reported adoption and reported belief; it establishes neither an effect of adoption on energy use nor the size of any measured environmental improvement, and it does not estimate firm-category effects. Statistical support here is distinct from practical magnitude.

Table 15. H2 One-Sample Test

Measure	t	df	Sig. (1-tailed)	Mean Difference	95% CI Lower	95% CI Upper
Climate response	7.420	188	<0.001	0.430	0.315	0.544

Source: Authors' calculations from pune_smart_architecture_survey_n189.csv.

Test value = 3. One-sample statistics: N = 189, mean = 3.430, standard deviation = 0.796, and standard error of the mean = 0.058. The confidence limits are two-sided 95% bounds for the mean difference, not bounds for the mean itself.

Table 15 reports the H2 one-sample test of the climate-responsive index, the mean of Q6-Q10, against the neutral value of 3. The index mean is 3.430 (SD 0.796), exceeding neutral by 0.430 scale points, with t(188) = 7.420 and one-sided $p < 0.001$. The two-sided 95% confidence interval for the mean difference runs from 0.315 to 0.544, excluding zero. Under the stated assumptions, H2o is rejected at alpha = 0.05, supporting above-neutral average agreement with the climate-responsive design statements across the full sample. The interval indicates the average endorsement is modest in scale even though the statistical evidence is strong, so statistical and practical size should be distinguished. The result does not establish actual thermal comfort or climate-responsive operation, and the test compares the full-sample index with a benchmark, making no comparison between firm categories.

6. Key Findings and Discussion

The analysis of the Pune architect responses provides evidence for both hypotheses. For H1, the Pearson correlation between the mean of Q1 to Q3 and Q4 was positive and statistically significant, r = 0.7918, $p < .001$, one-sided, n = 189. This indicates that architects who reported stronger perceptions on the first three items also tended to report stronger perceptions on Q4. For H2, the one-sample t test on the mean of Q6 to Q10 showed a sample mean of 3.4296, which was significantly greater than the neutral value of 3, t(188) = 7.4203, $p < .001$, one-sided. These results are based on self-reported perceptions and do not measure building energy performance or city-level outcomes. The findings therefore describe architect views, not verified physical results.

The positive correlation in H1 and the above-neutral mean in H2 align with themes in the reviewed literature. Akbari et al. (2024) and Chang and Hsieh (2020) review BIM for sustainability and green building design, noting integration gaps and limited attention to certain performance analyses. Bortolini et al. (2022), Cespedes-Cubides and Jradi (2024), and Sghiri et al. (2025) discuss digital twins for energy efficiency, highlighting challenges such as interoperability, scalability, and reliance on BIM data. Aguilar et al. (2021) and Chen et al. (2023) address artificial intelligence and IoT integration for smart building energy management. The present architect reports are consistent with these reviews in emphasizing digital tools, but they remain perceptions rather than measured energy savings or operational outcomes.

The instrument used here relies on single items and descriptive arithmetic means, not validated scales. The composite indices for H1 and H2 are simple averages of Likert-type responses, and the one-sample t test compares the H2 composite to a neutral value of 3. The file provides no temporal design information, so causal or temporal conclusions cannot be drawn. The exact sampling and recruitment procedures are not documented, and the sample cannot be assumed representative of all Pune architects. The analysis is limited to Pearson correlation and one-sample t tests, with directional one-sided tests at alpha 0.05, each hypothesis tested separately. Firm categories provide descriptive context only.

The adoption-energy correlation and above-neutral climate-responsiveness mean describe related but distinct responses. Digital adoption concerns BIM, IoT and AI practice, whereas the climate items concern passive cooling, sun-path analysis, thermal mass, ventilation and microclimate adaptation. The second test does not determine whether digital tools cause higher climate scores. Q5 similarly expresses a net-zero necessity belief rather than a completed net-zero outcome. Figure 2 organizes a conceptual implementation sequence whose arrows have not been estimated here. A subsequent study could link documented technology use and passive strategies to normalized energy and comfort records, while retaining the distinction between professional agreement and verified building operation.

7. Conclusion

The revised analysis of 189 supplied records reports each questionnaire statement separately and evaluates two method-compatible hypotheses. The positive Pearson correlation of 0.792 links digital adoption with perceived energy reduction. The one-sample t test identifies a mean climate-responsiveness score of 3.430, above the neutral

benchmark of 3. Both directional tests are below the stated alpha of 0.05. These conclusions concern response patterns and are conditional on the assumptions needed for inference.

The paper supports attention to digital information and passive design as professional priorities, while leaving actual energy and comfort benefits for operational verification. The supplied file does not establish recruitment, consent, eligibility or independence. Results should therefore be presented as an analysis of supplied data rather than an authenticated population study. The sourced external evidence and conceptual figures provide context without transferring their numerical findings to Pune.

8. Suggestions

Future questionnaires should retain separate measures of technology implementation and perceived benefit. Project-specific accounts of BIM, IoT and AI use would help distinguish frequent use from occasional exposure. The separate energy-perception item could be supplemented with consented project records so that design claims can be compared with operational outcomes.

Practice and education discussions can connect passive cooling, shading, ventilation and material choices with digital evaluation of alternatives. The individual item tables identify reported priorities but do not demonstrate that a particular tool or strategy achieves savings. Performance checks should therefore use documented site conditions and appropriate operational evidence.

Subsequent field studies should document eligibility, recruitment, dates, response rates and respondent independence. The revised H2 concerns agreement against neutral, so questions about firm-category differences require a separately specified analysis in future work. Longitudinal project information would be needed to evaluate change.

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