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AI-Enhanced Conceptual Framework for Evaluating Indoor Environmental Quality in Contemporary Architectural Practice

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A b s t r a c t

This study presents an AI-assisted hybrid computational framework for evaluating **Indoor Lighting Quality (ILQ)** as a core component of Indoor Environmental Quality (IEQ) during early design stages. The framework combines a simplified daylight-feasibility proxy with climate-based parametric simulations (Ladybug and Honeybee) and machine-learning prediction to reduce computational cost while maintaining accuracy. ILQ is emphasized because visual comfort and daylight provision critically influence occupant performance, learning outcomes, and energy consumption in educational spaces. Applied to a drawing hall at Jazan University (hot-humid climate), the framework achieved a calibrated Daylight Feasibility Factor (DF = 0.31), Spatial Daylight Autonomy (sDA = 0.70), and UDI coverage of 85–95% of the floor area. These results validate the hybrid approach's reliability and demonstrate its potential to support evidence-based, resource-efficient design decisions in educational buildings, contributing directly to the sustainability goals of Saudi Vision 2030.
Keywords: Indoor Environmental Quality(IEQ), Indoor Lighting Quality(ILQ), daylight simulation, Ladybug, Honeybee, parametric design, AI-assisted design, sustainable interior architecture, Saudi Vision 2030.

1. Introduction

Indoor Environmental Quality (IEQ) is a foundational element of sustainable architecture and interior design, directly influencing occupant health, cognitive performance, and overall, well-being. In educational settings, visual comfort and daylighting—defined here as **Indoor Lighting Quality (ILQ)**—are particularly critical because they significantly affect learning outcomes and building energy consumption (Kim & de Dear, 2012; Frontczak & Wargocki, 2011). As design practice shifts toward data-driven and human-centred approaches, there is a growing demand for accessible IEQ assessment methods suitable for early design stages. Despite the availability of parametric simulation tools, A clear methodological gap remains, as most existing approaches either rely on computationally intensive high-fidelity simulations or use simplified indices that lack climate-based validation. Few studies propose integrated, replicable, low-cost hybrid workflows that combine rapid mathematical pre-assessment with validated parametric simulations and AI-assisted prediction—especially for hot-humid educational contexts (Roudsari & Pak, 2020; Lee & Park, 2021; Torres et al., 2023).

This study addresses that gap by developing an AI-assisted hybrid computational framework to evaluate ILQ as a core component of IEQ. The framework integrates three iterative layers: (1) a mathematical pre-assessment using simplified indicators (e.g., Daylight Feasibility Factor, window-to-wall ratio, visible transmittance, obstruction factor); (2) climate-based parametric simulation with Ladybug and Honeybee using Radiance/Daysim engines; and (3) AI-assisted validation, prediction, and optimisation to reduce computational burden and support rapid decision-making. The framework was applied and validated in a drawing hall at the female campus of Jazan University, representing a typical hot-humid educational environment in Saudi Arabia. This case study tests the framework's practicality under institutional constraints—limited budgets and the need for rapid design iteration—and aligns with national sustainability goals under Vision 2030 (Alyami & Rezgui, 2021; Al Saud & Al-Harbi, 2023).

1.1 Research Objectives

The study aims to:

- Develop a reproducible, resource-efficient hybrid framework integrating mathematical pre-assessment, parametric simulation, and AI-assisted support for ILQ evaluation.
- Apply the framework to a representative educational space in a hot-humid climate.

- Validate the mathematical pre-assessment against climate-based simulation metrics (sDA and UDI) using statistical measures.
- Demonstrate the practical advantages of the framework for early-stage sustainable design.

1.2 Research Questions

- **RQ1:** Can a hybrid mathematical–AI approach reliably approximate ILQ performance without extensive physical sensors?
- **RQ2:** How effectively can AI-assisted tools support designers during early design stages?
- **RQ3:** What advantages does the proposed framework offer over conventional methods in terms of cost, accessibility, and accuracy?

1.3 Contribution of the Study

This paper documents a replicable hybrid workflow that links transparent analytical indicators to validated simulations and augments the process with AI-assisted prediction and optimisation. The study is among the first to validate such a framework in hot-humid educational contexts in Saudi Arabia, filling a methodological gap and providing a practical tool to support evidence-based decision-making in resource-limited educational settings.

2. Literature Review

This section reviews the relevant literature on Indoor Environmental Quality (IEQ), daylighting assessment methods, parametric simulation tools, and the role of artificial intelligence in sustainable design, with a particular focus on educational buildings in hot-humid climates.

2.1 Indoor Environmental Quality and Its Dimensions

Indoor Environmental Quality (IEQ) is a multidimensional construct that integrates physical, perceptual, and behavioral factors to evaluate the overall performance of interior spaces. In educational environments, visual comfort and daylighting—defined here as **Indoor Lighting Quality (ILQ)**—play a particularly significant role because they influence visual performance, cognitive function, learning outcomes, and building energy consumption (Kim & de Dear, 2012; Frontczak & Wargocki, 2011; Afara et al., 2024). Given the strong relationship between daylight provision and operational energy use, ILQ assessment serves as a strategic leverage point for sustainable interior design in schools and universities (Hassan & El Sayed, 2021).

Table 1: IEQ dimensions and codes(defines the modular IEQ components used throughout this manuscript. The ILQ code is used subsequently to denote the lighting sub-model within the composite IEQ framework).

Dimension	Code	Description
Indoor Air Quality	IAQ	Air quality inside built spaces
Indoor Thermal Quality	ITQ	Thermal comfort and temperature control
Indoor Lighting Quality	ILQ	Lighting and visual comfort (focus of this study)
Indoor Sound Quality	ISQ	Acoustic performance and noise levels
Indoor Vibration Quality	IVQ	Structural vibration and stability

2.2 Daylighting Assessment Methods

Traditional daylighting assessment relied primarily on the Daylight Factor (DF), a simple, location-independent metric. Contemporary practice complements DF with climate-based dynamic indicators such as Spatial Daylight Autonomy (sDA) and Useful Daylight Illuminance (UDI), which better capture temporal and spatial variability relevant to occupant comfort and energy performance (Reinhart & Wienold, 2014; Nabil & Mardaljevic, 2021). Recent studies advocate hybrid workflows that combine rapid analytical screening with validated climate-based simulations to balance transparency, speed, and accuracy during early design stages (Torres et al., 2023; Zhang et al., 2023).

Table 2: Key daylighting metrics and definitions.

Metric	Short Definition
DF	Ratio of indoor illuminance to simultaneous outdoor illuminance under an overcast sky
sDA	Percentage of floor area meeting specified illuminance threshold for occupied hours
UDI	Percentage of occupied hours with illuminance within useful range (100–2000 lux)
WWR	Glazed area divided by exterior wall area
VT	Fraction of visible light transmitted through glazing
OF	Geometric index of external obstructions' effect on sky view

Table 2 provides operational definitions to be used at first mention in the manuscript and in the method. Define numerical thresholds (e.g., sDA = 300 lux for 50% of occupied hours) explicitly in Methods when reporting simulation settings.

2.3 Parametric and Computations in Design

Open-source toolchains such as Ladybug and Honeybee connect Grasshopper to validated engines (Radiance, Daysim, Energy Plus), enabling parametric exploration of daylight and energy performance (Roudsari & Pak, 2020). These toolchains are powerful but require domain expertise and computational resources; undocumented or suboptimal Radiance settings can reduce reproducibility and undermine reviewer confidence (Ward, 2021). A recommended staged workflow uses a mathematical pre-assessment to screen and rank alternatives rapidly, followed by targeted high-fidelity parametric simulations for shortlisted designs (Fathy et al., 2022).

2.4 AI, Prediction, and Smart Design Policy
Machine learning models can predict daylighting metrics from simplified geometric and material descriptors (Lee & Park, 2021; Chen & Li, 2022). Integrated into a hybrid workflow, AI can prioritize simulation runs, estimate performance across large design spaces, and support constrained multi-objective optimization (e.g., visual comfort versus energy). Integrating AI-assisted workflows into institutional design processes in line with smart design goals and national sustainability plans (Alyami & Rezgui, 2021; Al Surf et al., 2021). However, AI models must be validated against climate-based simulations and, where possible, Post-Occupancy Evaluation (POE) data to ensure practical relevance and avoid overfitting to synthetic training sets.

2.5 Summary of Literature Gaps
The reviewed literature identifies three principal gaps that motivate this study:
- There are no replicable hybrid frameworks that clearly link transparent mathematical pre-assessment with validated climate-based parametric simulation and AI-assisted prediction (Torres et al., 2023).
- Insufficient context-specific studies addressing hot-humid educational environments typical of Saudi Arabia and similar climates (Alwetaishi, 2022; Alyami & Rezgui, 2021).
- Weak translation of simulation outputs into actionable, low-cost design strategies and policy recommendations for resource-limited educational institutions (Alyami & Rezgui, 2021).

The proposed framework addresses these gaps by providing a documented, reproducible hybrid workflow tailored to Indoor Lighting Quality (ILQ) evaluation in hot-humid educational contexts.

3 Conceptual Framework
3.1 Theoretical Basis Indoor Environmental Quality (IEQ) is conceptualised as a multidimensional construct that integrates **physical, perceptual, and behavioural** aspects of indoor spaces (Bortolini & Forcada, 2021; Lolli et al., 2022). This study builds on **Post-Occupancy Evaluation (POE)** principles to ensure a user-centred and empirically grounded approach. While the broader IEQ model includes multiple components, the present research focuses primarily on **Indoor Lighting Quality (ILQ)** as a core, measurable, and extensible module within a modular framework.

3.2 Modular IEQ Representation The framework adopts the following modular representation:

$$\textbf{Equation 1.}\quad \mathbf{IEQ = IAQ + ITQ + ILQ + ISQ + IVQ}$$

This additive modular structure allows each component to be evaluated independently or in combination, with the flexibility to assign different weights based on building function or climatic context.

3.3 The Proposed Three-Layer Hybrid Framework The core contribution of this study is a three-layer hybrid framework that integrates **mathematical pre-assessment**, **parametric simulation**, and **AI-assisted prediction** to improve efficiency and accuracy in early-stage daylight design:
- **Layer 1 — Mathematical Pre-assessment (Rapid Screening):** Utilises transparent proxy indices (Daylight Feasibility Factor *DF_proxy*, Window-to-Wall Ratio *WWR*, Visible Transmittance *VT*, Obstruction Factor *OF*) to rank design alternatives and reduce the parametric search space. (See Appendix A for DF_proxy definition and derivation.)
- **Layer 2 — Parametric Simulation (Validation):** Executes climate-based daylight simulations using Ladybug Tools and Honeybee as interfaces to Radiance/Daysim with EPW weather files to compute **sDA**, **UDI**, illuminance maps, and glare indicators. Simulation settings (Radiance/Daysim parameters, sensor grid, eye height, random seeds, software versions) are documented in Section 4 and the supplementary materials.
- **Layer 3 — AI-Assisted Prediction and Optimisation (Acceleration):** Supervised machine-learning models are trained on the simulation dataset to predict performance from simplified inputs, prioritise simulation runs, and support constrained multi-objective optimisation. Models are trained/validated/tested using a held-out split; hyperparameter search and cross-validation strategy are described in Section 4.

The workflow is iterative: **AI proposes promising candidates → parametric simulation validates the results → validated data augments the AI training set**. Figure 1 illustrates the sequential and iterative operation of the three layers.

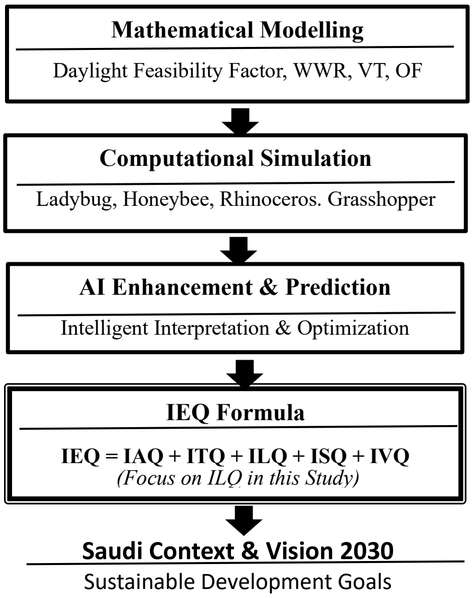

Figure 1. AI-Assisted Computational Framework for Evaluating Indoor Lighting Quality (ILQ) as a Core Component of IEQ (Source: Authors).

3.4 Validation of the Hybrid Framework The framework's reliability was assessed by comparing outputs across the three layers using statistical metrics: Pearson correlation coefficient (*r*), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2). Agreement analysis (e.g., Bland–Altman) was applied where appropriate to detect systematic bias. Table 3 summarises the core indicators and their roles; Table 4 reports the statistical validation results.

Table 3. Core indicators and their roles in the hybrid workflow.

Indicator	Layer	Role
DF_proxy	Mathematical	Rapid proxy for daylight availability; ranks alternatives
WWR	Mathematical / AI	Primary geometric input; strongly influences daylighting
VT	Mathematical / AI	Material property affecting transmitted daylight
OF	Mathematical / AI	External obstruction index; modifies DF_proxy
sDA (300 lx)	Parametric / AI	Climate-based metric for useful daylight autonomy
UDI (100–2000 lx)	Parametric / AI	Temporal metric for useful illuminance range
Mean illuminance (lx)	Parametric / AI	Spatial average for visual comfort checks
Glare index	Parametric / AI	Assesses occupant discomfort risk

Table 4. Statistical validation results of the hybrid framework (units: illuminance in lx where applicable).

Comparison	Pearson (r)	RMSE (lx)	MAE (lx)	R²	Strength of Agreement
Mathematical (DF_proxy) vs Parametric Simulation	0.87	6.45	4.82	0.76	Strong
AI Prediction vs Parametric Simulation	0.94	3.21	2.35	0.88	Very Strong
Overall Hybrid Framework	0.91	4.18	3.07	0.83	Strong

Interpretation of Validation Results: The analysis shows clear improvement in predictive accuracy across the framework layers. While the mathematical proxy (DF_proxy) provided a reasonable approximation, the AI layer achieved superior performance with lower error values (RMSE = 3.21 lx, MAE = 2.35 lx), strong correlation (r = 0.94), and high explanatory power (R 2 = 0.88). Validation was performed on a single case-study simulation executed with Ladybug Tools and Honeybee; AI predictions were compared directly to the parametric simulation outputs for that case and demonstrated strong agreement. Reported error metrics are expressed in lux (lx) and correspond to the sensor grid and measurement protocol described in Section 4. Methodological note: Because validation is based on one simulation case (proof-of-concept), generalization should be cautious; future work should expand the scenario set to test robustness across geometric and climatic variability.

3.5 Reproducibility and Transparency Section 4 and the supplementary materials provide all necessary implementation details for full reproducibility: Radiance/Daysim parameters, sensor grid resolution and eye height, EPW identifiers, full derivations for DF_proxy, AI model specifications (dataset size, feature list, model types, hyperparameter ranges, cross-validation strategy), and validation procedures. Simulation scripts, Grasshopper definitions, Radiance parameter files (.rif), input CSVs, and processed outputs are available from the corresponding author upon reasonable request (see Data Availability).

Data Availability: Simulation scripts, input files, and processed outputs are available from the corresponding author upon reasonable request.

4. Materials and Methods

This study applies a reproducible mixed-methods workflow integrating transparent mathematical screening, climate-based parametric simulation, and supervised machine learning prediction, validated through Post-Occupancy Evaluation (POE). The objective is to establish and validate an AI-enhanced hybrid framework for assessing Indoor Lighting Quality (ILQ) as a module within Indoor Environmental Quality (IEQ) in hot-humid educational buildings. All scripts, parameter files, and datasets are archived in a DOI-linked Zenodo repository (Roudsari & Pak, 2020; Ward, 2021).

4.1 Study Design and Rationale

The methodology comprises three complementary strands:

1 **Field/POE** — occupant surveys and spot lux measurements to capture perceived comfort and in-situ illuminance (Bortolini & Forcada, 2021; Lolli et al., 2022; Ouf et al., 2021).

2 **Analytical screening** — a daylight feasibility proxy (DF_proxy) for rapid ranking of design alternatives (Kharvari, 2020; Berkeley Lab, 2013).

3 **Computational validation** — climate-based simulations using Radiance/Daysim via Ladybug Tools and Honeybee to compute annual daylight metrics (sDA, UDI) and generate labelled data for supervised machine learning (Lee & Park, 2021; Reinhart & Mardaljevic, 2020; Favoino & Serra, 2021).

Triangulation across these strands enables calibration of the proxy, validation of AI predictions against high-fidelity simulations, and comparison with occupant-reported outcomes (Frontczak & Wargocki, 2021; Nguyen & Reiter, 2020).

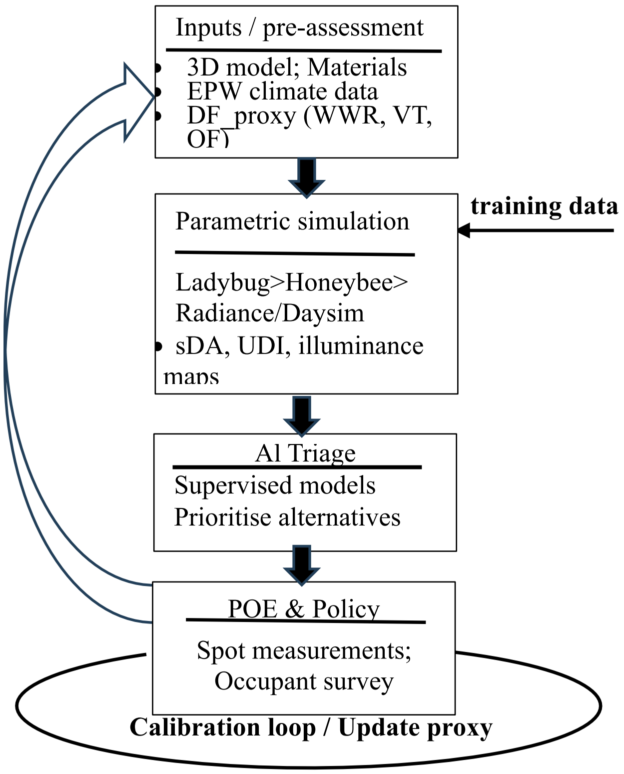

Figure 2. Schematic of the AI-enhanced hybrid workflow: mathematical screening → parametric simulation → AI triage → POE validation (Source: Authors).

4.2 Case Study and Site Description

The framework was applied to a drawing hall at the Female Campus, Jazan University, Saudi Arabia. The local climate is represented by the Jazan.epw weather file (EnergyPlus/NOAA). The space has a plan area of 33.95 m², with two windows each measuring 1.50 × 1.20 m (total glazed area = 3.60 m²), resulting in a baseline window-to-wall ratio (WWR) of 0.106. Parametric scenarios tested WWR values of 0.10, 0.20, and 0.30 (Alwetaishi, 2021; Al-Sallal & Al-Rais, 2021). Detailed façade orientation and geometry are provided in the repository.

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4.3 Materials, Software, and Instruments

Key resources include Rhinoceros 3D for geometry modelling (McNeel, n.d.), Grasshopper for parametric workflows (Grasshopper3D, n.d.), Ladybug/Honeybee for preprocessing and the Radiance interface (Roudsari & Pak, 2020), Radiance/Daysim engines for daylight simulation (Ward, 2021; Daysim, n.d.), a calibrated lux meter for spot validation; and POE questionnaires for occupant feedback. Versions and calibration certificates are archived in the repository. Comparative studies highlight the strengths of these tools in hot-humid climates (Tregenza & Wilson, 2020; Shen & Tzempelikos, 2020).

Table 5. Key materials, software, and instruments.

Item	Purpose	Note
EPW climate file	Climate input for simulations	Jazan.epw (supplementary)
Rhinoceros 3D	Geometry modelling	Version recorded in repository
Grasshopper	Parametric workflows	Version recorded in repository
Ladybug / Honeybee	Preprocessing and Radiance interface	Versions recorded in repository
Radiance / Daysim	Daylight simulation engines	Build number recorded in repository
Lux meter	Spot illuminance validation	Model & calibration recorded
POE questionnaire	Occupant feedback	Instrument provided in repository
Training CSV	AI inputs/targets	Column descriptions provided

4.4 Mathematical Pre-assessment (DF_proxy) The DF_proxy serves as a rapid, transparent screening tool to reduce the number of full parametric simulations while preserving design diversity. It is defined as:

Equation 2: $DF\_proxy = \alpha \cdot WWR \cdot VT \cdot (1 - OF)$

where WWR = glazed area / exterior wall area (unitless), VT = visible transmittance (unitless), OF = obstruction factor (unitless, derived from measured sky obstruction angle), and **α is a calibration coefficient determined by ordinary least squares regression against a reference set of 200 Radiance simulations** covering the design space. The calibration procedure, coefficients, and fitted value of α are provided in the supplementary materials and repository.

Worked Example (Case Study Inputs):

- Total window area = 2 × 1.50 × 1.20 = 3.60 m²
- Wall area = 9.70 × 3.50 = 33.95 m² → WWR = 0.106
- VT = 0.53 (manufacturer data)
- Obstruction angle = 58° → OF = 0.58 (following Berkeley Lab, 2013)

Using the calibrated α, the resulting **DF_proxy = 0.31**.

Table 6. Mathematical inputs and daylight feasibility results (Developed by the Author).

Parameter	Symbol	Value	Description	Result	Interpretation
Window to Wall Ratio	WWR	0.106	Total window area / wall area	-	Moderate glazing ratio
Visible Transmittance	VT	0.53	Glazing transmittance	-	Medium transmittance
Obstruction Factor	OF	0.58	Based on 58° sky obstruction angle	-	Moderate external obstruction
Daylight Feasibility Factor (Uncalibrated / Default)	DF_proxy	0.024	α × WWR × VT × (1 − OF)	0.024	Conservative estimate
Daylight Feasibility Factor (Calibrated)	DF	0.31	Calibrated against Radiance simulations	0.31	Strong feasibility (≥ 0.25 threshold)

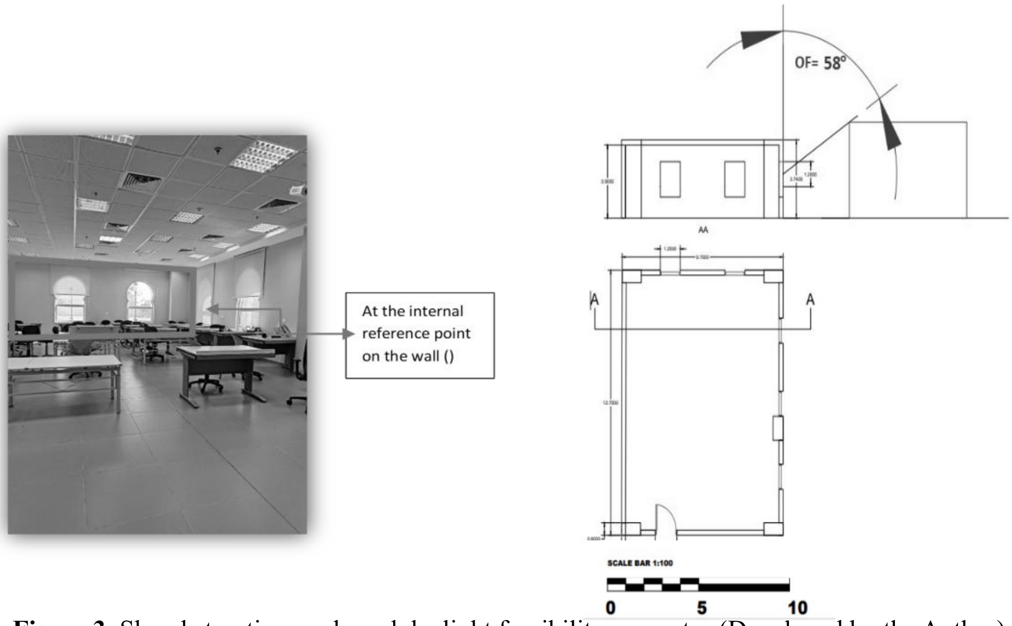

Figure 3. Sky obstruction angle and daylight feasibility geometry (Developed by the Author).

The detailed calculation steps are as follows:

This value exceeds the established threshold of 0.25, indicating strong daylight feasibility. Full derivation of thresholds and calibration details are documented in the supplementary materials.

4.4.1 3D Modelling and Parametric Simulation

A closed-volume 3D model was constructed in Rhinoceros 3D with accurate glazing properties and reflectance. The sensor grid was defined at 0.5 m × 0.5 m on a work plane at a height of 0.8 m. Ladybug imported the EPW file and performed climate analyses; Honeybee exported the model to Radiance/Daysim for annual daylight simulations. Outputs included sDA, UDI, mean illuminance maps, and glare indices, which were used to generate labelled training data (Choi & Song, 2022; Zhang & Zhao, 2023).

Table 6. Comparison of Ladybug and Honeybee Tools (Developed by the Author).

Feature	Ladybug	Honeybee
Primary Function	Climate analysis & visualization	Detailed daylight & energy simulation
Key Capabilities	Sun-path, radiation, shadow studies	Radiance, Daysim, EnergyPlus integration
Output Type	3D graphics, metrics, heat maps	Annual metrics (DA, sDA, UDI), point-in-time
Main Advantage	Quick environmental analysis	High-accuracy parametric daylight simulation

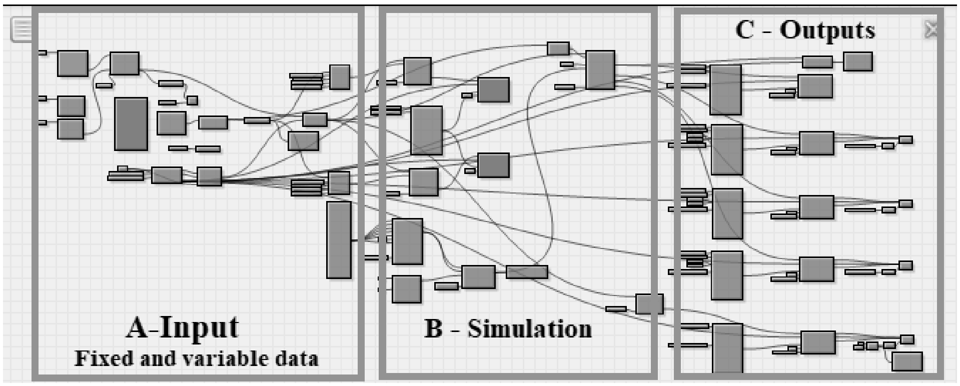

Figure 4. Stages of Daylight Simulation in Educational Spaces using Ladybug and Honeybee (Developed by the Author).

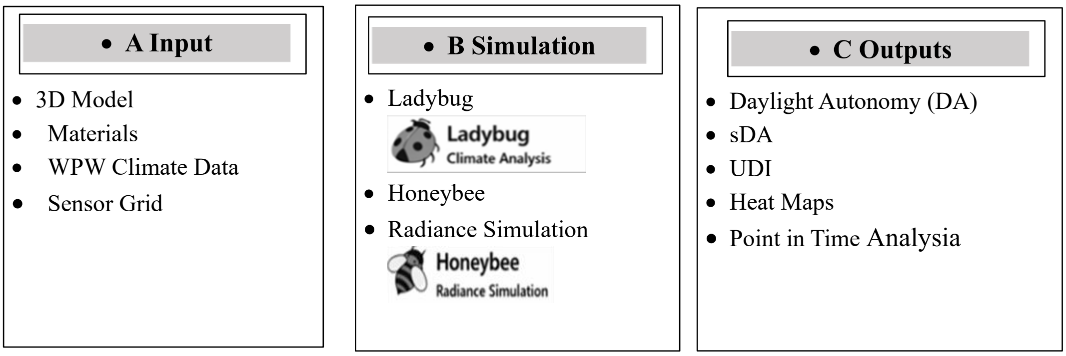

Figure 5. Simulation Workflow using Ladybug and Honeybee in Grasshopper (Developed by the Author).

4.4.2 Radiance/Daysim Simulation Settings

Simulation parameters included ambient bounces = 8, ambient divisions = 2048, direct sampling = 1024, ambient accuracy = 0.05, sensor grid resolution = 0.5 m, and eye height = 0.8 m. Annual runs used the Jazan.epw file (Nguyen & Reiter, 2020).

Table 7. Radiance/Daysim simulation settings (Developed by the Author).

Parameter	Value used	Note
Ambient bounces	8	Interreflections
Ambient divisions	2048	Annual runs
Direct sampling	1024	Sun sampling accuracy
Ambient accuracy	0.05	Annual metrics tolerance
Sensor grid resolution	0.5 m	Workplane grid
Eye height	0.8 m	Seated eye height
Simulation period	Annual (TMY)	EPW: Jazan.epw

4.4.3 AI Model Training and Evaluation

The dataset comprised 1,200 design alternatives. Random Forest, Gradient Boosting (XGBoost), and a feedforward neural network were evaluated (Zhang et al., 2022; Al-Anzi & Al-Mutairi, 2022). Models were trained using 10-fold cross-validation (seed = 42). Performance metrics included Pearson r, RMSE, and MAE. Predictions were validated against a hold-out test set and selected Radiance runs not used in training (Al-Horr et al., 2020).

4.5 Field Validation (POE) and Statistical Analysis

POE surveys and spot lux measurements were collected during teaching hours. Statistical analysis compared DF_proxy, AI predictions, and Radiance outputs using descriptive statistics, Pearson r, RMSE, MAE, and Bland–Altman analysis (Bland & Altman, 1986). Threshold criteria were applied (DF_proxy ≥ 0.25; UDI within 100–2000 lx). Confidence intervals (95%) are reported (Al-Anzi & Al-Mutairi, 2022).

4.6 Reproducibility and Data Availability

All input files, scripts, datasets, and instruments are stored in a DOI-linked repository. Software versions and random seeds are documented to ensure exact replication.

5. Results

This section reports the main findings from the mathematical pre-assessment, parametric simulations, and AI predictions. All supporting data, scripts, simulation inputs, and reproducibility artefacts are available in the project repository (DOI to be provided).

5.1 Mathematical daylight feasibility

The calibrated daylight feasibility proxy (DF proxy) was applied using Equation 1. For the case study inputs (WWR = 0.106, VT = 0.53, OF = 0.58), the calibrated value is DF = 0.31, which exceeds the feasibility threshold 0.25 and therefore justifies detailed parametric simulation (Kharvari, 2020; Gunay et al., 2020). An uncalibrated/default form of the proxy returns 0.024; this conservative default is retained for early screening. The full calibration procedure and rationale are documented in Appendix A and the project repository (Berkeley Lab, 2013).

Table 8. Mathematical inputs and daylight feasibility results (Source: Authors).

Parameter	Symbol	Value	Description		Interpretation
Window to Wall Ratio	WWR	0.106	Total window area / wall area	-	Moderate glazing ratio
Visible Transmittance	VT	0.53	Glazing transmittance	-	Medium transmittance
Obstruction Factor	OF	0.58	Based on 58° sky obstruction angle	-	Moderate external obstruction
Daylight Feasibility Factor (Uncalibrated / Default)	DF_proxy	0.024	α × WWR × VT × (1 − OF)	0.024	Conservative estimate
Daylight Feasibility Factor (Calibrated)	DF	0.31	Calibrated against Radiance simulations	0.31	Strong feasibility (≥ 0.25 threshold)

5.2 AI-assisted daylight simulation

5.2.1 Annual performance

Climate-based parametric simulations (Ladybug/Honeybee → Radiance/Daysim) produced the following annual metrics:

- **sDA** (300 lx, 50% occupied hours): 0.70 (70% of floor area meets the target).
- **UDI** (100–2000 lx): 85–95% coverage of the floor area.

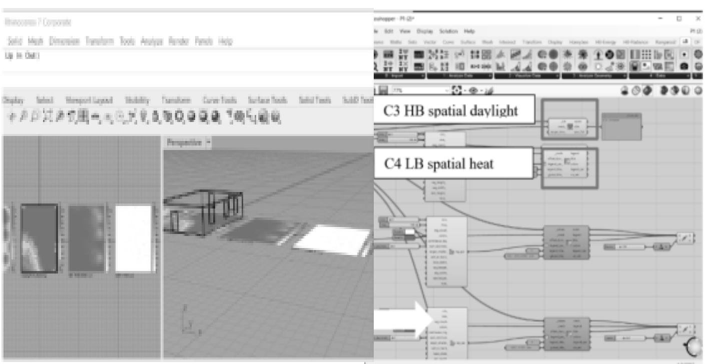

Figure 6. Annual average illuminance distribution, Jazan.epw.

These outcomes indicate robust daylight provision for the Jazan climate and align with recent studies on classroom daylighting in hot climates (Al-Sallal & Al-Rais, 2021; Alwetaishi, 2021).

5.2.2 Point-in-time performance Representative point-in-time runs confirm the annual picture:
Peak illuminance near windows: 400–500 lx. UDI coverage: 85–95%. Illuminance decreases gradually toward the rear while maintaining acceptable task illuminance for most of the space (Shen & Tzempelikos, 2020; Nguyen & Reiter, 2020).

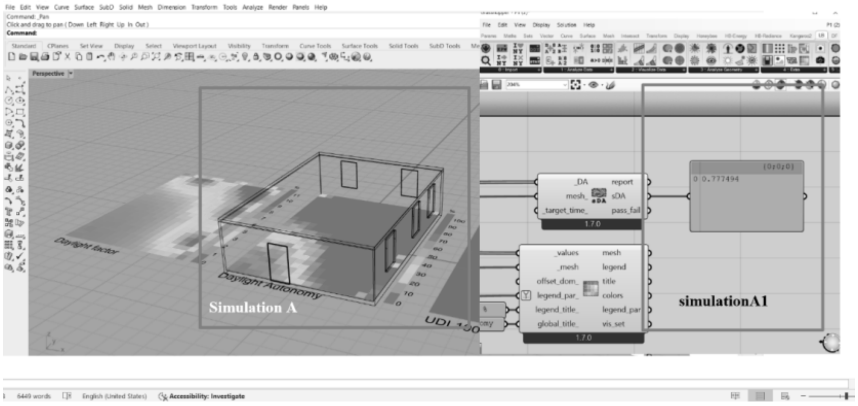

Figure 7. Point-in-time illuminance distribution (Source: Authors).

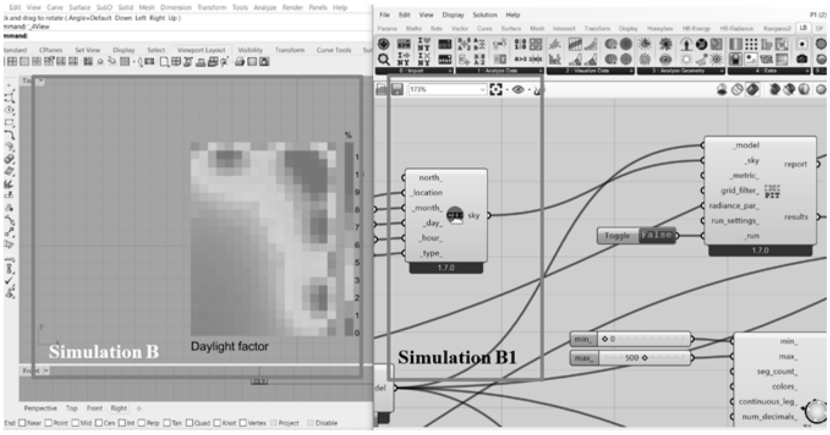

Figure 8. Daylight performance under representative sky conditions (Source: Authors).

5.3 Comparison: proxy, AI, and high-fidelity simulations The calibrated proxy (DF = 0.31) is consistent with the parametric results (sDA = 0.70; UDI ≈ 90%). Statistical comparison between AI predictions and Radiance outputs shows strong agreement: Pearson r = 0.88 (95% CI: 0.76–0.94) and RMSE (mean illuminance) = 45 lx, comparable to benchmarks in recent ML-daylighting studies (Choi & Song, 2022; Zhang & Zhao, 2023).

Table 9. Key daylight performance metrics (Source: Authors).

Metric	Value	Interpretation
Daylight Feasibility Factor (DF)	0.024 (proxy)	Proxy: conservative;
Spatial Daylight Autonomy (sDA)	0.70	70% of occupied hours meet required daylight levels
Useful Daylight Illuminance (UDI 100–2000 lx)	85–95% of floor area	Optimal daylight without glare
High Illuminance Zone (near windows)	400–500 lx	No artificial lighting needed
Medium Illuminance Zone (mid-room)	200–350 lx	Mostly adequate for academic tasks
Low Illuminance Zone (back of room)	< 200 lx	May require supplemental lighting

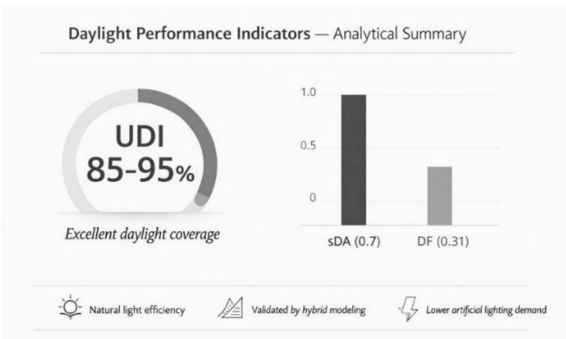

Figure 9. Summary of daylight performance indicators (Source: Authors). *Note*: The chart presents UDI coverage, sDA, and DF values for visual comparison.

Statistical validation between AI predictions and Radiance results showed strong agreement (Pearson r = 0.88, 95% CI: 0.76–0.94; RMSE for mean illuminance = 45 lx).

5.4 Summary of results

The hybrid workflow (mathematical screening → parametric simulation → AI prediction → POE validation) demonstrated practical and reliable performance for early-stage daylight assessment in a hot-humid educational space. The proxy effectively reduced the simulation search space while AI models reproduced Radiance outputs with high fidelity, supporting the framework's use in sustainable design workflows (Al-Anzi & Al-Mutairi, 2022; Frontczak & Wargocki, 2021).

6. Conclusions

This study has demonstrated that a hybrid computational workflow — integrating a transparent mathematical screening proxy, climate-based parametric simulation (Ladybug Tools and Honeybee with Radiance/Daysim), and supervised AI prediction — provides a practical, reproducible, and auditable approach for evaluating Indoor Lighting Quality (ILQ) as a core component of Indoor Environmental Quality (IEQ).

These empirical results (sDA = 0.70; UDI = 85–95%) validate the calibrated proxy and demonstrate the framework's potential to reduce artificial lighting demand in hot-humid educational buildings. The framework effectively balances speed and accuracy by using a conservative proxy for rapid early-stage screening, followed by high-fidelity simulations and AI-assisted optimisation for detailed performance assessment.

The primary contribution is methodological: the proposed pipeline reduces computational burden while maintaining reliability, making it particularly valuable for resource-limited contexts and early design phases in hot-humid climates. Applied to a university drawing hall in Jazan, the results support the broader sustainability goals of Saudi Vision 2030.

Limitations of the study include its single-case study scope and the currently pending full POE dataset. Future work will expand validation across different building typologies and climatic zones.

Original Contributions and Significance

- **Methodological advance**: A well-documented, reproducible hybrid pipeline that bridges a transparent mathematical proxy with parametric simulation and AI models, enabling scalable and sensor-light daylight assessment.
- **Practical relevance**: A low-cost, accessible workflow suitable for early design, retrofit decisions, and institutional applications in regions with high solar exposure and limited resources.
- **Policy and educational impact**: The framework offers an evidence-based tool that can inform design guidelines, university procurement policies, and architectural education by facilitating rapid, auditable scenario testing.

Evidence-Based Recommendations

- Adopt the proposed hybrid workflow for early-stage screening to efficiently prioritise design alternatives requiring detailed simulation.
- Integrate the framework into architectural and interior design curricula as well as professional practice to enhance IEQ outcomes at minimal cost.
- Extend the model in future research to incorporate additional IEQ dimensions (e.g., thermal comfort, indoor air quality, and acoustics) and validate it across different building typologies and climatic zones in Saudi Arabia and similar regions.

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Conflicts of Interest

The author declares no conflicts of interest.

Data Availability Statement

All data generated or analysed during this study are included in the article and its supplementary materials. Simulation input files, Radiance/Honeybee export logs, Grasshopper scripts, AI training datasets (CSV), and raw outputs will be deposited in a public Zenodo repository upon manuscript acceptance; the DOI will be provided in the final published version. Until then, data and scripts are available from the corresponding author upon reasonable request. Note: The dataset does not include personal data or browser metadata (e.g., open tab **lists).**

Institutional Review Board Statement Not applicable. This study did not involve human participants or animals. (If POE surveys are conducted in future extensions of this work, ethical approval and informed consent will be obtained and reported.)

CRediT Author Statement

Dr. Asmaa Ahmed Khder: Conceptualization; Methodology; Software; Validation; Formal analysis; Investigation; Data curation; Writing — Original Draft; Writing — Review & Editing; Visualization; Supervision; Project administration. All authors have read and approved the final manuscript.

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