Predicting Perceived Learning-Environment Quality in Classrooms Using Indoor Environmental Measurements and Machine Learning

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ABSTRACT

Indoor Environmental Quality (IEQ) plays a critical role in shaping students' classroom experience, yet linking objective environmental measurements to subjective perceptions remains methodologically challenging. This study investigates whether perceived learning-environment quality can be predicted from indoor environmental measurements and contextual variables using supervised machine learning. A longitudinal dataset containing repeated satisfaction surveys and temporally aligned environmental measurements from classrooms in Belgium was used. The targets included thermal, indoor air quality (IAQ), acoustic, and visual satisfaction scores measured on ordinal Likert scales. To ensure robust evaluation and prevent information leakage, a group-based train–test split was applied at the occupant level, guaranteeing generalization to unseen individuals. Multiple models were evaluated, including a median baseline, Ridge regression, Random Forest, and HistGradientBoostingRegressor. Performance was assessed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Quadratic Weighted Kappa (QWK) to capture ordinal agreement. All machine learning models significantly outperformed the baseline. Ensemble models achieved macro-average QWK values above 0.70, indicating strong ordinal consistency. IAQ and thermal satisfaction were most predictable, while acoustic and visual satisfaction showed greater variability. Most errors occurred between adjacent Likert categories, and extreme misclassifications were rare, demonstrating stable ordinal behavior. The results confirm that measurable environmental factors contain sufficient predictive signal to approximate subjective classroom satisfaction under realistic generalization conditions. Linear models captured much of the structure, while boosted trees provided marginal performance gains with improved flexibility. These findings support the feasibility of data-driven approaches for monitoring and improving classroom environments and provide a reproducible modeling framework for future research in educational building analytics.

Keywords Indoor Environmental Quality; Classroom Comfort Prediction; Machine Learning; Ordinal Regression; Educational Building Analytics

Introduction

Indoor Environmental Quality (IEQ) in classrooms is increasingly recognized as foundational for effective learning, with thermal comfort, indoor air quality (IAQ), visual comfort, and acoustic comfort forming the core IEQ domains that influence student comfort, attention, and perceived readiness to learn [1], [2], [3]. Although curriculum, pedagogy, and digital resources drive educational improvement, students and teachers spend long hours in physical spaces where ambient temperature, air freshness, noise, and lighting conditions shape

Submitted 12 January 2026
Accepted 14 February 2026
Published 1 March 2026

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DOI: 10.63913/ail.v2i1.15

How to cite this article: E.F.Mohammed and A.S.Bahurmuz, "Predicting Perceived Learning-Environment Quality in Classrooms Using Indoor Environmental Measurements and Machine Learning," *Artif. Intell. Learn.*, vol. 2, no. 1, pp. 60-72, 2026.

moment-to-moment instructional experiences, making the classroom a critical component of the learning system [1], [2], [3].

IEQ is inherently multidimensional and dynamic: thermal conditions vary across the day, ventilation effectiveness shifts with occupancy and window use, and noise levels depend on activity patterns and context, so even rooms that are average-acceptable may produce frequent short bouts of discomfort; hence real-time or near-real-time monitoring can yield richer insights than periodic inspections [2], [3]. Moreover, comfort comprises both physical and perceptual elements, with individual sensitivity, expectations, and adaptation producing divergent responses to similar conditions; thus, actionable signals for stakeholders typically relate to the likelihood that occupants perceive the environment as conducive or disruptive to learning, necessitating models that link objective sensor data to subjective satisfaction to inform proactive facility management and occupant-centric control strategies [1], [3], [4]. In this light, machine learning offers a powerful approach to capture nonlinear relationships and context-specific interactions among IEQ factors, enabling data-driven prediction of perceived learning-environment quality beyond fixed thresholds and supporting proactive interventions that prioritize learner experience [5], [4], [6].

However, applying machine learning in educational environments introduces methodological issues that are easy to overlook. Classroom IEQ datasets often include repeated responses from the same students, creating a risk that models appear accurate simply because they learn individual response tendencies. Likewise, temporal structure can lead to leakage if the model learns from nearly identical neighboring time points across train and test sets. A valid modeling design must therefore evaluate generalization to new occupants and, ideally, new classroom contexts.

Another challenge is that most educational datasets focus on learning outcomes such as grades or standardized test scores, whereas IEQ datasets more commonly measure perceptions and environmental conditions. This creates a gap between what schools may want to optimize (learning) and what is feasible to model directly (comfort and satisfaction). Yet perceived learning-environment quality remains educationally meaningful: it represents the immediate conditions under which learning activities occur and can be improved through operational interventions without altering curriculum.

This study addresses that gap by modeling perceived learning-environment quality from indoor environmental measurements and contextual variables collected in real classrooms. The core task is to predict satisfaction scores across multiple IEQ dimensions—including thermal comfort, indoor air quality, and acoustic comfort—using supervised learning. By framing the prediction target as occupant satisfaction, the model output aligns with how students and teachers experience the classroom.

To ensure that findings are practically relevant, the study adopts a leakage-resistant evaluation strategy that splits data by occupant identity. This setup tests whether models can generalize to individuals not observed during training, which is essential for deployment in real schools where new cohorts and changing class compositions are common. The workflow also emphasizes reproducibility and resumability, enabling transparent comparisons across models and configurations.

The contributions of this work are threefold. First, it provides a rigorous machine learning pipeline for predicting perceived learning-environment quality using mixed sensor and survey data, including preprocessing for missingness and categorical context. Second, it offers a comparative evaluation of baseline and advanced models under a group-based split that reflects real-world generalization requirements. Third, it adds explainability through feature-importance analyses, highlighting which measurable classroom conditions are most predictive of perceived satisfaction and thus most actionable for educational building management.

Literature Review

Research on classroom environments has long acknowledged that physical conditions influence student experience and instructional quality. Studies across education, environmental psychology, and building science have examined how temperature, air quality, acoustics, and lighting relate to comfort, attention, and perceived learning readiness. This body of work frames the classroom as a complex interaction between occupants and environment, where both objective conditions and subjective interpretations matter.

Thermal comfort, indoor air quality (IAQ), acoustics, and visual lighting conditions in educational buildings collectively shape classroom experience far beyond architecture or schedules alone, with occupant perceptions often diverging from fixed thresholds due to clothing, activity, and individual sensitivity that complicate universal “comfortable” standards in schools [7], [8], [9]. In classrooms, CO_2-driven ventilation trade-offs are central: occupancy rapidly fosters CO_2 buildup and noisy or thermally uncomfortable window opening can arise, creating tensions between air freshness and other IEQ aspects such as acoustics or temperature control [7], [3], [6].

Acoustics are especially critical for speech intelligibility and cognitive load, with reverberation, external and internal noise, and intermittently disruptive disturbances affecting perceived learning potential even when average decibel levels seem moderate [7], [10], [11], [12]. Visual comfort and lighting further influence satisfaction, as glare, insufficient illuminance, and daylight management interact with seating, time of day, and task demands, underscoring the need for inclusive design that accounts for differing sensitivities and learning activities [7], [13], [12], [14].

Across these domains, education literature repeatedly notes that high occupancy density, frequent schedule changes, and limited individual control differentiate classrooms from other buildings, yielding conditions where discomfort can impair restlessness, concentration, and perceived learning readiness; this motivates perception-focused modeling that links objective sensor data to subjective satisfaction to support proactive, learner-centered facility management and design strategies [1], [2], [3], [4], [6], [15].

Occupant-centered building research extends IEQ work by treating occupants not as passive recipients of conditions but as active agents whose preferences, behaviors, and perceptions shape outcomes. In schools, occupants include both students and teachers, who may have different comfort expectations and control behaviors (e.g., window opening, thermostat adjustments). This perspective motivates models that predict perceived satisfaction rather than relying exclusively on physical criteria, and it supports adaptive management strategies that respond to occupant feedback.

Within the last decade, machine learning has become a common methodological tool for predicting comfort and satisfaction in buildings. Compared to traditional regression or rule-based approaches, ML models can capture nonlinear effects, interactions, and context dependence. In IEQ applications, these methods have been used for tasks such as thermal preference prediction, indoor air quality estimation, and comfort classification, often demonstrating improved predictive performance over simple thresholds.

Despite these advances, a recurring methodological limitation is evaluation design in the presence of repeated measures and correlated observations. When the same occupant contributes many data points, random row-wise splits can inflate performance estimates because the model learns individual baselines. Similar issues arise when data are temporally clustered. Literature increasingly calls for group-based and time-aware validation strategies to ensure that models truly generalize beyond the training sample and remain robust under deployment conditions.

Finally, explainability has become an essential companion to predictive performance in applied ML for built environments and education. Stakeholders such as school administrators and facility managers need interpretable insights that translate into operational decisions. Feature attribution methods, sensitivity analyses, and model-agnostic importance measures help identify which environmental variables most influence predicted satisfaction. This interpretability is especially valuable in classrooms, where interventions must be feasible, cost-aware, and balanced across multiple IEQ dimensions rather than optimizing a single metric in isolation.

Methods

Dataset and Study Design

This study uses a longitudinal dataset that combines repeated occupant satisfaction surveys with temporally aligned indoor environmental measurements collected in educational classrooms in Belgium. The dataset covers three educational contexts (secondary school, primary school, and a university lecture room) and includes multiple dimensions of perceived indoor environmental quality (IEQ), such as thermal comfort, indoor air quality (IAQ), acoustic comfort, visual comfort, and overall IEQ where available. Each survey response is linked to the environmental conditions around the time of the vote, enabling supervised learning of perceived learning-environment quality from measured physical variables.

The unit of analysis is a single satisfaction assessment (i.e., one survey response event), and the modeling goal is to predict the ordinal satisfaction score(s) reported by the occupant. Because occupants may provide multiple responses over time, the dataset has a repeated-measures structure: multiple rows can correspond to the same individual under different classroom conditions and timepoints. This structure requires evaluation methods that prevent information leakage across repeated observations from the same person.

The primary outcomes (targets) are satisfaction ratings expressed on Likert-type ordinal scales (typically 1–5). In the implementation, target columns are identified by a predefined list of satisfaction variables (e.g., ThermalSatisfaction, IAQSatisfaction, AcousticSatisfaction) and extended by an automatic fallback mechanism that detects additional numeric “Satisfaction” columns consistent with Likert ranges. To ensure consistent supervision, we retain only rows where all selected targets are present, producing a clean multi-target dataset for training and evaluation.

Preprocessing and Feature Construction

Raw data are loaded and a cleaned checkpoint is stored as a column-preserving Parquet file to accelerate subsequent runs. A unique occupant identifier (`ID`) is used as the grouping variable, and any feature columns that would trivially leak identity (e.g., `ID` itself) are excluded from the predictive feature matrix. Time-related information is treated similarly: the raw timestamp column (`TimeVote`), if present, is removed from modeling inputs after extracting stable time features.

Timestamp parsing is performed using robust day-first datetime conversion to match the dataset's typical format (e.g., `29/11/2021 10:35`). From parsed timestamps, three simple temporal features are derived: `hour` (0–23), `dayofweek` (0–6), and `month` (1–12). These features represent coarse contextual signals that can capture systematic temporal patterns (e.g., morning vs afternoon or weekday differences) without allowing the model to memorize exact timestamps. If timestamps are missing or fail to parse reliably, these features are skipped to preserve dataset integrity.

Predictor variables include both numeric measurements (e.g., environmental sensor readings) and categorical contextual descriptors (e.g., `Moment` such as Start/End, subgroup labels, and other case/context fields). The preprocessing pipeline uses a column-wise transformation strategy: numeric features are median-imputed, while categorical features are imputed with the most frequent category and then one-hot encoded. Median imputation is chosen for robustness to skew and outliers, which are common in environmental measurements (e.g., CO_2 spikes), while mode imputation preserves category stability for sparse categorical variables.

The one-hot encoding uses `handle_unknown="ignore"` to ensure the model can safely process unseen categorical levels at test time (e.g., a subgroup label absent from training). The encoder is configured to output dense arrays (`sparse_output=False`) to support downstream estimators uniformly, including multi-output wrappers and permutation importance. All preprocessing steps are embedded in scikit-learn pipelines, ensuring transformations are fitted only on training data and consistently applied to test data, which is essential for leakage-free evaluation.

Experimental Setup, Reproducibility, and Data Splitting

To ensure repeatable results, the notebook enforces deterministic configuration at multiple levels. A fixed random seed (`SEED=42`) is applied to NumPy and all stochastic estimators, and the number of threads is constrained (`NUM_THREADS=1`) via environment variables controlling common BLAS/OpenMP backends (e.g., `OMP_NUM_THREADS`, `MKL_NUM_THREADS`, `OPENBLAS_NUM_THREADS`). Single-thread execution reduces nondeterminism that can arise from parallel floating-point reduction ordering and makes results more stable across runs on the same machine.

Each experiment records a run metadata file that includes the dataset's SHA-256 hash, platform information, Python version, and key hyperparameters (test size, seed, threading). On resumption, the notebook recomputes the dataset hash and aborts if it differs from the hash used previously under the same `RUN_NAME`. This prevents accidental reuse of checkpoints with a modified dataset file, which would compromise reproducibility and invalidate comparisons.

Because the dataset contains repeated measures per occupant, we use a grouped train/test split that prevents the same person from appearing in both sets. Specifically, we apply `GroupShuffleSplit` with `test_size=0.20` and `random_state=SEED`, using occupant `ID` as the grouping label. This design evaluates generalization to unseen occupants rather than memorization of an individual’s response tendencies, which is crucial for assessing practical deployment scenarios.

The generated split indices are saved as a checkpoint (`checkpoint_split.joblib`) and reused verbatim on subsequent runs. This makes model comparisons fair: all models are trained and evaluated on exactly the same train/test partition. It also enables resumption—if training is interrupted, rerunning the notebook continues from the saved split and previously trained models rather than generating a new split, ensuring the experiment remains identical.

Modeling Approach and Hyperparameter Choices

The prediction task is framed as supervised learning with one or more ordinal satisfaction targets. In the implementation, multi-target prediction is handled via `MultiOutputRegressor`, which fits one independent regressor per satisfaction dimension while sharing a common preprocessing pipeline. This approach allows joint evaluation across multiple IEQ dimensions and supports comparisons among models without requiring a custom multi-task neural architecture. Although the targets are ordinal, we initially model them as continuous scores and later round predictions for ordinal-specific agreement metrics.

We evaluate four model families representing increasing capacity and modeling flexibility. First, a baseline `DummyRegressor(strategy="median")` provides a non-informative benchmark that predicts the median satisfaction score for each target. Second, a regularized linear model (`Ridge`) captures additive relationships between environmental predictors and satisfaction while controlling overfitting through L2 regularization. This linear baseline is important because it is interpretable and often competitive in tabular data.

Third, a `RandomForestRegressor` is used as a nonlinear ensemble method robust to feature interactions and mixed feature types (after preprocessing). The forest uses `n_estimators=400` to stabilize variance and reduce sensitivity to sampling noise, while `random_state=SEED` ensures reproducible bootstrapping and feature selection. Parallelism is constrained by setting `n_jobs=NUM_THREADS`, which preserves determinism while remaining configurable if speed is prioritized.

Fourth, `HistGradientBoostingRegressor` provides a strong boosted-tree baseline with good performance on tabular datasets and native handling of nonlinearities. Hyperparameters are set to `max_depth=6` (to limit overfitting and encourage generalizable rules), `learning_rate=0.07` (moderate step size), and `max_iter=500` (sufficient boosting rounds to converge under the chosen learning rate). This configuration aims to balance bias and variance without extensive tuning; it can later be extended into systematic hyperparameter optimization if required.

Evaluation Metrics, Visualization, and Explainability

Model performance is evaluated using both continuous-error and ordinal-agreement metrics. For each target dimension, we compute Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) on continuous predictions. MAE provides a robust measure of typical deviation in Likert units, while RMSE penalizes larger errors more strongly. Because Likert outcomes are ordinal, we additionally compute Quadratic Weighted Kappa (QWK) using rounded predictions, which rewards near-misses more than far-off misclassifications and is widely used for ordinal rating agreement.

To compute QWK, model outputs are rounded to the nearest integer and clipped to the valid Likert range (1–5). This post-processing step reflects realistic use: an operational system would likely output either a discrete satisfaction level or a probability distribution over levels. We report per-target metrics and macro-averaged metrics across all targets to summarize overall predictive performance and enable straightforward model ranking. The best model is selected by highest macro QWK, with macro MAE used as a tie-breaker.

Visualization is integrated as part of the methodological pipeline to support diagnostic understanding and reporting. The notebook generates target distributions (training set histograms) to document label balance and identify skew. It also plots feature missingness rates to reveal whether substantial imputation is required for key predictors. For predictive quality, the notebook produces scatter plots of actual vs. predicted scores and confusion-matrix-like heatmaps computed from rounded predictions, making it easy to see systematic under- or over-prediction patterns (e.g., confusion between 4 and 5).

To identify which measurable factors best explain perceived learning-environment quality, we use permutation importance on the best-performing model for the first target dimension. Permutation importance measures the drop in performance (here, QWK) when each feature is randomly shuffled, providing a model-agnostic estimate of predictive contribution. To keep computation feasible and reproducible, importance is calculated on a deterministic subsample of the test set (`PERM_SAMPLE_N=1200`) with a fixed random seed and repeated shuffling (`PERM_REPEATS=8`). Results are exported to CSV and visualized as a top-20 bar chart, enabling interpretation and discussion of key environmental drivers.

Result

Overall Model Performance

The predictive performance results demonstrate that perceived learning-environment quality can be modeled effectively from indoor environmental measurements and contextual variables. The baseline median predictor yielded a macro-average MAE of approximately 0.91 and a QWK of 0.00, confirming that a constant prediction provides no meaningful ordinal agreement. In contrast, all machine learning models substantially outperformed the baseline, indicating that measurable environmental signals contain strong predictive information about occupant satisfaction.

Among the evaluated models, Random Forest achieved the highest macro-average QWK (≈0.708) and lowest macro MAE (≈0.551), while HistGradientBoostingRegressor (HistGBDT) achieved nearly identical performance (macro QWK ≈0.707, macro MAE ≈0.573). The linear Ridge model also performed strongly (macro QWK ≈0.685), suggesting that much of the relationship between environmental variables and perceived satisfaction is approximately linear or additive in structure. These results indicate that while nonlinear ensemble methods provide measurable improvements, simpler models already capture a substantial portion of the signal.

The magnitude of prediction error is practically meaningful. A macro MAE of approximately 0.55 on a 1–5 Likert scale implies that, on average, predictions deviate by about half a satisfaction level. This indicates that the model is typically within one adjacent category of the true value. Such performance is especially notable given the use of a group-based train–test split, which ensures that predictions are evaluated on occupants unseen during training.

From a computational perspective, the performance–efficiency tradeoff is also instructive. Random Forest required significantly longer training time compared to HistGBDT, while delivering only marginal gains. HistGBDT therefore represents the most favorable balance between predictive accuracy and computational cost. These findings suggest that boosted tree methods may be preferable for deployment scenarios requiring regular retraining or real-time updates in educational facilities.

Dimension-Specific Predictability

Performance varied across satisfaction dimensions, revealing important differences in predictability. IAQ satisfaction achieved the highest QWK (≈0.768 under Random Forest), followed by thermal satisfaction (≈0.749), acoustic satisfaction (≈0.689), and visual satisfaction (≈0.628). This ranking indicates that perceptions related to air quality and temperature are more directly inferable from measurable variables than acoustic or visual comfort.

The stronger performance for IAQ and thermal dimensions likely reflects the availability of clear, quantifiable environmental indicators such as CO_2 concentration, temperature, and humidity. These variables are physically measurable, temporally aligned with survey responses, and often exhibit structured relationships with occupant perception. As a result, the model can more reliably map sensor readings to reported satisfaction levels.

In contrast, acoustic satisfaction displayed greater ambiguity between adjacent categories, particularly between levels 3 and 4. Acoustic perception is influenced not only by background noise levels but also by intermittent disturbances, classroom activity, and individual sensitivity. If such contextual nuances are not fully captured by available features, the model naturally exhibits reduced separability between mid-to-high satisfaction categories.

Visual satisfaction showed the lowest predictive agreement among the dimensions. Visual comfort often depends on seat location, glare, task type, and personal tolerance, which may not be fully represented in standard environmental measurements. The lower QWK in this dimension suggests that additional spatial or task-specific features would be beneficial for improving prediction of visual comfort in classroom settings.

Error Structure and Ordinal Behavior

The scatter plots of actual versus predicted values reveal a clear clustering structure aligned with Likert levels. Predictions for higher satisfaction categories (4–5) are predominantly concentrated in the upper prediction range, while low satisfaction levels (1–2) cluster toward lower predicted values. This structured distribution confirms that the model captures the ordinal progression of satisfaction rather than producing random fluctuations.

The rounded confusion matrices provide further insight into error structure. For both IAQ and acoustic satisfaction, diagonal dominance is evident, particularly in mid and high categories. For example, large proportions of actual level 4 and level 5 cases are correctly classified as 4 or 5 after rounding. Importantly, extreme misclassifications (e.g., predicting 1 for an actual 5) are rare, indicating stable ordinal alignment.

Most misclassifications occur between adjacent categories, particularly between levels 3 and 4, and between 4 and 5. This pattern is consistent with ordinal uncertainty rather than systematic bias. In perceptual domains, the boundary between “neutral” and “satisfied” is inherently subjective, and slight environmental changes may shift responses across this boundary. The dominance of adjacent-category errors explains the strong QWK values despite moderate MAE.

A mild regression-to-the-mean pattern is also observable. Extreme values (1 or 5) are sometimes predicted closer to central categories (2 or 4), reflecting the averaging behavior of ensemble models and potential class imbalance. This phenomenon is common in regression-based modeling of ordinal scales and does not undermine predictive validity, particularly given the absence of catastrophic cross-scale errors.

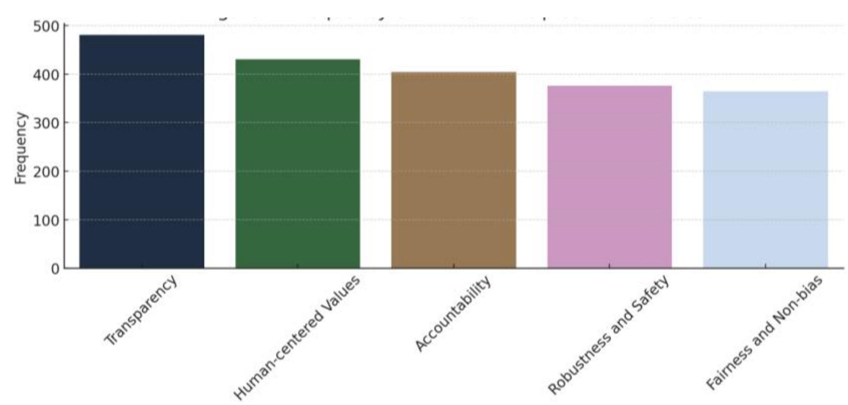

Figure 5 Frequency of Ethical Principles in AI Policies

Discussion

The results demonstrate that perceived learning-environment quality can be predicted with strong ordinal agreement using sensor-based environmental data. This finding supports the feasibility of data-driven classroom monitoring systems that anticipate occupant satisfaction rather than relying solely on static regulatory thresholds. Such systems could inform ventilation, temperature control, or acoustic interventions in a proactive manner. The relatively strong performance of linear Ridge regression suggests that additive environmental effects account for much of the variance in satisfaction. This is encouraging from a practical perspective, as linear models are easier to interpret and communicate to stakeholders. Facility managers and school administrators may benefit from simpler models that provide transparent relationships between environmental parameters and predicted comfort outcomes.

At the same time, ensemble models provide incremental improvements, particularly for IAQ satisfaction, where nonlinear interactions may play a role. For example, the joint effects of occupancy, ventilation, and time-of-day conditions may not be fully captured by linear assumptions. Boosted tree methods therefore offer a flexible yet computationally efficient solution for operational deployment. Overall, the findings highlight that objective environmental measurements contain sufficient information to meaningfully approximate subjective perceptions of classroom quality. By using group-based validation that generalizes to unseen occupants, the study provides evidence that these models capture environmental patterns rather than memorizing individual tendencies. This strengthens the case for applying machine learning approaches in educational building management to enhance learner experience and classroom comfort.

Conclusion

This study demonstrates that perceived learning-environment quality in classrooms can be reliably predicted using indoor environmental measurements and contextual variables under a leakage-resistant evaluation design. Across multiple satisfaction dimensions, machine learning models substantially outperformed a non-informative baseline, achieving strong ordinal agreement under group-based splitting by occupant identity. IAQ and thermal satisfaction were the most predictable dimensions, while acoustic and visual comfort exhibited greater ambiguity between adjacent Likert categories. Importantly, most prediction errors occurred between neighboring satisfaction levels, and extreme misclassifications were rare, indicating stable and behaviorally plausible model performance. The findings suggest that measurable environmental parameters contain meaningful signals that correspond to how occupants perceive classroom quality. Linear models captured a large portion of the predictive structure, while ensemble methods provided incremental gains with varying computational costs. By combining reproducible modeling practices, group-based validation, and interpretable performance metrics, this work provides a methodologically robust foundation for integrating machine learning into classroom environmental management. Future work may extend the framework with richer spatial features, temporal sequence modeling, or ordinal-specific learning methods to further enhance predictive precision and practical deployment.

Declarations

Author Contributions

Conceptualization: E.F.M.; Methodology: E.F.M.; Software: A.S.B.; Validation: E.F.M.; Formal Analysis: A.S.B.; Investigation: A.S.B.; Resources: E.F.M.; Data Curation: E.F.M.; Writing Original Draft Preparation: E.F.M.; Writing Review and Editing: A.S.B.; Visualization: A.S.B.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Funding

The authors received no financial support for the research, authorship, andor publication of this article.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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