Machine Learning-Based Prediction of Circadian Lighting Exposure: A Practical Framework for Nursing Homes

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Abstract. Healthcare facilities face a critical challenge: elderly residents and patients with dementia experience heightened vulnerability to circadian disruption, yet practical methods to assess and optimize circadian light exposure remain limited by equipment costs, technical expertise requirements, and occupant compliance barriers. This paper presents a machine learning framework that predicts circadian stimulus (CS) exposure from readily observable environmental and behavioral parameters distance to window, blind angle, body position, and viewing direction without requiring wearable sensors or specialized measurement equipment. Developed using 512 spectral measurements from a nursing home environment over 13 weeks, ensemble models achieved test R^2 values of 0.83 (Horizontal CS) and 0.78 (Vertical CS), demonstrating sufficient accuracy for environmental decision-making. This work directly addresses the practical barriers limiting circadian-aware care in healthcare facilities, providing a deployable tool accessible to facility staff without specialized training or capital investment, thereby supporting environmental optimization for vulnerable populations.

Keywords. circadian lighting, healthcare environments, machine learning, occupant behavior modeling, environmental intervention

1 Introduction and Literature

1.1 Circadian Photobiology: From Discovery to Clinical Application

The human circadian system, a sophisticated biological mechanism governed by the suprachiasmatic nucleus (SCN) in the hypothalamus, regulates sleep-wake cycles, hormone secretion, body temperature, and cognitive performance [1]. For centuries, light was understood exclusively through its visual function. The landmark discovery of intrinsically photosensitive retinal ganglion cells (ipRGCs) containing the photopigment melanopsin fundamentally transformed our understanding of how light influences circadian physiology [2]. These specialized photoreceptors, maximally sensitive to short-wavelength blue light around 480 nm, mediate non-visual light responses including circadian phase shifting, melatonin suppression, and alertness modulation [3][4]. Critically, ipRGCs transmit photic information directly to the SCN, bypassing the visual cortex entirely and operating independently of conscious vision [2].

To quantify circadian light's effects, standardized metrics have been developed. The Commission Internationale de l'Éclairage (CIE) S026 system defines melanopic equivalent daylight illuminance (mEDI), weighting spectral irradiance according to melanopic action spectra [5]. The Circadian Stimulus (CS) model, developed by Rea and colleagues, provides a dose-response relationship incorporating spectral content, intensity, duration, and prior light exposure history, expressed on a normalized 0-1 scale [6][7]. Recent international recommendations suggest minimum daytime exposures of approximately 250 melanopic lux for adequate circadian entrainment [5][8], though individual variability remains substantial. These metrics have been extensively validated in relevant settings [6][7].

1.2 Healthcare Vulnerability and Evidence for Circadian Lighting Interventions

Healthcare populations exhibit vulnerability to circadian disruption due to multiple converging factors. Elderly individuals experience age-related changes in the visual system including reduced pupillary diameter and increased lens opacity, resulting in approximately 50% reduction in retinal light transmission compared to younger adults [9]. Individuals with Alzheimer's disease and related dementias demonstrate additional circadian system deterioration, including suprachiasmatic nucleus degeneration and altered melanopsin expression [10].
Research has consistently demonstrated that inappropriate lighting in healthcare facilities contributes to sleep disturbances, increased agitation, depressive symptoms, and cognitive decline among patients [11][12][13]. Conversely, numerous intervention studies have documented benefits of enhanced and appropriately timed light exposure. A landmark randomized controlled trial by Emad et al. (2024) found that bright light and melatonin interventions significantly improved cognitive and noncognitive function in elderly residents of group care facilities [14]. Figueiro et al. (2020) demonstrated that long-term exposure to circadian-effective lighting improved sleep efficiency, mood, and behavior in persons with dementia living in long-term care facilities [15]. Meta-analytic evidence confirms light therapy significantly improves circadian activity rhythm

parameters and nighttime sleep in individuals with dementia [16]. However, many healthcare facilities provide insufficient daytime light exposure measurements in nursing homes frequently reveal illuminance values below recommended levels [17][18]. Architectural constraints compound this challenge: limited window access, orientation restrictions, and interior layouts that place occupied spaces distant from daylight sources fundamentally limit available light resources [19].

1.3 The Complexity of Human-Lighting Interaction

The circadian effectiveness of lighting in any given space depends not solely on architectural light sources, but on the complex interplay between building design, light spectral characteristics, and human behavior. Research by Lahmar et al. (2018) demonstrates that room surface reflectance exerts dominant influence on corneal illuminance [20]. Window design parameters including window-to-wall ratio, glazing visible transmittance, and spectral characteristics significantly impact light delivery [21]. Natural daylight exhibits continuous variation in spectral power distribution, intensity, and incident angle throughout the day and across seasons (Rockcastle & Andersen, 2014) [22]. This temporal dynamism, absent in most electric lighting installations, provides critical circadian signals that artificial lighting systems struggle to replicate [23].
Human occupants are not passive recipients of light but active agents whose movements, postural changes, viewing directions, and spatial preferences dramatically influence actual light exposure [24]. An individual's position within a room, their orientation relative to windows, and even subtle changes in head position can result in substantial variations in corneal illuminance [25]. Traditional lighting calculations based on horizontal workplane illuminance poorly predict vertical illuminance at the eye, particularly in daylit environments where direct sun penetration and view direction become critical [26]. Age-related changes in ocular media transmittance, variations in circadian phase preference (chronotype), prior light exposure history, and individual sensitivity to light all contribute to heterogeneity in circadian light requirements [27][28].

1.4 Current Assessment Barriers and Implementation Gap

Traditional lighting simulation tools, while valuable for predicting illuminance distributions, cannot efficiently model the full complexity of dynamic human-lighting interactions across extended time periods and diverse behavioral scenarios [29]. This limitation represents a critical barrier to evidence-based circadian lighting design in healthcare facilities.

Current assessment methods for circadian light exposure face three specific practical barriers in nursing home settings: (1) Wearable Sensors face compliance challenges with cognitively impaired residents, require ongoing investment and replacement, and cannot be reliably worn throughout the day; (2) Spectrophotometric Equipment is large, expensive, requires technical expertise to operate and interpret, and captures only point-in-time measurements that may not reflect typical resident light exposure; and (3) Computational Simulations demand detailed architectural data, significant computing resources, and struggle to incorporate dynamic factors like blind adjustments and resident positioning changes throughout the day. This gap between theoretical understanding and practical implementation necessitates alternative approaches accessible to facility staff without specialized training or capital investment.

1.5 Machine Learning for Building Performance Assessment

Machine learning techniques have demonstrated substantial potential for accelerating building performance assessment during design and operational phases, providing rapid predictions that would otherwise require computationally expensive simulation [30]. Random forest regression, an ensemble method combining multiple decision trees with bootstrap aggregation, has shown effectiveness for predicting daylight metrics from architectural parameters [31]. The method exhibits robustness to overfitting, handles mixed categorical and continuous variables effectively, and provides inherent feature importance rankings. Gradient boosting machines and their variants have achieved state-of-the-art performance in numerous building performance prediction tasks [32]. Interpretability remains a critical consideration for machine learning applications in building design, with techniques such as SHAP (SHapley Additive exPlanations) providing model-agnostic attributions grounded in game theory [33].

1.6 Research Question and Paradigm Shift

This research addresses a fundamental paradigm shift: Can circadian stimulus exposure be accurately predicted from remote observation of human-lighting behavioral interactions alone, without specialized measurement equipment? This question reflects a shift from direct measurement (requiring devices at the point of light reception) to predictive inference (using observable environmental and behavioral proxies).

https://doi.org/10.1051/e3sconf/202671605042

The appeal of this behavior-based approach is threefold: (1) minimal equipment (measuring tape, visual observation only), (2) integration with existing workflows (documentation during standard care rounds), and (3) scalability (no per-resident device costs or compliance challenges). Viability depends on whether the relationship between observable environmental-behavioral factors and CS metrics is sufficiently predictable to achieve accuracy suitable for environmental decision-making (typically $R^2 \geq 0.70$).

2. Methods

2.1 Study Setting and Data Collection

Field-based data collection occurred in a skilled nursing facility featuring multi-directional windows with adjustable horizontal blinds, typical room depths of 12–18 feet, and standard ceiling lighting. Spectral measurements were conducted using a Konica Minolta CL-500A illuminance spectrophotometer (360–780 nm, 1-nm intervals) at 15-minute intervals throughout daylight hours (9:00 AM–3:00 PM), at locations corresponding to typical resident positions within shared spaces and individual rooms (Figure 1). Concurrent documentation recorded: resident body position (lying, sitting, standing), viewing direction (facing window, perpendicular, or away from window), proximity to nearest window (feet), blind angle setting (categorical: 45°, 90°, 135°, or 180° fully open), and window orientation (N/S/E/W). Over a 13-week period, 512 valid spectral data points were acquired, with observations containing missing or unreliable readings excluded.

Fig. 1. Spectral data collection setup with CL500-A spectrophotometer in the nursing home location of the study.

2.2 Circadian Stimulus Quantification

Circadian stimulus (CS) was calculated from spectral power distribution data using the Circadian Stimulus model, which provides a dose-response relationship on a 0–1 scale (0 = minimal circadian activation, 1 = saturation). CS was selected over alternative metrics because: (a) the 0–1 scale provides intuitive interpretation for non-specialist staff; (b) CS incorporates saturation effects at high light levels; (c) CS has been extensively validated in relevant settings; (d) CS can be modeled from observable parameters without specialized spectrophotometers; and (e) CS emphasizes spectral characteristics relevant to architectural interventions.

2.3 Machine Learning Model Development

Two complementary ensemble models were trained on the nursing home dataset split 85%/15% into training and test sets using Random Forest and Gradient Boosting algorithms [31][32]. Random Forest and Gradient Boosting were selected over black-box neural networks to enable transparent, explainable predictions suitable for healthcare stakeholder decision-making. Feature importance was quantified using SHAP values, providing game-theory-grounded attribution analysis [33].

3. Results

3.1 Model Performance

Both models demonstrated strong predictive capability on the nursing home dataset. The Horizontal CS model achieved test $R^2 = 0.83$ (RMSE = 0.04, MAE = 0.03) with training $R^2 = 0.92$. The Vertical CS model achieved test $R^2 = 0.78$ (RMSE = 0.10, MAE = 0.06) with training $R^2 = 0.89$. Five-fold cross-validation confirmed comparable performance across data partitions. Residual distributions show symmetric error patterns with minimal systematic bias (Table 1).

Table 1. Model performance and comparison

Model	Dataset	R^2	RMSE	MAE	Notes
Horizontal CS	Training	0.92	0.04	0.03	Strong fit with low error
Horizontal CS	Test	0.83	0.04	0.03	High predictive accuracy
Vertical CS	Training	0.89	0.10	0.06	Strong fit with moderate error
Vertical CS	Test	0.78	0.10	0.06	Good predictive accuracy
Both models	Cross-valid	—	—	—	5-fold CV showed comparable performance across

Model	Dataset	R^2	RMSE	MAE	Notes
					folds; residuals were symmetric with minimal bias

3.2 Feature Importance and Environmental Factors

SHAP-based feature importance analysis reveals that distance to window emerges as the dominant predictor in both models. At 0–5 feet proximity, mean Horizontal CS = 0.65 and Vertical CS = 0.57; at 15+ feet, both metrics dropped below 0.40. Blind angle settings significantly affected stimulus; fully open blinds (180°) yielded mean Horizontal CS = 0.623 versus 0.384 for half-closed positions a 62% improvement. Hour of day substantially influenced Vertical CS predictions (reflecting solar elevation angle variations) but showed negligible impact on Horizontal CS. Room depth demonstrated non-significant importance, with test R^2 unchanged whether included or excluded ($p = 0.73$). This null finding indicates that window proximity overwhelms room geometry effects in typical nursing home configurations (12–18 feet), simplifying deployment by eliminating the need for detailed architectural measurements (Table 2).

Table 2. Feature importance

Feature	Horizontal CS Impact	Vertical CS Impact	Key Finding
Distance to window	Dominant predictor	Dominant predictor	0–5 ft: mean H-CS = 0.65, V-CS = 0.57; 15+ ft: both <0.40 google
Blind angle	Strong effect	Strong effect	180° (fully open): H-CS = 0.623 vs. 90°: H-CS = 0.384 (62% improvement)
Hour of day	Negligible	Substantial	Reflects solar elevation angle variations for vertical exposure
Room depth	Non-significant	Non-significant	Test R^2 unchanged when excluded ($p = 0.73$); window proximity dominates in 12–18 ft rooms

4. Discussion

4.1 Interpretation and Comparison with Prior Literature

This work directly addresses practical barriers to circadian-aware care. Unlike wearable devices, models utilize observable environmental parameters documented during routine care rounds. Unlike spectrophotometric equipment, predictions require only basic measurements (distance, blind angle) achievable with a measuring tape and visual observation, eliminating capital costs and expertise barriers. Unlike computational simulations, empirically validated models capture dynamic positioning and mobility constraints inherent to nursing home populations, executing predictions in seconds on standard devices.

Test R^2 values of 0.74–0.85 demonstrate that readily observable parameters contain sufficient information to predict both Horizontal and Vertical CS with accuracy suitable for environmental decision-making. The null effect of room depth has practical deployment implications: facilities need not measure room dimensions. Window proximity alone sufficiently captures spatial light attenuation, dramatically simplifying data collection protocols. This finding aligns with research showing that window proximity dominates architectural effects in moderate-sized rooms.

Findings reinforce evidence that access to daylight and control over circadian light exposure correlates with better sleep, mood, behavioral outcomes, and cognitive function in institutionalized older adults.

4.2 Limitations and Future Work

Generalizability assumptions include: (1) relationships learned from training data transfer to operational settings; (2) seasonal effects are limited; (3) facility-specific architectural features may introduce variation. Facilities should implement pilot testing with resident subsets and validate projected improvements against measured CS outcomes before facility-wide rollout. Future research should expand validation across multiple facilities, capture seasonal variations, evaluate long-term health outcomes correlated with CS improvements, and integrate predictions into electronic health record systems.

5. Conclusion

This work demonstrates that machine learning models can reliably predict circadian stimulus exposure from observable environmental and behavioral parameters, enabling practical circadian-aware care in nursing homes without specialized equipment or technical expertise. By translating complex building performance relationships into accessible, deployable tools, this framework supports environmental optimization for vulnerable populations, achieving measurable improvements in circadian light exposure through staged, facility-feasible interventions. The combination of scientific rigor and practical accessibility creates a pathway for meaningful health improvements in healthcare facilities.

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Author Contributions

S.B. led field measurements, machine learning model development, primary manuscript authorship, and conference adaptation. J.W. supervised research, provided methodological guidance, and contributed substantially to manuscript revision.

Conflict of Interest

The authors declare no competing financial interests or personal relationships influencing this work.

Data Availability

Raw spectral data (512 measurements) and model training datasets are available in supplementary materials upon request from the corresponding author.