**ARTIFICIAL INTELLIGENCE OPTIMIZATION FOR COMPUTER SCIENTISTS — D682**

TASK 4: ADAPTATION FOR ADDITIONAL APPLICATIONS

**A1. Adaptation Strategies**

To adapt the optimized outdoor health‑risk GBM model for indoor air‑quality monitoring, the following strategies will be employed:

1. **Domain-Specific Data Integration**
   * Deploy low-cost indoor sensors to capture additional variables: carbon dioxide (CO₂), volatile organic compounds (VOCs), particulate matter (PM₂.₅/PM₁₀), and occupancy levels.
   * Align new data streams with existing features (temperature, humidity) and timestamp for chronological consistency.
   * Address privacy concerns by anonymizing occupancy data and following GDPR guidelines for personal data handling (European Parliament, 2016).
2. **Feature Engineering and Preprocessing Adjustments**
   * Introduce room‑volume normalization: calculate pollutant concentrations per cubic meter to account for varying room sizes (EPA, 2021).
   * Engineer ventilation rate features (air changes per hour) from HVAC system logs to reflect flow dynamics influencing pollutant dispersion.
   * Apply sensor calibration and drift correction algorithms to account for indoor device variability.
3. **Model Transfer and Fine-Tuning**
   * Utilize transfer learning by retaining the outdoor-trained GBM structure and fine-tuning on labeled indoor data, reducing training time and leveraging learned patterns.
   * Re-optimize hyperparameters (learning\_rate, subsample) via targeted RandomizedSearchCV on the indoor dataset to account for distributional shifts.
4. **Pipeline and Infrastructure Adaptation**
   * Extend the existing preprocessing pipeline (ColumnTransformer) to incorporate new numerical and categorical indoor features, ensuring seamless integration.
   * Deploy the adapted model within an edge‑computing framework to enable real‑time inference on embedded devices, satisfying latency requirements for indoor alerts.

**A2. Rationale for Modifications**

* **Additional Indoor Variables:** CO₂, VOC, and PM levels directly influence occupant health indoors; omitting them would reduce predictive accuracy in the indoor context.
* **Room‑Volume Normalization:** Without normalization, sensor readings from small vs. large rooms would be non‑comparable, leading to biased predictions.
* **Ventilation Features:** Air changes per hour drive pollutant removal; including them enhances the model’s ability to forecast risk events tied to HVAC performance.
* **Transfer Learning:** Fine‑tuning the pre‑trained GBM leverages existing learned relationships (e.g., temperature‑risk link) while accommodating indoor‑specific distributions, reducing data requirements and convergence time.
* **Edge Deployment:** Real‑time indoor monitoring demands low latency; edge computing supports quick alerts without constant cloud connectivity, improving reliability in off‑network scenarios.

**A3. Potential Impact of the Adapted Solution**

1. **Scalability:** The modular pipeline and transfer‑learning approach allow rapid rollout across multiple rooms or buildings, with new sensor data pipelines added via configuration rather than code changes.
2. **Integration:** The adapted model can be embedded into existing Building Management Systems (BMS) via RESTful APIs, facilitating centralized dashboarding and control.
3. **Performance:** By fine‑tuning on indoor data and normalizing by room volume, prediction error (RMSE/MAE) is expected to remain within ±0.10 risk units, supporting reliable real‑time alerts.
4. **Regulatory Compliance:** Incorporates ASHRAE Standard 62.1‑2019 guidelines for indoor air quality (ventilation requirements) and GDPR‑compliant occupancy data handling, ensuring legal and safety adherence.