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RESEARCH ARTICLE

Integrated BIM–Machine Learning Models for Green and Healthy Building Performance at the Conceptual Design Stage

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Abstract: Green building (GB) and healthy building (HB) performance are commonly assessed through separate tools, while conventional simulation requires detailed inputs that may be unavailable during conceptual design. This study developed BIMLY, a Building Information Modeling (BIM) and machine learning (ML) integration architecture and interface prototype for early GB and HB performance assessment. The research comprised three stages: identification of predictive variables, development of GB and HB prediction models, and design of a BIM-based integration architecture. The study identified 12 GB indicators and 14 HB indicators, including 12 synthetically generated HB outputs. The GB model combined a feedforward artificial neural network for three water-consumption indicators with deterministic IF-ELSE rules for the remaining nine. The HB model used a multilayer perceptron and achieved a mean absolute error of 3.02. The proposed architecture connects an Autodesk Revit plug-in to both models through a Python REST API, with JSON used for data exchange. BIMLY provides an integration design and interface prototype for GB and HB during conceptual design.

Keywords: Building Information Modeling; green building; healthy building; machine learning

I. INTRODUCTION

Buildings use close to 40% of the world's energy and account for a similar share of global greenhouse gas emissions [1,2]. Much of this performance is determined during the early design stage, long before construction starts [3,4]. Poor early design choices can result in high energy costs and poor indoor environmental quality (IEQ) for decades. This concern becomes more important when occupant health is considered [5,6].

Even buildings with green certification may experience this problem. A study that followed employees after they moved into a certified green building (GB) found signs of sick building syndrome, along with complaints about odor and poor mental concentration [7]. This shows that certification does not necessarily reflect all aspects of occupant health. This highlights the need to consider actual occupant health alongside design-based performance assessment.

One reason for this issue is that the industry often treats green performance and occupant health as separate areas. Many GB rating systems still place greater emphasis on energy and resource use than on health and wellbeing [8,9], and even newer prediction methods often focus on one dimension and do not provide the broader assessment designers need [10]. Previous studies developed separate machine learning (ML) models for GB [11] and healthy building (HB) [12] but did not integrate them within a Building Information Modeling (BIM) environment. This study draws on those models as established components and integrates them within the BIMLY architecture.

II. LITERATURE REVIEW AND STUDY GAP

A. GB AND HB STANDARDS

GB rating systems such as LEED, BREEAM, GBCI, and Green Star were developed mainly to assess energy use, water use, and material impacts, and they remain widely used to assess building sustainability [13,14]. A review of eight major rating systems found that most focus on the product and construction stages, while indicators related to occupant wellbeing are often considered later, after the building is already in use [15]. HB standards emerged in response to this gap. The WELL Building Standard and similar schemes focus on occupant comfort, air quality, and wellbeing, but HB and GB standards are still applied separately in most projects. A recent scoping review found a similar pattern, with GB systems giving limited attention to health attributes and limited integration between GB and HB assessment [16].

B. PREDICTING BUILDING PERFORMANCE

For decades, simulation software has been used to assess a building's expected performance before construction. Although these tools can provide accurate results, they require substantial computing time and detailed inputs, which limits their use when architects are still testing multiple design options [17]. ML has emerged as a

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faster alternative to these simulations. Studies have trained models on simulation outputs to predict thermal load, daylight performance, and energy use in less time, with accuracy close to that of the original simulations [18]. A broad review found that ML now covers major performance areas, from energy design to retrofit management [19].

C. COMBINING ML WITH BIM

More recent studies have linked ML directly to BIM so that predictions can be performed within the same environment [20,21]. Reviews describe growing interest in integrating BIM with AI for tasks such as energy analysis, clash detection, and automated design checking [22]. One study combined BIM with 11 ML algorithms and a genetic algorithm to optimize energy use and thermal comfort [23], while another compared four ML methods using data from 11 BIM design parameters and found that the neural network (NN) best predicted annual energy use [24].

However, most of these tools require a developed BIM model before they can produce useful predictions. A review of BIM data readiness for AI identified barriers, including limited ability to extract geometric data from a BIM model and a lack of pipelines to convert BIM data into a form that ML can use [25]. In practice, architects usually must define building systems, materials, and layouts in some detail before these tools become useful. This places the prediction closer to the middle of the design process instead of the early planning stage, when major decisions are made.

D. RESEARCH GAPS

Three research gaps were identified. First, no common tool assesses GB and HB simultaneously. Second, most ML models for building performance were developed and tested as standalone tools instead of as components of an integrated system. Third, existing BIM-linked prediction tools still require a developed BIM model as input. Few studies have addressed all three gaps by combining GB and HB models within a BIM framework from the early planning stage. This study responds to these gaps through four research objectives (ROs): RO1 identifies the variables and indicators of GB and HB performance that can be predicted at the planning stage, RO2 identifies the ML model that best predicts GB performance, RO3 identifies the ML model that best predicts HB performance, and RO4 develops a BIM-based integration architecture and interface prototype for the two models.

III. METHODOLOGY

This study follows a mixed-methods design based on the four ROs. Archival analysis was used to define variables, algorithms, tools, and standards, while benchmarking and case studies were used to compare and test the developed models. The interface prototype was evaluated by five purposively selected practitioners with 14–18 years of experience. They rated five statements on interface clarity, user experience, information usefulness, time efficiency, and readiness for conceptual design using a four-point scale from strongly disagree to strongly agree and provided additional comments. Figure 1 shows the research workflow.

A. IDENTIFYING PREDICTIVE INDICATORS

RO1 identifies GB and HB performance variables and indicators that can be predicted during planning. A literature review classified controllable design parameters as independent variables (X) and building performance indicators as dependent variables (Y), which include GB indicators for energy efficiency, IEQ, and water use [26,27], and HB indicators for ventilation, air quality, thermal

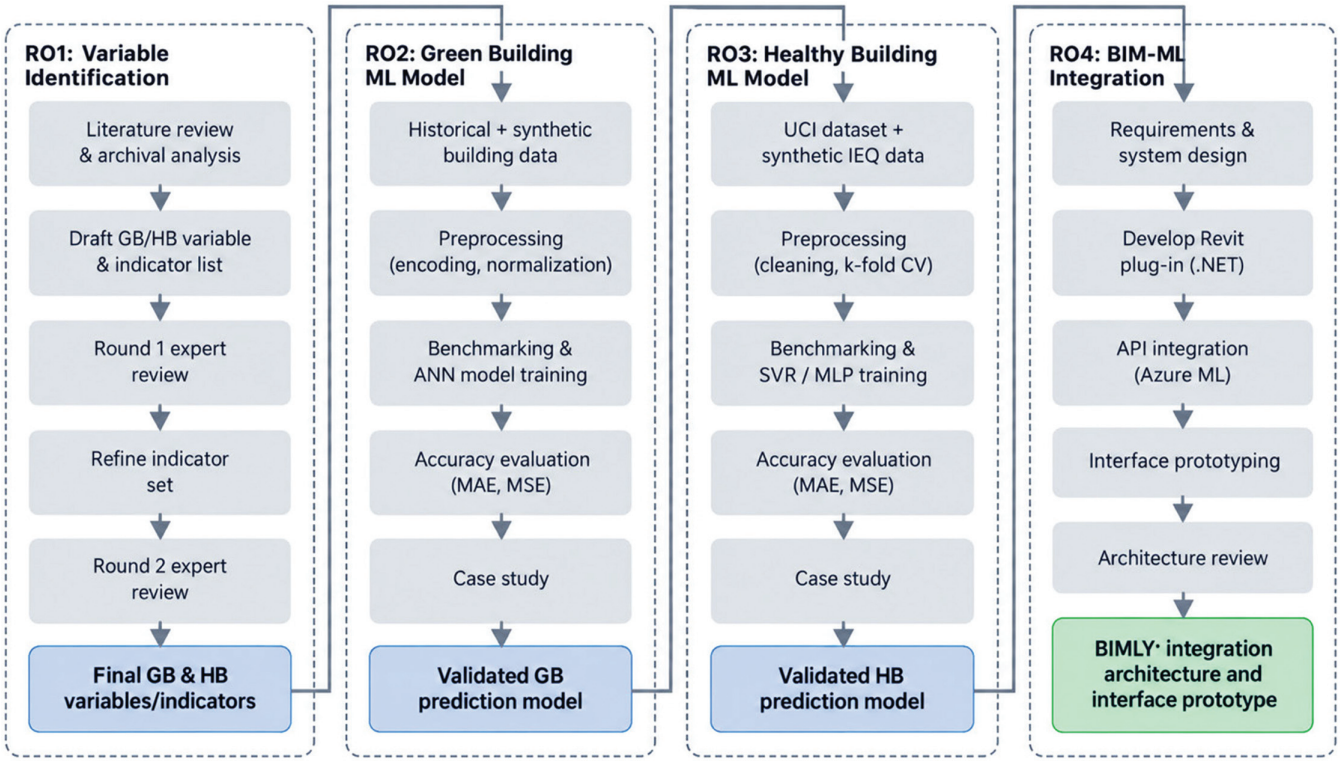


Fig. 1. Overall research workflow.

comfort, humidity, lighting, acoustics, water quality, and safety [28,29] (see Table I).

The variable set was reviewed in two expert rounds with the five experts listed in Table II. In the first round, researchers and academics reviewed the candidate variables, followed by practitioner review of their completeness and relevance to conceptual design in the second round. The resulting indicator set was then used in the RO2 and RO3 prediction models.

B. DEVELOPING ML MODEL FOR GB PERFORMANCE

Building data came from a Jakarta construction company and covered 62 actual projects. The data included building function, ground-floor area, building area, number of basements, and number of floors. Variables with missing values included orientation, window-to-wall ratio (WWR), glazing U-value, indoor illuminance, air temperature, relative humidity, sound level, water-fixture consumption, rainwater-harvesting capacity, landscape area, and bicycle facilities. The original dataset did not retain cell-level provenance records that identify whether each value was observed or standards-derived.

The standards used included GBCI criteria, Jakarta Governor Regulation 38 of 2012, Ministry of Public Works and Housing Circular No. 01/SE/M/2022, BREEAM requirements, and related studies. Each record combined historical project data with these standards-derived values.

Categorical features were encoded with scikit-learn's LabelEncoder and then standardized using scikit-learn preprocessing functions. Model development used Python 3.11 in Google Colaboratory. Keras and TensorFlow handled model development, scikit-learn handled preprocessing, and pandas and NumPy handled data and array operations, with Matplotlib for output check.

Four artificial neural network (ANN) configurations were tested. Experiments 1 and 2 used all 12 GB indicators, while Experiments 3 and 4 used WWR and three water-consumption indicators, respectively. Experiments 2–4 used a configured batch size of 31, independent of the dataset split. The final hybrid model used six inputs: building function, ground-floor area, total building area, number of basements, number of floors, and orientation, obtained from BIM or entered manually. The ANN estimated washbasin, toilet-flushing, and urinal consumption. The other nine indicators were calculated using deterministic IF-ELSE rules based on standards, regulations, and predefined calculations: WWR, glazing U-value, indoor illuminance, air temperature, relative humidity, sound level, rainwater-harvesting capacity, landscape area, and bicycle facilities. Their values were derived from GB regulations, standards, and published studies. The final model limits ANN learning to the three water-consumption indicators, while Experiments 1 to 3 are retained only to document model development.

Table II. Experts' profiles

Designation	Educational background	Work experience
GB practitioner	Master's	12 years
HB practitioner	Doctoral	25 years
Architect	Master's	15 years
Building researcher	Master's	19 years
Sustainability researcher	Master's	16 years

The 62 building records were split into 50 training and 12 test records. Five-fold cross-validation was applied to the training set, with preprocessing fitted separately within each fold. The test set was excluded from training and model selection. Indicators based on standards, regulations, or fixed calculations were processed through an IF-ELSE rule component instead: WWR, glazing U-value, indoor illuminance, air temperature, relative humidity, sound level, rainwater-harvesting capacity, landscape area, and bicycle facilities.

Model performance was checked with mean absolute error (MAE) and mean squared error (MSE), based on standard forecast accuracy practice:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \tag{1}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

where y_i is the reference value, $\hat{y}_i$ is the predicted value, and n is the number of evaluated values. MAE measures the average absolute prediction error, while MSE assigns greater weight to larger errors.

A separate apartment building was then evaluated using the completed model to demonstrate the prediction procedure. This case was used for demonstration only and was separate from the 62-record development dataset. Figure 2 shows the GB model development process.

C. DEVELOPING ML MODEL FOR HB PERFORMANCE

To obtain RO3, five HB domains were identified: lighting, indoor air quality (IAQ), thermal comfort, acoustic comfort, and energy use [30,31]. The UCI Energy Efficiency dataset [32] provided 768 simulated residential building records with eight geometric inputs: relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area, and glazing-area distribution. Heating and cooling loads (Y1–Y2) were retained from the dataset,

Table I. Candidate GB and HB indicators

Type	Category	Indicators
GB	Energy efficiency	Building geometry (length, width, floor area, orientation, floors); window-to-wall ratio (WWR); glazing type; heating, ventilation, and air conditioning (HVAC), lighting, and elevator loads; renewable energy use
	IEQ	Visual comfort (interior/exterior lighting); thermal comfort (temperature, relative humidity, air speed, ventilation); acoustic comfort (noise level)
HB	Health and safety	Dust and pest control, water quality, safety and security
	Energy	Energy efficiency
	IEQ	Ventilation, air quality, thermal comfort, humidity, lighting and views, acoustics

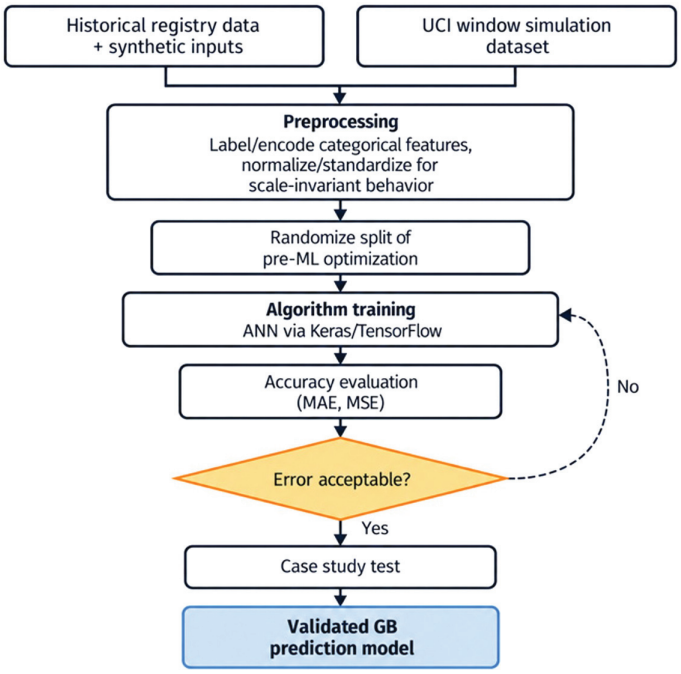


Fig. 2. GB ML model development process.

while 12 additional outputs (Y3–Y14) were constructed using thresholds and ranges from BREEAM, RESET, EN 12464-1, EN 15251, and BASIX.

Illuminance, unified glare rating, and color rendering index were assigned fixed reference values, as expressed in Eq. (3):

$$Y_3 = 500,\ Y_4 = 19,\ Y_5 = 80 \tag{3}$$

View out was determined by glazing area (X7) using the conditional rule in Eq. (4):

$$Y_6 = \begin{cases} 1, & X_7 \geq 0.20 \\ 0, & X_7 < 0.2 \end{cases} \tag{4}$$

IAQ indicators were generated using Excel's RANDBETWEEN function, corresponding to discrete uniform distributions in Eq. (5):

$$Y_7 \sim U_d(12{,}35) \quad Y_8 \sim U_d(400{,}500) \quad Y_9 \sim U_d(600{,}1000) \quad Y_{10} \sim U_d(0{,}9) \tag{5}$$

where $U_d(a,b)$ denotes uniform integer sampling between inclusive bounds. Y7–Y10 represent PM2.5, total volatile organic compounds (TVOC), CO_2, and CO, respectively. The remaining outputs were constrained to the ranges recorded in the dataset: predicted mean vote (PMV) (Y11) 0–0.20, predicted percentage of dissatisfied (PPD) (Y12) 0–6%, operative temperature (Y13) 21–25.5°C, and acoustic performance (Y14) 26–32 dB(A). The view-out rule linked Y6 to glazing area, whereas the IAQ formulas contained no geometric inputs or imposed intervariable correlations.

Preprocessing included regression-based data cleaning, Spearman's correlation analysis, and normalization to 0–1 due to differences in variable scales and the unknown distribution of standards-derived data.

Two supervised multi-output regression models were compared: support vector regression (SVR) and multilayer perceptron (MLP). The SVR model used LinearSVR as the base estimator in scikit-learn's RegressorChain, which predicted the 14 outputs in sequence. Each predicted output was added as an input for the next one.

The MLP used a Keras Sequential architecture with eight input nodes, one hidden Dense layer with 20 nodes, and a Dense output layer with 14 nodes. The hidden layer used Rectified Linear Unit (ReLU) activation and He-uniform weight initialization, and the output layer used linear activation. Training used the Adam optimizer, MAE as the loss function, 100 epochs, and the default Keras batch size of 32.

Model development used Python 3 through Anaconda 3 and Jupyter Notebook. NumPy and pandas handled data processing, scikit-learn handled SVR and cross-validation, TensorFlow and Keras handled MLP, Openpyxl handled spreadsheet processing, and Matplotlib handled graphical analysis. Both models were evaluated using ten-fold cross-validation, repeated three times with different data partitions. Each cycle used nine subsets for training and one for validation until every subset had served as the validation set. The average MAE was used to measure prediction accuracy, and Fig. 3 shows the HB model development process.

D. CONCEPTUAL FRAMEWORK FOR BIM–ML INTEGRATION

RO4 developed the BIMLY integration architecture and interface prototype to connect the GB and HB models with Autodesk Revit. A literature review of BIM-integrated building performance tools defined the required components, functions, data, and system structure. Revit served as the BIM platform, the GB and HB models as the computational components, and Python linked the plug-in to the models through a REST API. The API exchanged building parameters and prediction results as JSON data, while the plug-in handled inputs, prediction requests, and result display.

BIMLY development focused on requirements analysis, system design, and interface prototyping. The resulting architecture and interface prototype illustrate how GB and HB predictions can be presented within the BIM during conceptual design.

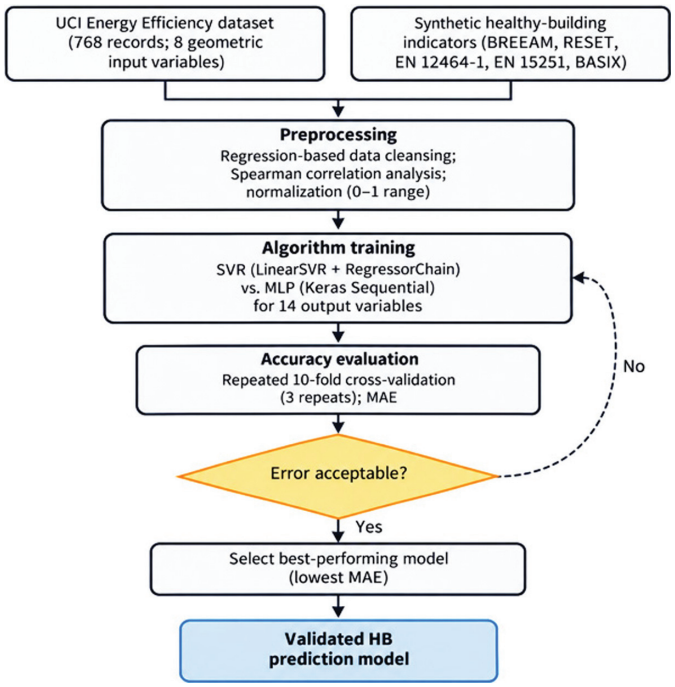


Fig. 3. HB ML model development process.

IV. RESULTS

A. GB AND HB INDICATORS

The literature review and two expert rounds produced two indicator sets: five criteria for 12 GB indicators (Table III) and five variables for 14 HB indicators (Table IV).

The five practitioners rated all five statements positively, with mean scores of 3.4–4.0 and all responses indicating agreement or strong agreement. They suggested adding reference ranges, clearer prediction-method information, and broader GB and HB indicator coverage.

B. GB PERFORMANCE PREDICTION MODEL

Table V shows ANN experiments' results.

Experiments 1 and 2 yielded MSE values of 5,119,586 and 443,484, respectively. Experiment 3 achieved an MSE of 128.9, while Experiment 4 achieved an MSE of 1.3 for the three water-consumption indicators. Because the experiments involved different output sets and measurement scales, their MSE values are not comparable. These experiments document changes in model scope and are not used for model comparison. The final configuration separates ANN-predicted outputs from standards-based calculations.

Based on these results, the final GB model uses two calculation methods. The ANN uses six building descriptors as inputs: building function, ground-floor area, total building area, number of basements, number of floors, and orientation. It predicts three water-consumption indicators: washbasin, toilet-flushing, and urinal consumption. The other nine indicators are calculated through deterministic IF-ELSE rules based on standards, regulations, and predefined calculations.

C. HB PERFORMANCE PREDICTION MODEL

A Spearman correlation check found no strong correlations among the input variables, which supports their use as separate regression features. After preprocessing, MAE decreased from 16.818 to 5.66 for SVR and from 16.574 to 3.02 for MLP. MLP showed a lower MAE than SVR throughout testing, consistent with previous NN studies of IEQ prediction. The final MLP model, with an MAE of 3.02, was selected for HB.

D. BIM–ML INTEGRATION

RO4 produced the BIMLY integration architecture, shown in Fig. 4 as a proposed four-stage workflow. In Stage 1, the user builds a 3D model in Revit. Stage 2 links this model to the plug-in through Revit's API, forming the interoperability layer between the BIM model and the prediction system. In the proposed workflow, Stage 3 transfers building data to the GB and HB models. Stage 4 presents the predicted performance values through the interface and supports their evaluation.

Table IV. HB indicators used in the model

Variable	Indicators
Lighting	Illuminance level, unified glare rating, color rendering index, view out
IAQ	PM2.5, TVOC, CO2, CO
Thermal comfort	PMV, PPD, operative temperature
Acoustic	Noise level, dB(A)
Energy use	Heating load, cooling load

Table V. GB model training experiments.

Exp	Output scope	Hidden layers	Batch size	MSE
1	All 12 indicators	1	–	5,119,586
2	All 12 indicators	7	31	443,484
3	WWR only	7	31	128.9
4	Washbasin, toilet flush, urinals	7	31	1.3

Selecting GB retrieves six design inputs through the Revit API: building function, ground-floor area, total building area, number of floors, number of basements, and orientation. Users can accept these values or enter them manually (Fig. 6a). The values are then passed to the GB workflow for ANN prediction of water-consumption indicators and deterministic calculation of nine other indicators. Fig. 6b presents the 12 GB outputs. The six design inputs are not ANN outputs.

The HB workflow follows the same pattern. Data are entered for each level: relative compactness, exterior surface area, wall area, roof area, level height, orientation, glazing area percentage, and glazing distribution (see Fig. 7).

Figures 5–7 present the BIMLY interface prototype for the integrated GB and HB assessment workflow. The figures illustrate the proposed input and output interfaces. End-to-end system operation and usability in live projects have not been evaluated in this study.

V. DISCUSSION

A. PREDICTING PERFORMANCE WITHOUT FULL SIMULATION

The GB model's output scope became narrower and more clearly defined across the experiments. Predicting multiple indicators with different characteristics introduced challenges, as some followed standards-based rules while others required statistical prediction.

Table III. GB indicators used in the model

Criteria	Subcriteria	Example indicators
Energy	Building geometry	Building area, orientation, number of floors
Fenestration	Fenestration	WWR, glazing type
IEQ	Visual, thermal, acoustic comfort	Illuminance, air temperature, relative humidity, sound level
Water	Water usage, water recycling	Washbasin, toilet flush, urinals, rainwater harvesting
Site planning	Site planning	Landscape area, bicycle facilities

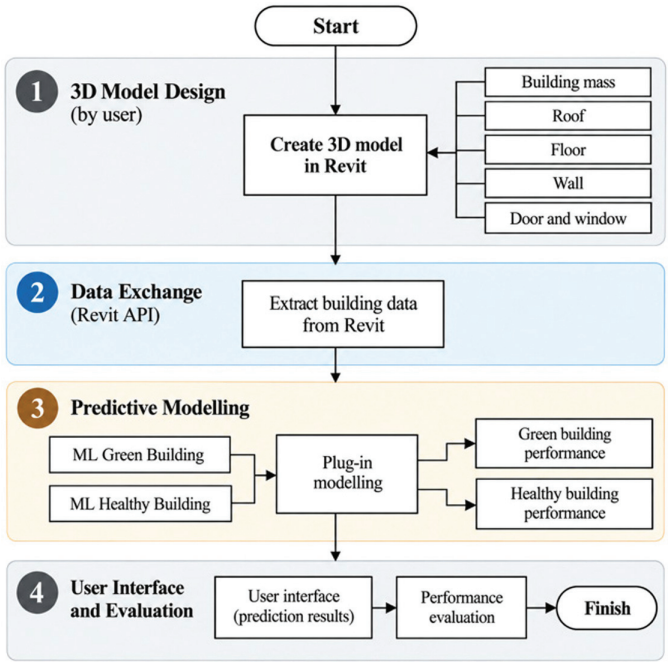


Fig. 4. BIM–ML integration process.

The GB model combined an ANN with an IF-ELSE rule component. The standards-derived values in the original dataset limit the empirical basis of the early multi-output experiments. Although cross-validation was used during model development, the small test set limits the reliability of the performance estimates. Further evaluation with a larger and independent building dataset is needed to assess generalization. For HB performance, the MLP achieved a lower error than SVR on the constructed dataset. However, errors for Y3–Y10 reflect agreement with predefined values and generation rules, not demonstrated predictive accuracy against measured building performance. Further validation with real building data is required.

This interpretation is consistent with studies showing that ML can approximate building simulations when matched to task complexity [17], while most ML studies address only one aspect of building performance [19]. Combining GB and HB prediction from early design inputs addresses this gap and supports early evaluation before the detailed building models required for simulation are available.

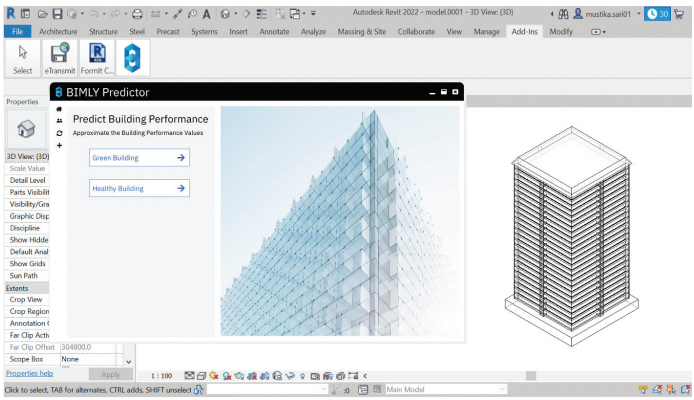


Fig. 5. BIMLY interface prototype.

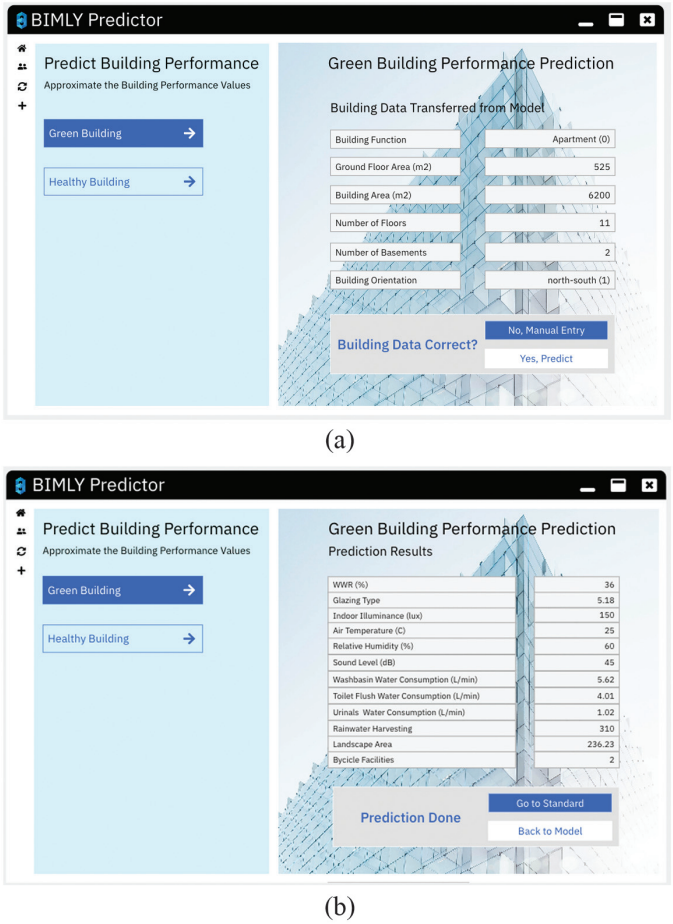


Fig. 6. Interface of GB prediction in BIM.

B. PRACTICAL VALUE FOR EARLY DESIGN DECISIONS

BIMLY aims to present GB and HB predictions within a single BIM interface. Most BIM-linked prediction tools require a developed BIM model [25], while BIMLY uses conceptual design parameters, such as building function, floor area, and orientation. The proposed workflow allows architects to adjust design parameters, developers to check options against LEED or WELL targets, and regulators to use the outputs to review submitted designs.

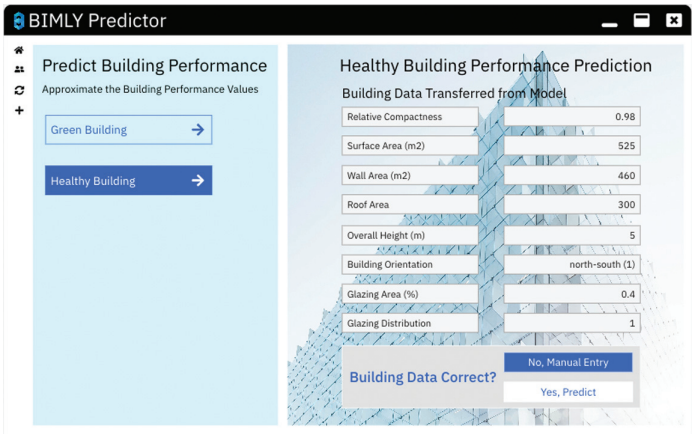


Fig. 7. Interface of HB prediction in BIM.

BIMLY also combines performance areas usually assessed separately. Previous BIM–ML studies focused on specific objectives, including energy use and thermal comfort optimization [23] and GB energy design [33], without extending BIM-linked optimization to occupant health.

Rule-based outputs are easier to trace and explain to regulators, while NN outputs are less transparent, which may affect practitioner trust.

VI. CONCLUSION

This study developed BIMLY to combine green and HB performance assessment at the conceptual design stage. It identified GB and HB indicators and developed separate GB and HB prediction models using limited early design inputs.

The study also developed a Revit-based integration architecture and interface prototype, with a proposed Python REST API and JSON data exchange. The combined workflow is designed to support GB and HB performance assessment within the same early design process.

BIMLY remains at the architecture and interface prototype stage and has not undergone verified end-to-end testing or live-project practitioner evaluation. The models were also built using Indonesian data and have not been tested in other regions. Future work should complete and test the plug-in, assess practitioner usability, and validate the models with data from other regions.

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DATA AVAILABILITY STATEMENT

The 62-project GB dataset is subject to company confidentiality and may be shared with its permission. Other datasets are available from the corresponding author on reasonable request.

AI DISCLOSURE STATEMENT

Claude AI was used to assist with improving flow, grammar, and image creation. The authors reviewed and edited the content and take full responsibility for the manuscript.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest to report regarding the present study.

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