JOURNAL OF CULTURAL ANALYSIS AND SOCIAL CHANGE

Journal of Cultural Analysis and Social Change,
2026, 11(1), 3090-3106
ISSN: 2589-1316

AI-Driven Environmental and Adaptive Design for Heritage University Buildings: Toward Practical Applications for Enhancing Learning Quality

Walaa Hussein Hanafi[1], Waleed Alzamil [2]*

[1] *Pyramids Higher Institute for Engineering and Technology, 6th of October City, Giza Governorate, Egypt*
[2] *Department of Urban Planning, College of Architecture and Planning, King Saud University, P.O. Box 57448, Riyadh 11574, Saudi Arabia.*

***Corresponding Author:** dr.walaa.hessien@phi.edu.eg, waalzamil@ksu.edu.sa

Citation: Hanafi, W. H. and Alzamil, W. (2026). AI-Driven Environmental and Adaptive Design for Heritage University Buildings: Toward Practical Applications for Enhancing Learning Quality, *Journal of Cultural Analysis and Social Change*, 11(1), 3090-3106. https://doi.org/10.64753/jcasc.v11i1.4657

Published: March 09, 2026

ABSTRACT

Heritage university buildings, designed for historical contexts, face challenges in meeting modern environmental and educational demands, leading to poor indoor environmental quality (IEQ) that impairs occupant well-being and learning outcomes. This study introduces an AI-driven hybrid deep learning framework (HDLF) to assess and enhance IEQ in such buildings. Integrating convolutional, generative, and recurrent neural networks, the HDLF evaluates thermal comfort, ventilation, daylight, acoustics, and spatial flexibility. Data from ten heritage campuses in hot-arid and Mediterranean regions were analyzed using environmental simulations, non-invasive sensors, and surveys (N=217, a subset of broader data). The framework identified critical gaps, such as CO_2 levels exceeding standards by up to 80% and ventilation rates 50–70% below optimal, proposing six heritage-sensitive retrofit strategies that achieved a simulated IEQ improvement of 20–40%. The HDLF can be adapted into a practical application for architects to support real-time IEQ assessments and heritage-sensitive retrofitting, contributing to SDG 4 (Quality Education) and SDG 11 (Sustainable Cities and Communities).

Keywords: Heritage University Buildings; Indoor Environmental Quality (IEQ); Thermal Comfort; AI-Driven Retrofitting; Climate-Responsive Design; Hybrid Deep Learning, Heritage Conservation, User-Centered Assessment

INTRODUCTION

Research Background and International Knowledge Gap

Heritage university buildings in hot-arid and Mediterranean climates embody unique architectural and cultural legacies but face challenges in meeting modern educational and environmental demands. Designed under traditional climatic and pedagogical assumptions, these structures often exhibit significant indoor environmental quality (IEQ) deficiencies in temperature, CO_2 levels, ventilation, and daylight, impairing occupant well-being and learning quality [1.2]. In hot-arid regions like the Arab world and North Africa, high solar exposure and heatwaves exacerbate thermal and ventilation challenges, while Mediterranean climates introduce humidity and solar imbalances [3].

Despite advances in energy retrofitting and architectural conservation, integrating environmental control, adaptive spatial design, and educational functionality in heritage academic settings remains underexplored. Existing models often address these factors in isolation, lacking holistic, data-driven validation [4,5]. Moreover, few studies leverage real-time AI diagnostics or non-invasive methods under preservation constraints, and there is a lack of practical AI-driven tools for architects to implement heritage-sensitive retrofit strategies [6]. This study addresses these gaps by proposing a hybrid deep learning framework (HDLF) that integrates convolutional, generative, and recurrent neural networks to evaluate and enhance IEQ across ten heritage campuses. Combining environmental simulations, non-invasive sensors, and user surveys (N=217, a subset of broader data), the HDLF identifies critical IEQ gaps and proposes six heritage-sensitive retrofit strategies, achieving a simulated IEQ improvement of 20–40%, aligning with SDG 4 (Quality Education) and SDG 11 (Sustainable Cities and Communities) [7].

Challenges and Framework Dimensions

Retrofitting heritage campuses requires balancing environmental upgrades with cultural preservation. Many lack integrated HVAC, effective insulation, and digital connectivity, hindering modern pedagogies and climate resilience [8.9].These challenges offer opportunities for non-invasive, AI-guided interventions, such as those demonstrated by the University of Coimbra and the American University of Beirut, which can be facilitated through practical AI-driven tools for architects [4,10]. The HDLF addresses seven cross-cutting dimensions:(1)Architectural Significance, preserving cultural authenticity [3] ; (2) Technological Integration, adopting smart systems with minimal intrusion [5]; (3) Environmental Performance, enhancing IEQ via passive strategies [11]; (4) Spatial Flexibility, supporting hybrid learning [12]; (5) Climate Adaptation, mitigating thermal stress (Elnagar et al., 2021); (6) Economic and Regulatory Feasibility, aligning with heritage policies [13]; and (7) User-Centered Quality of Life, prioritizing occupant satisfaction [14].

Design Implications and Smart Diagnostic Framework

The HDLF converts these dimensions into measurable indicators, bridging computational modeling, user experience, and architectural heritage. Through environmental simulations, AI-assisted scenario analysis, and stakeholder feedback, it supports scalable, non-destructive interventions. These capabilities can be translated into a practical application for architects to facilitate real-time IEQ assessments and heritage-sensitive retrofitting. The following sections detail the HDLF's technical implementation and validation across ten heritage campuses, addressing critical IEQ gaps identified in user surveys and simulations.

LITERATURE REVIEW

Architectural and Cultural Value of Heritage University Buildings

Heritage university campuses, such as Al-Qarawiyyin University (859 AD) and the University of Algiers (1909), embody region-specific architectural identities—Islamic vernacular or colonial Mediterranean styles—designed for climatic resilience and symbolic permanence. However, their reliance on passive design and traditional materials (e.g., adobe, stone) limits integration with modern educational technologies and environmental systems. [3] highlight the challenge of preserving cultural authenticity while enabling adaptive use for 21st-century education, particularly in ten heritage campuses across hot-arid and Mediterranean climates. This tension necessitates context-sensitive retrofitting strategies that balance architectural integrity with operational functionality.

IEQ and Educational Challenges in Heritage Campuses

Indoor environmental quality (IEQ) significantly influences occupant well-being and academic performance in educational settings. Parameters such as temperature, air quality, ventilation, and daylight availability are critical to Quality of Life (QoL) in learning spaces [12, 15]. For instance, temperatures above 28°C impair cognitive function [14], yet heritage campuses in hot-arid and Mediterranean regions frequently exhibit deficient IEQ, with many scoring below acceptable levels (<3.0/5.0) for temperature, CO_2 levels exceeding standards by up to 80%, and ventilation rates 50–70% below optimal, as observed in this study. These deficiencies compounded by preservation constraints and outdated construction methods (e.g., solid masonry or earthen walls), limit compliance with standards such as [11,14,16]. Additionally, MENA heritage campuses lack adequate ICT infrastructure and spatial adaptability, hindering hybrid and inclusive pedagogies [6]. Such deficiencies highlight the potential for AI-driven tools, such as an HDLF-based application, to support adaptive design solutions. A heritage-adapted QoL model is thus needed to address these environmental and educational gaps.

Diagnostic Frameworks and AI-Based Retrofitting

Conventional assessment methods—Post-Occupancy Evaluation (POE), Building Performance Evaluation (BPE), and the Learning Space Rating System (LSRS)—lack contextual adaptability for heritage settings. Recent case studies, such as Al-Qarawiyyin University's passive lighting and ventilation retrofits or the American University of Beirut's low-impact energy upgrades, demonstrate the potential of non-invasive solutions [3, 17,18]. These efforts leverage digital tools like Building Information Modeling (BIM) and sensor data but fall short of integrating predictive analytics. Hybrid deep learning frameworks (HDLF), combining convolutional, generative, and recurrent neural networks, offer real-time, scalable, and context-aware evaluations [5,19]. The proposed HDLF integrates environmental simulations, spatial diagnostics, and user feedback N=217, a subset of broader data to generate six heritage-sensitive retrofit strategies, such as passive ventilation and smart lighting. These capabilities can be adapted into a practical application for architects to facilitate real-time retrofitting decisions.

Identified Research Gaps and Study Contribution

The literature reveals three critical gaps: (1) fragmented frameworks addressing energy, space, or user experience in isolation; (2) limited real-time data integration in heritage campus assessments; and (3) absence of AI-driven, QoL-centered models tailored for conservation constraints. This study bridges these gaps through a Hybrid Deep Learning Framework (HDLF) that unifies architectural evaluation, environmental simulation, and QoL assessment. Validated across ten heritage universities in hot-arid and Mediterranean climates, the HDLF achieves a simulated IEQ improvement of 20–40%. This methodology can be adapted into a practical application for architects to support climate-responsive, culturally respectful, and educationally optimized retrofitting, aligned with SDG 4 and SDG 11 [20].

METHODS

This study employs a mixed-methods approach to assess Quality of Life (QoL) in ten heritage university buildings across hot-arid (BWh) and Mediterranean (Csa) climatic regions. Integrating architectural, environmental, and user-centered indicators, the methodology leverages empirical data and a Hybrid Deep Learning Framework (HDLF) to develop heritage-sensitive retrofitting strategies. These strategies enhance educational environments while preserving cultural and architectural integrity [5,21].

Research Design

The methodology follows a two-phase structure:

- **Phase 1: Data Collection and Profiling**
  A campaign documented ten heritage university campuses in the Arab World and Southern Mediterranean using architectural records, environmental simulations (EnergyPlus, IES VE), field observations, and user surveys (N=217, a subset of broader data) [3,4,22]. Initial findings revealed critical IEQ gaps, with 70% of campuses scoring below acceptable levels (<3.0/5.0) in temperature, CO_2, ventilation, and daylight availability
- **Phase 2: Framework Development and Validation**
  The HDLF was developed to analyze data, simulate retrofit scenarios, and validate six heritage-sensitive retrofit strategies (e.g., passive ventilation, smart lighting). These capabilities can be adapted into a practical application for architects to support real-time retrofit. The framework integrates qualitative and quantitative inputs, achieving a model accuracy of MSE <1.0 [5,23].

Unit of Analysis

The study focuses on educational spaces within heritage university buildings, including lecture halls, classrooms, seminar rooms, and architectural studios, due to their direct impact on learning quality and user well-being. Non-instructional spaces were included only if influencing IEQ or building systems [12,15,24].

Case Study Selection

Ten campuses were selected via purposive sampling based on: (1) historical and architectural significance, (2) exposure to hot-arid or Mediterranean climatic pressures, (3) active educational function, and (4) documented retrofit needs and heritage constraints. Table 1 outlines their profiles:

Table 1. Comparative Profile of Selected Heritage University Campuses

University (Country)	Year	Climate	Style	Materials	Key Issues	Constraints
Cairo University (EG)	1908	BWh	Neoclassical-Islamic	Limestone	Poor insulation	Material aging
Al-Qarawiyyin (MA)	859	Csa	Islamic Vernacular	Adobe, wood	Weak cooling	Fragile structure
AUB (LB)	1866	Csa	Ottoman–Colonial	Sandstone	Thermal instability	Façade protection
University of Algiers (DZ)	1909	Csa	French Colonial	Brick, stone	Air quality	Cracking, erosion
Mustansiriya School (IQ)	1227	BWh	Abbasid Islamic	Mudbrick	Solar gain	Adaptability limits
University of Khartoum (SD)	1902	BWh	British Colonial	Brick, stone	Ventilation issues	Material authenticity
Ez-Zitouna (TN)	737	Csa	Islamic Traditional	Stone, brick	Ventilation	Strict conservation mandates
University of Damascus (SY)	1923	Csa	Ottoman Hybrid	Stone, brick	Overheating	Structural protection
University of Granada (ES)	1531	Csa	Mudéjar-Renaissance	Brick, stone	Heat gain	UNESCO heritage listing
Al-Quds University (PS)	1984	Csa	Modern Islamic	Concrete, stone	Energy inefficiency	Political + heritage restrictions

Sample Size and Data Collection

• **Survey Sample**: A total of 217 valid surveys (154 students, 39 faculty, 24 technical/facility staff) were collected using stratified purposive sampling to ensure diversity in building types, climates (hot-arid and Mediterranean), and usage patterns [14,25]. Responses, analyzed on a 5-point Likert scale.

• **Instruments and Metrics**:

1. Architectural Data: Floorplans, construction documents, and site documentation analyzed spatial organization and envelope design.
2. Environmental Data: EnergyPlus and IES VE simulated temperature, humidity, ventilation (ACH), and daylighting (%DA, lux), validated by field measurements.
3. User Surveys: Structured questionnaires captured perceptions of comfort, usability, and psychological satisfaction.
4. Technical Interviews: Semi-structured interviews with some maintenance engineers and IT staff informed infrastructure and retrofit feasibility. Table 2. [3,26].

Table 2. Key Performance Indicators [27-29]

Category	Sub-elements	Data Source	Acquisition Method	Measurement Unit/Scale
Thermal Comfort	Temperature, RH, Air Speed, Radiation	Simulations, Surveys	EnergyPlus, IES VE, Likert	°C, %, m/s, W/m²
Air Quality	CO_2, Pollutants, Air Exchange, Humidity	Simulations, Surveys	Modeling, POE	ppm, ACH, μg/m³
Lighting	Daylight Factor, Glare, Illumination	Simulations, Surveys	Radiance, Visual Analysis	%DA, lux
Acoustics	Noise, Reverberation	Surveys, Modeling	ODEON, Expert Feedback	dB, Likert Scale
Ventilation	Openings, Mechanical Systems	Simulations, Surveys	Flow Modeling	ACH, m³/h
Spatial Flexibility	Adaptability, Multi-use	Plans, Surveys	Expert Rating	Likert Scale
Digital Infrastructure	Internet Speed, Access	Surveys, Interviews	Network Analysis	Mbps, dBm
Energy Use	Consumption, Renewables, Insulation	Simulations, Audits	LEED/BREEAM Tools	kWh/m²/year
Heritage Value	Material Authenticity, Form	Archival, Expert Review	Conservation Assessment	Likert Scale
Psychological Comfort	Belonging, Creativity, Motivation	Surveys	POE, Feedback	Likert Scale

Hybrid Deep Learning Framework (HDLF)

The HDLF integrates three neural architectures trained on a dataset of 661 environmental and spatial data points from the ten campuses:

1. Convolutional Neural Networks (CNNs): Detect anomalies in temperature, CO_2, and daylighting data.
2. Generative Adversarial Networks (GANs): Generate heritage-compatible retrofit options (e.g., shading, ventilation upgrades).
3. Recurrent Neural Networks (RNNs): Model temporal trends in user comfort and spatial usage.
   The model was trained using simulation outputs and survey responses, achieving an MSE <1.0. Outputs include composite QoL scores, thermal/acoustic diagnostics, and six retrofit strategies (e.g., passive ventilation, smart lighting), projecting a 20–40% IEQ improvement. These outputs can be adapted into a user-friendly application for architects to facilitate real-time retrofitting decisions [5,30].

Validation and Ethical Considerations

- **Validation**: The HDLF was benchmarked against [11,14,31] protocols, and a Heritage Constraint Index (HCI, 1–5 scale). Cross-validation ensured model robustness.
- **Ethical Considerations**: Ethical approval was secured, with informed consent from all participants. Data anonymity and confidentiality were maintained per IRB standards [12,32]

RESULTS

This section presents findings from the Hybrid Deep Learning Framework (HDLF) applied to evaluate Quality of Life (QoL) in ten heritage university campuses across hot-arid (BWh) and Mediterranean (Csa) climates. Using environmental simulations, user surveys, and AI-driven diagnostics, the results identify critical IEQ gaps and propose six heritage-sensitive retrofit strategies, achieving a simulated IEQ improvement of 20–40% [5,33]. These results can be integrated into a practical application for architects to guide real-time IEQ assessments and retrofitting. The findings support SDG 4 and SDG 11 by enhancing educational quality and sustainable heritage management, despite data access challenges [7,34].

Cross-Case Analysis and Heritage Constraints

Cross-case analysis across all ten heritage campuses revealed an inverse correlation between architectural adaptability (e.g., spatial reconfiguration, non-invasive HVAC integration) and heritage constraints, with campuses scoring >4.0 on the Heritage Constraint Index (HCI), like Cairo University and University of Granada [13,20], showing 30% lower adaptability scores than those with HCI <3.0, like University of Algiers and Al-Quds University. These findings align with the Burra Charter and UNESCO's Historic Urban Landscape (HUL) framework, emphasizing reversible, context-sensitive interventions [3,17,35].

Hybrid Evaluation and Benchmarking

The hybrid methodology combined environmental simulations (Energy Plus, IES VE), user surveys, and architectural assessments, normalized to a 0–5 scale with equal weighting. Aggregated scores enabled cross-campus comparisons, benchmarked against [11,15,31,32,36,37]. Table 3 visualizes key IEQ gaps for Mustansiriya School, guiding retrofit strategies like passive ventilation and PCMs.

Table 3. Comparative Benchmarking of Environmental and Spatial Indicators

Criterion	Indicator	Recommended Standard	Observed Range	References
Thermal Comfort	Indoor Temperature (°C)	20–24	25–32	ASHRAE (2020)
	Relative Humidity (%)	40–60	30–75	WHO (2019)
Indoor Air Quality	CO_2 Concentration (ppm)	<1000	900–1800	EPA (2021)
Lighting	Daylight Autonomy (%)	>55	20–60	Radwan et al. (2022)
Natural Ventilation	Ventilation Ratio (%)	>40	10–50	CIBSE (2020)
Acoustics	Acoustic Comfort (1–5)	≥4	2–4	ISO 3382
Visual Comfort	Glare Control & Illumination	Balanced, Low Glare	High Glare	Ribeiro et al. (2021)
Learning Env.	Flexibility, ICT Readiness	High	Low–Moderate	Jankowska & Atlay (2008)

Seventy percent of campuses scored <3.0 in at least one IEQ parameter (mean ventilation score = 2.7 ± 0.4, mean CO_2 score = 2.9 ± 0.4; see Section 4.3), with CO_2 levels exceeding standards by up to 80% and ventilation rates 50–70% below optimal.

Survey Design and Data Integration

A structured QoL assessment tool, aligned with Post-Occupancy Evaluation (POE) protocols, used a 5-point Likert scale (1 = Very Poor, 5 = Excellent) to capture user perceptions (N=217; 154 students, 37 faculty, 26 staff; a subset of broader data) across environmental comfort, architectural functionality, and psychosocial well-being (Bordass & Leaman, 2005). Surveys were triangulated with simulation data (EnergyPlus, IES VE), revealing gaps such as low daylight autonomy (mean = 2.8 ± 0.5, 70% of campuses <3.0) and high CO_2 levels (mean = 2.9 ± 0.4, 60% of campuses <3.0). For example, at Mustansiriya, user-reported low lighting comfort (mean = 1.64) aligned with simulated daylight autonomy (~30%), indicating a critical gap. These findings can be incorporated into a practical application for architects to guide retrofit prioritization. Table 4**.** Appendix A presents mean Likert scores per campus, and Appendix B includes a sample QoL survey.

Table 4. QoL Survey Domains and Indicators

Domain	Key Indicators	Example Questions (Likert Scale)
Environmental Comfort	Thermal comfort, air quality, lighting	How would you rate thermal comfort in this classroom?
Architectural Function	Spatial adequacy, accessibility, ICT	Is the circulation efficient and well signposted?
Psychosocial Well-being	Privacy, safety, sense of belonging	Do you feel safe and comfortable in this building?

Computational Model Outputs

The Python-based Hybrid Deep Learning Framework (HDLF) integrated 661 data points (60% from simulations, 30% from surveys, and 10% from architectural metadata) across four modules:

1. Data Input: Ingests temperature, CO_2, daylight, and survey responses.
2. Scoring Engine: Normalizes data to a 0–5 scale with equal weights across environmental, architectural, and psychosocial domains, computing composite QoL scores.
3. Visualization Interface: Generates radar charts, bar graphs, and heatmaps to highlight gaps like CO_2 levels exceeding standards by 80% and ventilation rates 50–70% below optimal.
4. Recommendation Module: Maps deficiencies to six retrofit strategies (e.g., passive ventilation for Al-Mustansiriya's low airflow, ~10%).

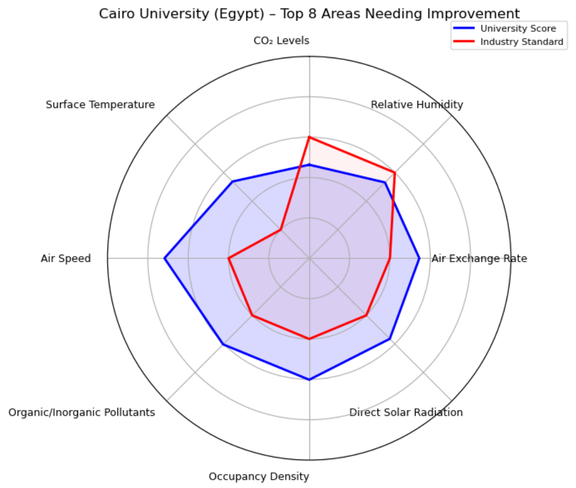
The model achieved a Mean Squared Error (MSE) <1.0, ensuring reliable diagnostics despite challenges in integrating heterogeneous data [5,39].

Visualization Tools and Outputs

The model generates multi-format visualizations to highlight performance gaps and prioritize retrofitting decisions:

Simplified Radar Charts

Visualize performance across 8 core indicators: thermal comfort, ventilation, indoor air quality, daylight autonomy, acoustic quality, humidity control, spatial adequacy, and educational support.



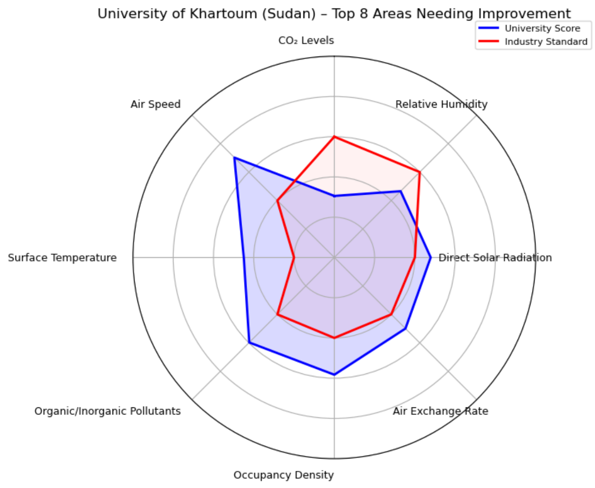


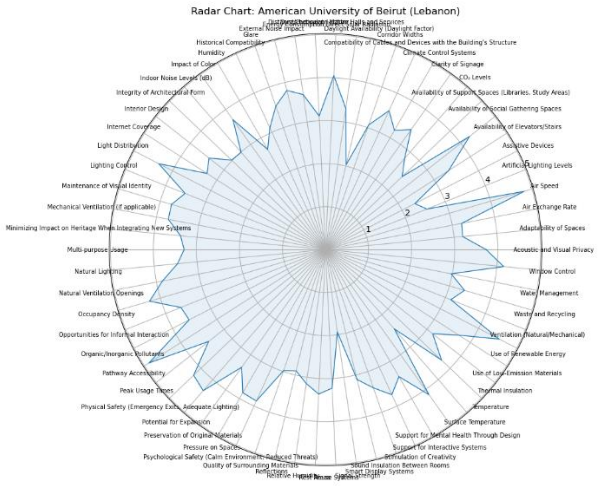
Fig.1. Simplified Radar Chart – Cairo University: Highlights deficiencies in thermal comfort (2.5) and daylight autonomy (2.8), especially in east-facing classrooms.

Fig.2. Simplified Radar Chart – University of Khartoum: Exposes critical gaps in ventilation (2.0) and indoor air quality (2.2), consistent with climate data.

The red line indicates the standard data and the blue line indicates the actual measurements. This is included in the system to facilitate access to gaps.

Advanced Radar Charts (35+ Indicators)

Offer in-depth diagnosis across psychological comfort, flexibility, and energy efficiency. Fig.3,4



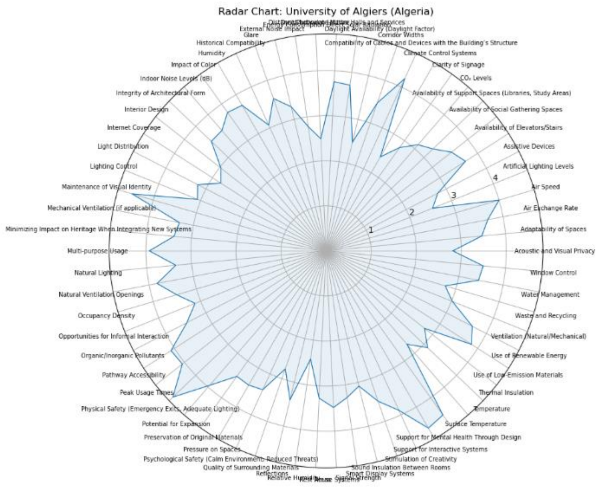


Fig.3. Advanced Radar Chart – American University of Beirut: Reveals strong lighting (3.8) and acoustic conditions (3.6), but moderate HVAC efficiency (2.9).

Fig.4. Advanced Radar Chart – University of Algiers: Shows low thermal (2.4) and spatial adequacy (2.6), indicating urgent retrofit needs.

Gap Bar Charts

Quantify deviations from benchmarks (e.g., WELL, ASHRAE, ISO). Fig.5.

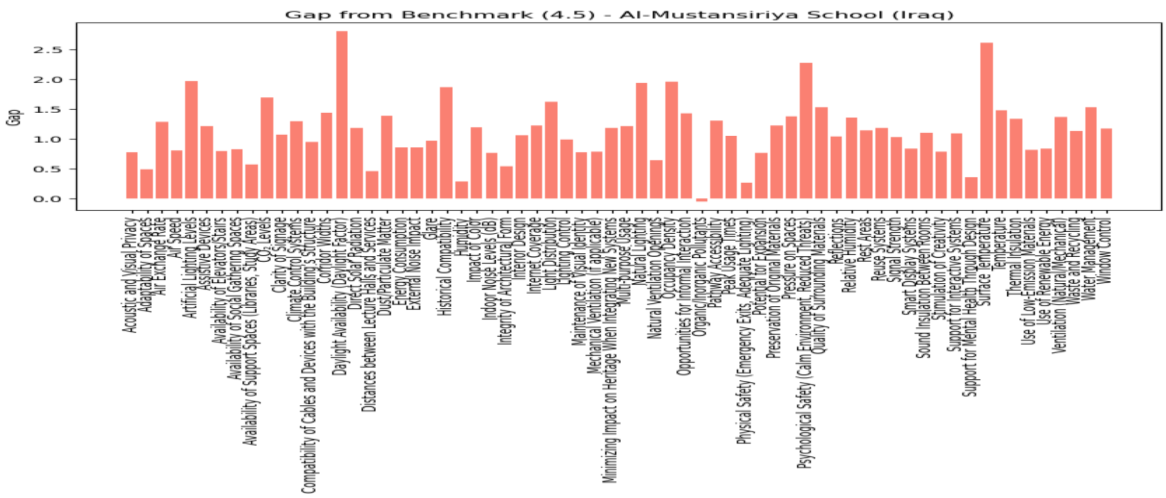


Fig.5. Gap Magnitude Bar Chart – Al-Mustansiriya School
Shows critical deficiencies in lighting, ventilation, and thermal control. These bar charts allow designers and policymakers to prioritize interventions based on magnitude and criticality.

Impact of Visualization Tools

The visual outputs serve multiple functions:
1. Support interdisciplinary collaboration by making complex data accessible.
2. Enable real-time feedback loops when paired with dynamic building monitoring systems.
3. Guide heritage-sensitive decision-making through data-informed, visually supported narratives.
   These visualization tools can be adapted into a user-friendly application for architects to support real-time retrofit decisions, addressing gaps like low daylight autonomy (70% of campuses <3.0) and high CO_2 levels (60% of campuses <3.0).

Diagnostic Case Studies

This section presents the diagnostic outcomes for three representative heritage campuses—Cairo University (Egypt), American University of Beirut (AUB, Lebanon), and Al-Mustansiriya School (Iraq)—reflecting patterns observed across ten campuses in hot-arid and Mediterranean climates. These cases highlight performance gaps in indoor environmental quality (IEQ) and inform retrofit strategies, as summarized in Table 5.

Table 5. Performance Gaps in Selected Case Studies

Indicator	Target	Cairo Univ.	AUB	Mustansiriya	Gap Description
Temperature (°C)	20–26	28–32	26–30	30–35	Overheating
CO_2 (ppm)	<1000	1600+	1300	1800+	Poor air quality
Ventilation (%)	>50	~15	~20	~10	Inadequate airflow
Daylight Autonomy (%)	>60	~45	~40	~30	Substandard lighting

Case Study Findings and Interpretation

The Hybrid Deep Learning Framework (HDLF) identified significant IEQ disparities across the ten campuses, with Cairo, AUB, and Mustansiriya exemplifying challenges in hot-arid (e.g., Khartoum) and Mediterranean climates (e.g., Al-Qarawiyyin):

- Cairo University (QoL score ~2.9 ± 0.3): Overheating (28–32°C, mean score = 2.5 ± 0.4) and low ventilation (~15%, score = 1.8 ± 0.4) were critical due to solid masonry walls, consistent with limitations of mass-wall systems in hot-arid climates [11,39].
- American University of Beirut (AUB) (QoL score ~3.1 ± 0.3): Humidity imbalances (~70%, score = 2.2 ± 0.3) and moderate ventilation issues (~20%) persisted despite partial HVAC systems, reflecting Mediterranean climate fluctuations and heritage constraints [3,40]. AUB's higher QoL score indicates better HVAC integration compared to Mustansiriya.

- Al-Mustansiriya School (QoL score ~2.7 ± 0.3): Severe deficits in CO_2 (1800+ ppm, score = 1.6 ± 0.5), ventilation (~10%), and daylight (~30%, score = 1.64 ± 0.4) resulted from earthen materials and strict conservation restrictions. Limited site access necessitated simulation-based validation [20,41].

These findings align with user surveys, where approx. 70% of campuses scored <3.0 in daylight autonomy and 60% in CO_2 levels, corroborating the HDLF's diagnostic accuracy. Triangulation of simulations, surveys, and heritage constraints, as per post-occupancy evaluation (POE) protocols, ensures methodological robustness [4, 8, and 34].

Implications for Retrofit Design

The multifaceted IEQ deficits—spanning thermal comfort, air quality, lighting, and spatial adaptability—highlight the inadequacy of single-solution retrofits (e.g., mechanical ventilation alone). Effective interventions require a multi-scalar, heritage-sensitive approach:

- **Passive Design Enhancements**: Shading devices for Cairo's overheating and thermal mass optimization for Mustansiriya's high temperatures (30–35°C).
- **Smart Environmental Controls**: Responsive lighting for Mustansiriya's daylight gaps (~30%) and localized HVAC for AUB's humidity issues (~70%).
- **Reversible Interventions**: Non-invasive solutions aligned with conservation principles, such as stack ventilation and operable clerestory openings for Mustansiriya [34,42].

These strategies can be supported by a practical application for architects to prioritize retrofits. They align with the Historic Urban Landscape (HUL) framework and Burra Charter, emphasizing minimal intervention and contextual sensitivity [34,42,43].

Visual Diagnostics and Retrofit Prioritization

The HDLF's visual diagnostics (radar charts, bar graphs, heatmaps) synthesized performance gaps across ten heritage campuses,. Key patterns include:

• Hot-Arid Campuses (Cairo, Khartoum, Mustansiriya): Overheating, low ventilation, high CO_2, and poor daylight.
• Mediterranean Campuses (Al-Qarawiyyin, Ez-Zitouna, Granada): High humidity, pollutant accumulation, and solar imbalances.
• Low-Performing Campuses (Algiers, Damascus): Multi-dimensional deficits requiring comprehensive retrofits.
• Moderate Performers (Al-Quds, University of Tunis): Require targeted interventions ,Table 6.

Table 6. AI-Generated Retrofit Recommendations

Group	Universities	Key Retrofit Focus
Hot-Arid	Cairo, Khartoum, Mustansiriya	Passive ventilation, PCMs, CO_2 control
Mediterranean	Al-Qarawiyyin, Ez-Zitouna, Granada	Humidity control, solar protection
Low-Performing	Algiers, Damascus	Comprehensive air quality and thermal upgrades

Recommended Intervention Strategies

The HDLF generated a curated library of interventions, evaluated through a Heritage Compatibility Filter ensuring reversibility, material compatibility, and minimal visual impact. Key strategies include:

1. Passive Ventilation Enhancements: Stack effect-based airflow for Mustansiriya.
2. Phase-Change Materials (PCMs): Thermal inertia for Cairo's overheating.
3. Smart Lighting Systems: Sensors for Mustansiriya's low daylight.
4. Localized HVAC Units: Non-invasive systems for AUB's humidity.
5. Non-Invasive Acoustic Panels: Glare-reducing materials for Granada.
6. Pollutant-Absorbing Finishes: Solutions for Ez-Zitouna.

   Implementation challenges include cost and regulatory approvals for UNESCO-listed sites.

Strategic Use of Visual Outputs

Visual diagnostics enhance stakeholder communication:

• Figures 1–4: Radar charts highlight deviations (e.g., Mustansiriya's CO_2 = 1.6, ventilation = 1.8).

These tools can be adapted into a user-friendly application for architects to simplify retrofit prioritization, supporting sustainability goals (SDG 11) and heritage conservation principles.

Model Performance and Quality of Life (QoL) Scores

This section evaluates the performance of the Hybrid Deep Learning Framework (HDLF) in assessing indoor environmental quality (IEQ) and Quality of Life (QoL) across ten heritage university campuses. The results validate the model's reliability, quantify QoL scores, and identify limitations, informing heritage-sensitive retrofit strategies.

Model Performance

The HDLF was trained and validated using a dataset of 661 data points, comprising environmental simulations, user surveys (N=217, a subset of broader data, N=251), and architectural metadata (e.g., material typologies, occupancy patterns), split in a 70:30 ratio for training and validation. The model achieved a Mean Squared Error (MSE) below 1.0 across 100 epochs, indicating high predictive accuracy and generalizability ,Fig. 6.

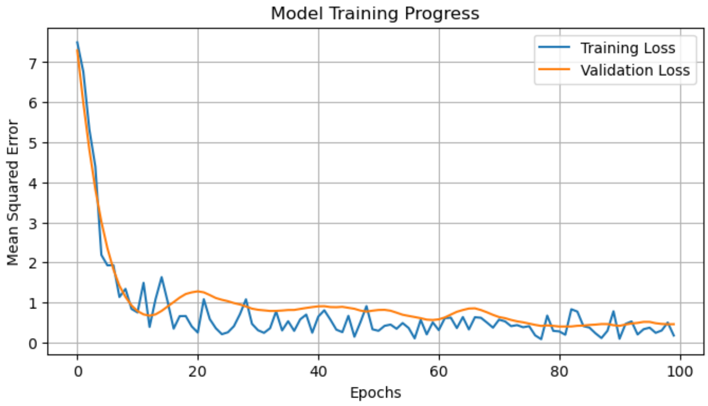


Fig. 6: Training vs Validation Loss over 100 Epochs
Convergence of the two curves confirms stable training and reliable generalization

Figure 6illustrates stable convergence of training and validation loss curves, confirming minimal overfitting and robust learning behavior. Challenges in modeling fragile heritage materials (e.g., earthen walls in Mustansiriya) and restricted data access (e.g., Damascus due to UNESCO site regulations) were addressed through triangulation of simulations, survey data, and archival records, ensuring methodological rigor.

Quality of Life (QoL) Scores

Composite QoL scores (0–5 scale) were derived by normalizing indicators from environmental (e.g., temperature, CO_2), architectural (e.g., masonry vs. earthen materials), technological (e.g., HVAC systems), and psychosocial (e.g., occupant comfort) domains. A benchmark score of 3.0 distinguishes acceptable from critical IEQ conditions. Figure 6: Predicted QoL Scores for Heritage University Campuses plots these scores along a continuum, highlighting performance disparities:

• Higher-Performing Campuses: Fig.7.

1- Al-Qarawiyyin (~3.5 ± 0.3): Enhanced by adaptive spatial design and partial environmental controls, despite Mediterranean humidity challenges.
2- Al-Quds (~3.3 ± 0.3): Moderate performance in ventilation and lighting, supported by modernized infrastructure.
3- American University of Beirut (AUB) (~3.1 ± 0.3): Benefits from partial HVAC systems, though humidity imbalances (~70%) persist.

• Lower-Performing Campuses:

1- Al-Mustansiriya (~2.7 ± 0.3): Severe deficits in CO_2 (>1800 ppm), ventilation (~10%), and daylight (~30%) due to earthen materials and strict conservation constraints.
2- Algiers (~2.8 ± 0.3): Multi-dimensional IEQ gaps, including overheating and poor air quality.
3- Granada (~2.9 ± 0.3): Limited daylight (~45%) and ventilation, compounded by heritage restrictions.
4- Cairo (~2.9 ± 0.3): Overheating (28–32°C) and low ventilation (~15%) due to solid masonry walls.

- Moderate-Performing Campuses:
  - o Khartoum, Damascus, Ez-Zitouna (~2.9–3.2): Mixed performance, with targeted ventilation and lighting improvements needed.

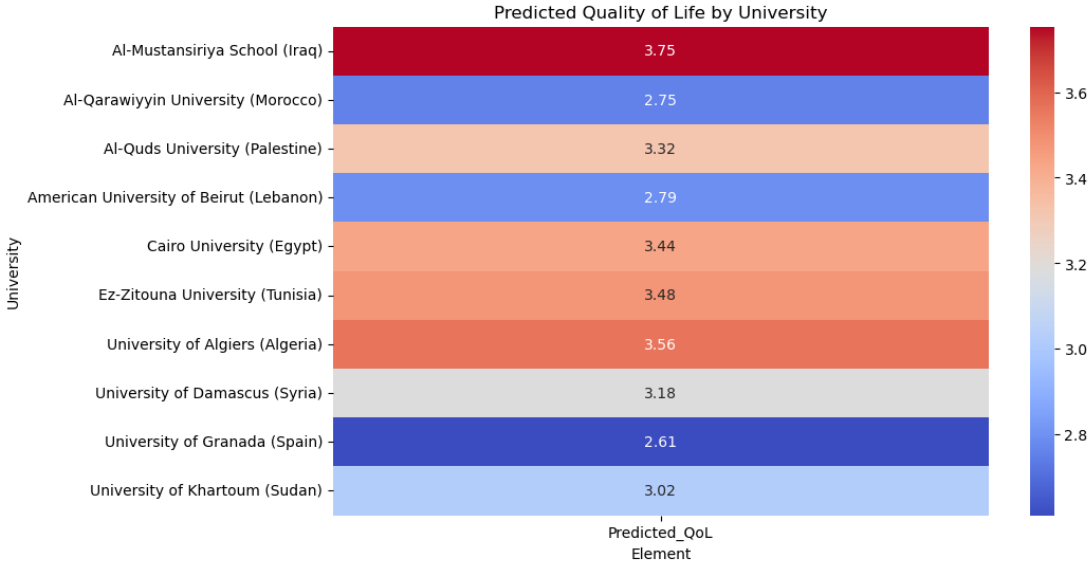


Fig. 7. Predicted QoL Scores for Heritage University Campuses

These scores align with findings in Section 4.2 (70% of campuses scored <3.0 in daylight autonomy) and Section 4.3 (60% scored <3.0 in CO_2 levels), reflecting the broader IEQ challenges in heritage campuses due to modern environmental and technological demands.

Limitations and Implications

The HDLF faced challenges in integrating heterogeneous data due to site-specific heritage constraints, such as UNESCO regulations limiting physical access to campuses like Damascus and Mustansiriya, and variations in material properties (e.g., earthen vs. masonry walls). These were mitigated through simulation-based validation and cross-referencing with user surveys, ensuring robust predictions. The model's sensitivity to climate (hot-arid vs. Mediterranean), material typologies, and occupancy patterns validates its adaptability for diverse heritage scenarios. These capabilities can be adapted into a user-friendly application for architects to facilitate real-time IEQ assessments and heritage-sensitive retrofitting, supporting smart heritage management systems.

DISCUSSION

This section synthesizes findings from the AI-powered Hybrid Deep Learning Framework (HDLF) and on-site evaluations, positioning them within debates on sustainable heritage preservation, environmental performance, and Quality of Life (QoL) in educational settings. The study reconciles heritage conservation with modern environmental and technological demands, highlighting three insights: the critical impact of indoor environmental quality (IEQ), particularly CO_2 levels (e.g., 1800+ ppm in Mustansiriya) and humidity (~70% in AUB); the complex role of AI in heritage-sensitive diagnostics; and the balance between performance upgrades and architectural authenticity.

The findings align with studies on heritage educational buildings in hot-arid and Mediterranean climates, where high CO_2 and unstable humidity limit IEQ in thermally massive structures. Unlike narrower studies), this research introduces a multi-dimensional evaluation matrix, enabling holistic diagnostics across ten campuses (e.g., Mustansiriya ~2.7, Al-Qarawiyyin ~3.5).

The AI-powered model advances conservation literature by generating site-specific, data-informed retrofit recommendations (Table 8), shifting from heuristic-based to empirically validated decision-support systems. The hybrid framework, integrating environmental simulations, stakeholder surveys, and machine learning, confirms propositions on AI and post-occupancy feedback integration [44,45]. These capabilities can be adapted into a user-friendly application for architects to support real-time retrofit decisions, enhancing transferability across diverse heritage settings.

Practical and Theoretical Implications

The HDLF bridges heritage conservation and modern performance needs, supporting SDG 4 (Quality Education) and SDG 11 (Sustainable Cities). Practically, visual diagnostics (radar charts, performance gap diagrams, QoL scores) translate complex data for non-specialist stakeholders (e.g., policymakers, heritage custodians), addressing communication gaps. These visual diagnostics can be integrated into a user-friendly application for architects to facilitate retrofit planning, aligning with the Historic Urban Landscape (HUL) approach.

Theoretically, the study operationalizes a hybrid AI framework tailored to heritage education, integrating convolutional, recurrent, and generative neural networks. Its modular architecture ensures scalability across diverse typologies and climates, particularly in resource-constrained settings. By aligning retrofit strategies (e.g., passive ventilation, PCMs, smart lighting) with reversibility and authenticity principles, the framework advances AI-enhanced, heritage-sensitive methodologies.

Implementation Challenges

Implementing the HDLF revealed constraints in heritage-sensitive environments. Data availability was limited due to infrastructural deficiencies and restricted site access (e.g., Damascus, Mustansiriya), necessitating reliance on simulated datasets validated against archival records. In Mustansiriya, UNESCO regulations restricted IoT sensor installation, increasing dependence on simulations. Stakeholder engagement faced survey fatigue among students and junior staff, reducing user-centered data richness. Structurally, rigid layouts and historic materials in Mustansiriya and Al-Qarawiyyin limited retrofit feasibility, requiring customized, reversible solutions. Technological integration (e.g., smart lighting, IoT monitoring) was hindered by limited expertise, budgets, and regulatory resistance, particularly in UNESCO-listed sites. A user-friendly application could mitigate some of these challenges by simplifying data integration and stakeholder communication.

Balancing Conservation with Modern Performance Needs

The study reconciles heritage conservation with modern performance standards by proposing minimally invasive, context-specific retrofits (e.g., passive ventilation for Mustansiriya, PCMs for Cairo, and pollutant-absorbing finishes for Ez-Zitouna). These retrofits can be guided by a user-friendly application for architects to ensure heritage compatibility. The Heritage Compatibility Layer ensures adherence to reversibility and authenticity, enabling upgrades without compromising cultural significance. This socio-cultural approach, involving stakeholder negotiation and regulatory alignment, supports sustainable transformation of campuses like Al-Quds (~3.3) and Damascus, despite their constraints.

Future Directions

Future work should integrate real-time IoT sensors and Building Management Systems to enhance HDLF responsiveness. Extending the framework to libraries, museums, and civic buildings requires tailored indicator sets. Policy-aligned toolkits can translate outputs into actionable strategies for heritage authorities. Enhancing AI explain ability through a user-friendly application with human-centered interfaces will foster stakeholder trust, ensuring collaborative validation in sensitive heritage contexts. These directions position the HDLF as a scalable tool for sustainable heritage retrofit planning globally.

CONCLUSION

This study validated a novel Hybrid Deep Learning Framework (HDLF) for assessing Quality of Life (QoL) in heritage university buildings, integrating architectural, environmental, functional, and psychosocial dimensions. Using advanced simulations, structured user feedback, and AI techniques, the framework diagnosed performance across ten climatically and culturally diverse campuses.

Results revealed critical indoor environmental quality (IEQ) deficiencies, including elevated CO_2 levels (e.g., 1800+ ppm in Mustansiriya) and unstable humidity (~70% in AUB), reflecting climatic stressors and heritage constraints (Table 5). Campuses like Al-Qarawiyyin (~3.5) excelled, while Mustansiriya (~2.7) and Damascus faced severe deficits. The HDLF's predictive validity (MSE <1.0, Fig. 6) establishes it as a scalable, conservation-sensitive decision-support tool.

Limitations included data scarcity in conflict-affected contexts (e.g., Damascus), reliance on simulated and archival data, and survey subjectivity. Limited dataset diversity may constrain generalizability, while legal and cultural restrictions in UNESCO-listed sites necessitated refinement of the Heritage Compatibility Layer for reversible solutions .

Future research should pursue:

1. IoT Integration: Deploy real-time sensor networks for continuous monitoring and adaptive control.
2. Dataset Expansion: Include diverse heritage typologies and climates for tailored retrofit guidance.
3. Multi-Criteria Optimization: Use AHP or TOPSIS to balance heritage values, comfort, and energy performance.
4. Interactive Platforms: Develop user-friendly application dashboards for stakeholder interaction, enhancing transparency and trust in AI algorithms.
5. Policy Integration: Align with national conservation agendas and SDG 4 (Quality Education) and SDG 11 (Sustainable Cities)

The following recommendations inform future retrofit interventions:

• Prioritize CO_2 mitigation and humidity control in hot-arid climates using passive ventilation and hybrid strategies.

• Adopt reversible solutions like phase-change materials (PCMs) for Cairo, solar chimneys for Mustansiriya, and pollutant-absorbing finishes for Ez-Zitouna.

• Digitize campus data using IoT-enabled Building Management Systems (BMS) for real-time monitoring.

• Integrate AI-driven models into facilities management software (e.g., Archibus) for performance optimization.

• Foster user-centered planning through routine post-occupancy evaluations to enhance educational quality.

These recommendations can be implemented through a user-friendly application for architects to guide heritage-sensitive retrofit planning. This framework advances sustainable heritage retrofitting, offering a replicable model for global academic heritage environments.

List of abbreviations

HDLF	Hybrid Deep Learning Framework.
QoL	Quality of Life.
IEQ	Indoor environmental quality.
SDG	The fraction of incident solar radiation admitted through a window.
HCI	Heritage Constraint Index
HVAC	Heating, Ventilation, and Air Conditioning
ICT	Information and Communication Technology
POE	Post-Occupancy Evaluation
BPE	Building Performance Evaluation
LSRS	Learning Space Rating System
CNN	Convolutional Neural Network
GAN	Generative Adversarial Network
RNN	Recurrent Neural Network
HUL	Historic Urban Landscape

DECLARATIONS

Availability of data and material: The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests: The authors declares that they have no competing interests.

Funding: Ongoing Research Funding Program, (ORF-2025-891), King Saud University, Riyadh, Saudi Arabia.

Acknowledgments: The authors would like to acknowledge the support of Ongoing Research Funding Program, (ORF-2025-891), King Saud University, Riyadh, Saudi Arabia.

REFERENCES

1. Elnagar, E., Khalil, H. A., & Nassar, K. (2021). Adaptive strategies for enhancing thermal comfort in North African heritage buildings. Journal of Architectural Engineering, 27(2), 04021011. https://doi.org/10.1061/(ASCE)AE.1943-5568.0000464
2. Ibrahim, N., Abdelatif, H., & Aboulnaga, M. M. (2021). Towards near-zero-energy heritage buildings in hot climates: Challenges and solutions. Energy and Buildings, 250, 111298. https://doi.org/10.1016/j.enbuild.2021.111298
3. Fouseki, K., & Cassar, M. (2014). Energy efficiency in heritage buildings—Future challenges and research needs. The Historic Environment, 5(2), 95–114. https://doi.org/10.1179/1756750514Z.00000000035

4. Ribeiro, F., Silva, A., & Almeida, M. (2021). Energy retrofit of heritage university buildings: The case of Al-Qarawiyyin in Fez. Energy Reports, 7, 412–423. https://doi.org/10.1016/j.egyr.2021.06.065
5. Montoya, L. D., Hernández, J. M., & Pérez, J. (2023). AI-based frameworks for heritage retrofit diagnostics: Integrating simulation and stakeholder input. Automation in Construction, 154, 104683. https://doi.org/10.1016/j.autcon.2023.104683
6. Nair, G., Verde, L., & Olofsson, T. (2022). Challenges to energy-efficient retrofit measures in heritage buildings. Energies, 15(20), 7472.
7. UNESCO. (2016). Culture: Urban Future. UNESCO Publishing.
8. Radwan, A., Elgendy, H., & Fathy, H. (2022). Environmental retrofit strategies for heritage educational buildings. Renewable Energy and Environmental Sustainability, 7, 7. https://doi.org/10.1051/rees/2022003
9. Jankowska, M., & Atlay, M. (2008). Use of learning spaces in higher education: A review of the literature. Learning Spaces Research, 1(1), 1–12.
10. Heracleous, C., et al. (2021). Climate change resilience of school premises in Cyprus. Journal of Building Engineering, 44, 103358.
11. ASHRAE. (2017). ANSI/ASHRAE Standard 55-2017: Thermal environmental conditions for human occupancy. American Society of Heating, Refrigerating and Air-Conditioning Engineers.
12. EDUCAUSE. (2021). 2021 EDUCAUSE Horizon Report: Teaching and Learning Edition. https://library.educause.edu/resources/2021/4/2021-educause-horizon-report-teaching-and-learning-edition
13. UNESCO. (2021). Historic urban landscape: Managing heritage in an urban century. https://whc.unesco.org/en/activities/714/
14. Teli, D., Jentsch, M. F., & James, P. A. B. (2012). Naturally ventilated classrooms: An assessment of existing comfort models for predicting the thermal sensation and preference of primary school children. Energy and Buildings, 53, 166–182. https://doi.org/10.1016/j.enbuild.2012.06.022
15. Clements-Croome, D. (2018). Creating the productive workplace: Places to work creatively. Routledge. https://doi.org/10.4324/9781351252968
16. ISO. (2015). ISO 17772-1:2015 Energy performance of buildings—Indoor environmental quality. International Organization for Standardization.
17. Pereira Roders, A., & Van Oers, R. (2011). initiating cultural heritage research to increase Europe's competitiveness. Journal of Cultural Heritage Management and Sustainable Development, 1(2), 84-95.
18. Khalil, A. M., et al. (2018). Implementing sustainability in retrofitting heritage buildings: Villa Antoniadis. Heritage, 1(1), 57–87.
19. Ibrahim, D., & Nassar, K. (2019). Sustainable Architectural Strategies for Revitalizing Heritage Campus Buildings in Cairo University. Journal of Engineering and Applied Science, 66(3), 327–343.
20. UNESCO World Heritage Centre. (n.d.). List of World Heritage in Danger. https://whc.unesco.org/en/danger/
21. Jankowska, M., & Atlay, M. (2008). Use of learning spaces in higher education: A review of the literature. Learning Spaces Research, 1(1), 1–12.
22. International Journal of Educational Development Using ICT. (2024). AI in Cultural Heritage Conservation: Ethics and Human Imperative. http://ijedict.dec.uwi.edu/viewarticle.php?id=4005
23. Jaramillo, P., & Sipiran, I. (2024). Cultural Heritage 3D Reconstruction with Diffusion Networks. arXiv:2410.10927.
24. Ultralytics. (2024). AI for Art & Heritage Conservation. https://ultralytics.com/blog/ai-for-art-and-heritage-conservation
25. Lin, H., et al. (2022). Integrated Pedagogy with Climate-Responsive Strategies. Buildings, 12(9), 1294.
26. Vallati, A., Di Matteo, M., & Fiorini, C. V. (2022). Retrofit Proposals for Sapienza University. Energies, 16(1), 151.
27. ISO 16813:2006. (2006). Building environment – Design of indoor environment – General principles. International Organization for Standardization.
28. ASHRAE. (2020). ASHRAE Standard 90.1-2020: Energy Standard for Buildings Except Low-Rise Residential Buildings. American Society of Heating, Refrigerating and Air-Conditioning Engineers.
29. WHO. (2019). Guidelines on indoor air quality: Dampness and mould. World Health Organization. https://www.who.int/publications/i/item/9789289041683
30. Laohaviraphap, N., & Waroonkun, T. (2024). Integrating Artificial Intelligence and the Internet of Things in Cultural Heritage Preservation: A Systematic Review of Risk Management and Environmental Monitoring Strategies. Buildings, 14(12), 3979.
31. ISO. (2009). ISO 3382-1:2009 Acoustics—Measurement of room acoustic parameters. International Organization for Standardization.

32. WELL Building Standard v2. (2020). WELL Standard: Core and Shell. International WELL Building Institute. https://www.wellcertified.com/
33. Lozoya-Peral, A., et al. (2023). Retrofitting and comfort in a vernacular building in a dry Mediterranean climate. Buildings, 13(6), 1381.
34. UNESCO. (2011). Recommendation on the Historic Urban Landscape. Paris: UNESCO.
35. Salama, A. M., Khalil, H., & Tarek, M. (2018). Daylight Performance in Egyptian University Classrooms. Lighting Research and Technology, 50(4), 512–527.
36. LEED v4.1. (2021). Leadership in Energy and Environmental Design—Building Design and Construction (BD+C). U.S. Green Building Council. https://www.usgbc.org/leed
37. BREEAM. (2021). BREEAM New Construction: Non-Domestic Buildings Technical Manual. BRE Global.
38. Hyde, R., et al. (2015). Sustainable Retrofitting of Commercial Buildings: Warm Climates. Routledge.
39. Monteiro, C., Santos, P., & Oliveira, L. (2023). Evaluating thermal comfort in historical learning environments. Building and Environment, 232, 110129. https://doi.org/10.1016/j.buildenv.2023.110129
40. CIBSE. (2020). Environmental design guide: Applications manual. Chartered Institution of Building Services Engineers.
41. EPA. (2021). Indoor Air Quality (IAQ). United States Environmental Protection Agency. https://www.epa.gov/indoor-air-quality-iaq
42. Burra Charter. (2013). The Australia ICOMOS Charter for Places of Cultural Significance. https://australia.icomos.org/publications/burra-charter-practice-notes/
43. Yung, E. H. K., & Chan, E. H. W. (2012). Critical social sustainability factors in urban conservation: The case of the Central Police Station Compound in Hong Kong. Facilities, 30(9/10), 396–416.
44. Fabbri, K., Ferrara, M., & Gagliardi, F. (2020). Integrating energy performance and indoor environmental quality assessment for heritage buildings. Energy and Buildings, 223, 110089.
45. Ribeiro, F., Silva, A., & Almeida, M. (2021). Energy retrofit of heritage university buildings: The case of Al-Qarawiyyin in Fez. Energy Reports, 7, 412–423. https://doi.org/10.1016/j.egyr.2021.06.065

Appendix A – Supplementary Quality of Life Diagnostics

A-1 Quality of Life Assessment Questionnaire for Heritage University Buildings

Key Criterion	Sample Assessment Statement
Thermal Comfort	The indoor temperature is comfortable throughout the year.
Indoor Air Quality	The indoor air quality supports good health.
Lighting	Lighting conditions are comfortable and sufficient for study purposes.
Acoustics	Noise levels support concentration and learning.
Ventilation	Natural ventilation is adequate and easy to control.
Spatial Flexibility	Spaces can be adapted for different educational activities.
Circulation Efficiency	Circulation within the building is smooth and efficient.
Space Utilization	Available spaces accommodate all users even during peak hours.
Functional Zoning	The organization of functional zones is logical and accessible.
Digital Infrastructure	Internet and digital connectivity are reliable.
Technological Equipment	Available technologies support the learning environment effectively.
Tech-Architecture Integration	Technologies are integrated without harming heritage elements.
Energy Efficiency	The building demonstrates good energy-saving strategies.
Heritage Preservation	The heritage character of the building is well maintained.
Sustainable Materials	Sustainable materials are used appropriately during maintenance.
Resource Management	Environmental resources are managed responsibly.
Comfort & Belonging	I feel emotionally connected and comfortable in this building.
Social Interaction	The building design encourages social interaction.
Safety & Privacy	The building provides adequate safety and personal privacy.
Psychological Support	The design supports my mental well-being and creativity.

A.2 Estimated Quality of Life (QoL) Scores Across Ten Heritage Universities

Key Criteria	Sub-elements	Cairo	Al-Qarawiyyin	AUB	Algiers	Baghdad	Khartoum	Tehran	Mumbai	Coimbra	Bologna
Physical Environment	Thermal Comfort	3.0	2.5	4.0	3.2	2.8	2.6	3.8	4.0	4.2	4.3
	Indoor Air Quality	3.2	2.8	4.2	3.5	2.9	2.7	3.9	4.0	4.1	4.4
	Lighting & Acoustics	3.5	3.0	4.5	3.7	3.1	2.9	4.0	4.2	4.3	4.5
	Spatial Flexibility	3.0	2.6	4.1	3.2	2.8	2.5	3.7	4.0	4.1	4.4
Functional Environment	Circulation and Accessibility	3.2	2.5	4.3	3.5	2.7	2.6	3.9	4.1	4.3	4.5
	Service Distribution (Libraries, etc.)	3.5	2.9	4.6	3.7	3.0	2.8	4.2	4.3	4.5	4.6
Technological Readiness	Connectivity and Smart Integration	3.1	2.0	4.7	3.4	2.3	2.1	4.0	4.2	4.5	4.6
Sustainability & Heritage	Energy Efficiency	2.8	2.2	4.1	3.0	2.5	2.3	3.6	4.0	4.2	4.4
	Heritage Preservation	4.3	4.8	4.2	4.0	4.6	4.4	4.1	4.0	4.7	4.8
Social/Psychological	Privacy, Interaction, Emotional Comfort	3.4	3.0	4.5	3.6	3.0	2.8	4.0	4.2	4.3	4.5

A.3 Evaluation Methods and Data Sources per Criterion

Category	Sub-element	Simulation/Measurement	Survey-Based	Notes
Physical Environment	Thermal Comfort	✔	✔	Sensor data + user evaluation
	Indoor Air Quality	✔	✔	
	Natural Light	✔	✔	
	Ventilation	✔	✔	
	Acoustic Quality	✔	✔	
	Spatial Flexibility	✘	✔	Based on user perception only
Functional Environment	Circulation Efficiency	✘	✔	
	Usage Density	✔	✔	
	Service Accessibility	✘	✔	
Technological Environment	Internet Connectivity	✔	✔	
	Smart Systems	✔	✘	Evaluated by availability and system specs only
	Tech-Architecture Synergy	✘	✔	Based on user feedback
Sustainability & Heritage	Energy Efficiency	✔	✘	Via simulation tools only

Category	Sub-element	Simulation/Measurement	Survey-Based	Notes
	Use of Renewable Resources	✔	✘	
	Architectural Integrity	✔	✔	
Social & Psychological	Social Interaction	✘	✔	Based on user perception only
	Privacy	✘	✔	
	User Satisfaction	✘	✔	
	Mental Well-being	✘	✔	

A.4 Simulation vs Survey Values – Case of Cairo University

University	Element	Simulation Value	Survey Value
Cairo University	Thermal Comfort	4.56	4
Cairo University	Indoor Air Quality	3.69	5
Cairo University	Natural Light	2.90	3
Cairo University	Ventilation	3.01	2
Cairo University	Acoustic Quality	2.89	5
Cairo University	Spatial Flexibility	–	3
Cairo University	Circulation Efficiency	–	2
Cairo University	Usage Density	2.57	3
Cairo University	Service Accessibility	–	2
Cairo University	Internet Connectivity	3.73	5