Evaluating the use of photobiology-driven alertness and health measures for circadian lighting design

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Abstract

We compare a new, novel lighting design workflow based on human photobiology with existing metrics for non-visual lighting design. There are a variety of light simulation methods and a lineage of circadian system biological models, but they are not connected into a cohesive workflow. We applied this novel workflow to two design variables: window spectral transmittance and surface reflectance. This article reviews and compares existing frameworks of circadian design to our novel workflow in terms of material spectrum sensitivity and the resulting evaluation of architecture in terms of circadian health. Our results highlight how architectural design can directly impact an occupant's circadian health. Our comparative analyses demonstrates how direct photobiology-driven alertness and health metrics differ from previous circadian design metrics.

Key Innovations

- Novel workflow based upon light's impact on human photobiology-driven alertness and health.
- Relationships and visual comparisons between various light simulation methods and design variables
- Relationship between circadian health metrics and design variables

Practical Implication

Lighting simulation methods need to be validated as there are discrepancies in their treatment of the spectral qualities of materials. Circadian design metrics should consider the direct biological symptoms of the circadian system.

Introduction

The non-visual effects of light are mediated by intrinsically photosensitive retinal ganglion cells (ipRGCs) (Provencio et al., 2000) which have a different spectral sensitivity curve than the visual system. Currently, designers cannot capture the multidimensional contributions of light to instantaneous and daily physiological symptoms which are sensitive to the illuminance, history of light exposure, timing, spectrum, and homeostatic body rhythms in a single workflow.

Previous work to develop a framework tends to utilize an illuminance threshold-based approach. Amundadottir et al.'s (2017) threshold was determined based on 824 lx of CIE D65 equivalent illuminance for 5 hours. Konis (2019) used 200 equivalent melanopic lux (EML) as the threshold to adhere to the WELL requirements at the time of his paper. The limitation of the simplified threshold approach is that it undervalues the timing of light exposure. Light can problematically delay melatonin onset or supress melatonin production, and light will have a greater advancing effect early in the morning rather than close to noon. Existing frameworks for evaluating building lighting design translate physical light measurements, irradiance or illuminance, to circadian equivalent values based on the sensitivity of ipRGCs. However, the non-visual system has many physiological effects that independently respond to light. A single circadian equivalent value (i.e., EML) does not capture the effect light has on people.

Although daylighting outperforms artificial light in circadian efficacy (Pechacek et al, 2008), the ability to incorporate electric lighting into an evaluative model is important because most buildings have electric lighting. Electric lighting can be beneficial when daylight is not sufficient, and it can be harmful when light stimulus is provided at biologically disruptive times. All published architectural circadian lighting design models are based upon daylighting; therefore, they do not capture the negative effects of electric lighting at night (Pechacek et al., 2008; Amundadottir et al., 2017; Konis, 2019; Danell et al., 2020). This is a continued limitation to most threshold-based evaluation criteria that do not consider time of light exposure (Anderson et al., 2012; Mardaljevic et al., 2013).

Anderson et al. (2012) and Mardaljevic et al. (2013) used a threshold but divided the day into three distinct periods to accommodate changing biological effects depending on exposure time: "circadian resetting" from 6:00-10:00, "alerting" from 10:00-18:00, and "light avoidance" from 18:00-6:00. Thresholds were illuminance values that changed depending on the spectral power distribution of the light source derived from Cajochen et al. (2000) and Phipps-Nelson et al. (2003). The work of Anderson et al. (2012) also included a novel visualization technique to summarize circadian potential (CP) for each period of the day. CP is the percentage of time one viewpoint experiences levels above a threshold in a year. This annual approach is one of two main strategies to summarize the biological effects of light. However, it is limited to spectrally neutral spaces and is not spectrally accurate.

Pechacek et al. (2008), Mardaljevic et al. (2013), Konis (2017), and Konis (2019) adopt an annual strategy. Konis's (2019) annual model calculates EML from daylight illuminance with a conversion limited to three colour channels simulated using Lark (Inanici et al., 2015).

Kryzsztof (2006), Geisler-Moroder and Dür (2010), Inanici (2015), Amundadottir et al. (2017), and ALFA (Solemma, 2020) estimate circadian values from point-in-time simulations. These studies provide detailed information including spectral information for a single viewpoint but are difficult to visualize for daily or annual outcomes. ALFA and Inancici et al.'s (2015), point-in-time simulations expanded the number of colour channels to 81-channels and 9-channels respectively.

Based on the results from experiments under tested light conditions, several frameworks in the medical field have been developed to predict alertness, sleepiness, performance, the amount of circadian phase shift per day, the time of peak melatonin concentration, and the percent of total melatonin suppression per day due to acute light exposure (Abeysuriya et al., 2018; Postnova, 2018; Tekieh et al., 2020). These frameworks assume a time-varying input of melanopic irradiance, and they describe biological rhythms and timing, but do not describe a workflow from simulating melanopic irradiance in a space to visualizing circadian system outputs in a design process.

The aim of this paper is to compare a new, novel lighting design workflow based on human photobiology with existing metrics for non-visual lighting design. This comparative analysis will showcase how predicting alertness and health measures differs from previous work and impacts the evaluation of architecture. The novel method, being published in a separate submission to the conference (Jakubiec and Alight, 2021), works by translating timeseries spectrally resolved light simulation data into photobiologically driven measures mediated by the response of ipRGCs in the human eye. These measures are used as input to a dynamic photobiological framework that accounts for light history, timing, spectrum, and homeostatic body rhythms. To demonstrate the utility of this process, the predicted non-visual biological effects (Abeysuriya et al., 2018; Postnova et al., 2018; Tekieh, 2020) of two design variables (window spectral transmittance and surface reflectance) are simulated. To the best of our knowledge, the novel workflow in this comparative analysis is the only one that predicts explicit biological effects of light and spectrum over time in daylit architectural spaces rather than circadian light potential. To illustrate the difference between the novel method and existing circadian design metrics, the design variables are also applied to the frameworks suggested by Mardaljevic et al. (2013), Amundadottir et al. (2017), and Konis' (2019) Circadian Design Assist Tool (CDAT). We were interested in comparing how these models respond to variations in spectrum and light exposure and how they differ in the resulting evaluation of architectural design.

Methods

A ward based on the Ng Teng Fong hospital in Singapore (HOK) was constructed in the Rhinoceros 3D modelling software. Ng Teng Fong has a floor plan shape and window orientation which aims to provide each bed with more daylight (Figure 3). The range of materials used for simulations are detailed in Table 1 in terms of their visible and ipRGC-related (or melanopic, named for the ipRGC photopigment) reflectance. The wall, ceiling, and floor materials were chosen to have similar visual reflectance, but different melanopic/photopic (M/P) ratios.

For spectral glazing material data, a similar process was employed. Transmittance data was selected with similar visible transmittance levels but different M/P ratios using the LBNL Optics software tool (Lawrence Berkeley National Laboratory, 2019). The material and glazing properties and spectral plots are detailed in Table 1, Figure 1, and Figure 2.

Table 1: Materials and Glazing Details.

Material	Visible Reflectance	Melanopic Reflectance	M/P
High M/P			
Wall	49.68	68.51	1.38
Ceiling	71.23	78.06	1.10
Floor	14.71	21.46	1.46
Neutral M/P			
Wall	51.49	51.92	1.01
Ceiling	71.01	68.06	0.97
Floor	15.76	15.27	0.97
Low M/P			
Wall	51.99	27.34	0.53
Ceiling	71.20	50.33	0.71
Floor	15.79	9.49	0.60
Glazing 5 mm VFloat Clear w/	**Visible Transmittance**	**Melanopic Transmittance**	**M/P**
6mm Arctic Blue	44.2	52.9	1.20
4mm Filtrasol	45.4	46.0	1.01
6mm Optifloat Bronze	41.2	35.9	0.87

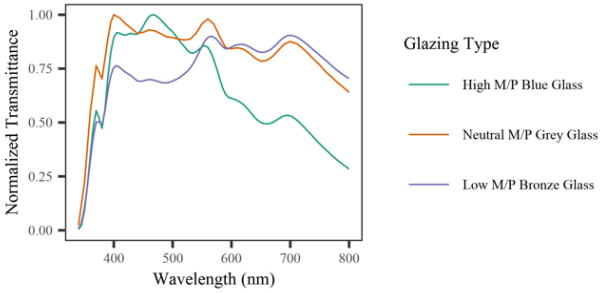

Figure 1: Glazing spectral Power Distribution (SPD).

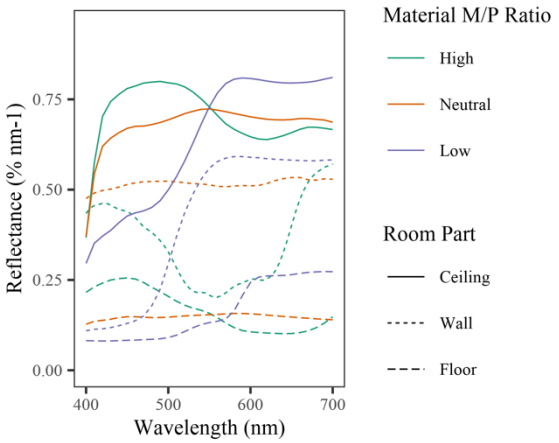

Figure 2: Material Spectral Power Distribution (SPD).

In total, 9 hospital models (three material pallets, and three types of glazing) were simulated. All simulations are performed in the Toronto, Canada climate with no exterior obstructions. The windows face East. Twelve occupant locations, at the head of each bed, are simulated for each method. As seen in Figure 3, eight view directions are simulated for each location.

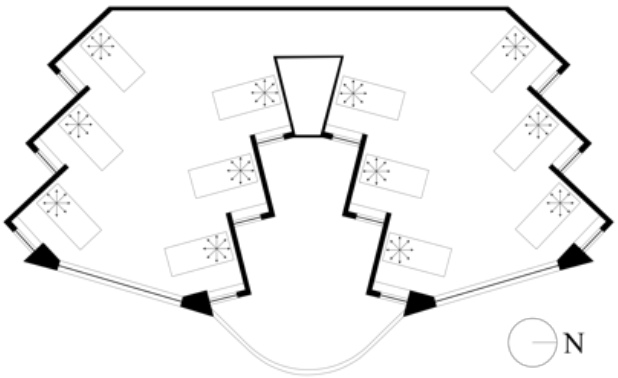

Figure 3: Floor plan of Ng Teng Fong Hospital Ward with occupant locations and view directions.

Light Simulation

Light calculations are performed in ALFA, Lark (Inanici et al., 2015, Inanici, 2015), and using the methods proposed by Konis (2019) and Mardaljevic et al. (2013). All the methods use the spectral sensitivity curve recommended by Lucas et al. (2014), which is used to evaluate melanopic or ipRGC illuminances.

EML was used to compare the existing methods because they are all currently based on EML, although ALFA and Lark will report spectral irradiances at 81- or 9-bands respectively. Melanopic irradiance (CIE S 026, 2018) is input for the novel method with biological modelling from Postnova (2018) and Tekieh (2020), derived from ALFA's calculations. To avoid ipRGC saturation in a well-daylit space and to elucidate how the circadian health evaluations change with material variables, we halved the simulated irradiance for all calculations in this paper.

The ALFA tool determines sky spectra based on physical atmospheric processes calculated using libRadtran (Mayer and Kylling, 2005). A sampling and interpolation strategy derived from the Lightsolve framework and the associated solar positions for Toronto (Anderson et al., 2008; Kliendienst et al, 2008), determined the instantaneous simulation times. As detailed in Table 2, we ran 21 instantaneous simulations, seven simulations a day for both solstices and the spring equinox using a clear sky condition.

For Lark, sky colour was determined based on Inanici et al. (2015) as before 9am and after 6pm 25000 K CCT, between 9am to 6pm we interpolated between 8000 K and 6500 K (D65) with noon being 6500 K. The Excel Daylight Series Calculator (Munsell Color Science Laboratory, 2002) was used to generate the daylight spectral data from the sky Correlated Color Temperature (CCT). The same sampling and interpolation strategy that was used for ALFA was used to determine 21 instantaneous simulations times for Lark and is recorded in Table 2 as well. Furthermore, the Lark simulations were run using four ambient bounces.

The sky colour for the CDAT (Konis, 2019) was chosen based on sky condition: 25000K for 0% cloud cover, 7000K for 10-50% cloud cover, and 5000K for 60-100% cloud cover. Because the CDAT (Konis, 2019) uses the standard climate files, we chose the clearest sky within 7 days of the Lightsolve solar positions used for Lark and ALFA. These dates and times are in Table 2. We ran the CDAT simulations using four ambient bounces as well.

Mardaljevic et al. (2013) converts sunlight into the D55 'circadian-equivalent' illuminance depending on the sky condition from clear (D75) to overcast (D65). Like the CDAT, we chose the clearest sky within 7 days of the Lightsolve solar positions used for Lark and ALFA from the standard climate files. Simulation times are detailed in Table 2.

Table 2: Simulation Times.

Lark and ALFA			CDAT and Mardaljevic et al. (2013)		
Month	Day	Hour	Month	Day	Hour
3	9	7.6	3	15	8
3	9	9.2	3	15	9
3	9	10.9	3	15	11
3	9	12.5	3	15	13
3	9	14.1	3	15	14
3	9	15.7	3	15	16
3	9	17.3	3	15	17
6	7	5.8	6	9	6
6	7	8.0	6	9	8
6	7	10.1	6	9	10
6	7	12.3	6	9	12
6	7	14.4	6	9	14
6	7	16.6	6	9	17
6	7	18.8	6	9	19
12	7	8.4	12	8	8
12	7	9.6	12	8	10
12	7	10.9	12	8	11
12	7	12.2	12	8	12
12	7	13.4	12	8	13
12	7	14.7	12	8	15
12	7	16	12	8	16

To directly compare the sensitivity of lighting simulation results to design changes, Spearman rank-order correlations were calculated to determine the relationship between simulated M/P and our two design variables (material M/P reflectance and glazing M/P transmittance) for each method: Mardaljevic et al., 2014, the CDAT (Konis, 2019), Lark (Inanici et al., 2015), and ALFA. The material M/P reflectance and glazing M/P transmittance was ordered from low M/P ratio to high M/P ratio. Further Spearman rank-order correlation coefficients were calculated to explore the relationship of the difference between melanopic and photopic (M-P) and our two design variables.

Circadian Health Evaluation

Using the outputs from the light simulation methods, we followed the model by Amundadottir et al. (2017) which calculates "non-visual health potential" using the "non-visual direct-response (nvRD) model", Mardaljevic et al. (2013) which predicts potential for a "non-visual effect" (N-VE), and Konis (2019) which indicates the extent to which the WELL standard (2018) is met by daylight called the circadian frequency (CF). Post-processing of simulation data determined how these building evaluations relate to Abeysuriva et al. (2018), Postnova et al., (2018) and Tekieh's (2020) predicted total melatonin suppression, mean alertness, and phase shift after two days in the simulated space. The modelling from Tekieh (2020) is an evolution from Abeysuriya et al. (2018) and Postnova et al. (2018) with 4100 K CCT illuminance converted to melanopic irradiance, instantaneous alerting for KSS, and refined melatonin dynamics. Each design variable (material M/P reflectance and glazing M/P transmittance) is also analyzed to see how the novel workflow responds to specific design changes and how design changes affect predicted alertness and health circadian measures. In our novel design method, the simulated human occupant is a young adult that is entrained to sleep from 24:00-6:00. Using Abeysuriva et al. (2018), Postnova et al., (2018) and Tekieh et al. (2020) modelling we simulated the non-visual effects of light on sleepiness, phase shifting, and percent melatonin suppression. These are converted to daily performance measures as detailed in another submission to the conference [redacted for review]. Subjective sleepiness is measured by the Karolinska Sleepiness Scale (KSS). KSS evaluates in a range from 1 (extremely alert) to 9 (extremely sleepy, fighting sleep). Phase shifting is compared using the change in time of peak melatonin secretion in hours. As mentioned in the introduction, the inability to simulate artificial electric light is a limitation of most circadian design models. Because all of the other models are daylight-only, we have constrained our model to only assess daylight impacts as well in this paper; however, our other paper submitted to this conference investigates the combined effects of electric lighting and daylighting [redacted for review]. Since our novel method and Amundadottir et al. (2017) are daily metrics we directly compared the relationship between the two. The relationship between predicted biological effects (Tekieh, 2020) and the raw nvRD score (Amundadottir et al., 2017) was explored using a Pearson correlation. We also analyzed the relationship between passing the Amundadottir et al. (2017) nvRD threshold (nvRD > 4.2) and the predicted biological effects with spearman rank correlations. Scores above the threshold were coded as 1 and those below were coded as 0. To explore the relationship between the annual circadian health metrics, we directly compare the CDAT's CF and Mardaljevic et al.'s (2013) N-VE for the "resetting", "alerting", and "avoidance" periods with Pearson correlations. Similar to our light simulation analysis, to compare the sensitivity of the circadian health metrics to our design changes we used spearman rank order correlations to determine the relationship between each method's health metric(s) ("resetting" N-VE, "alerting" N-VE, "avoidance" N-VE, CF, nvRD, subjective sleepiness, phase shift, and melatonin suppression) and our two design variables (material M/P reflectance and glazing M/P transmittance).

Results

Light Simulation

As presented in Table 3, the Mardaljevic et al. (2013) method there was no relationship between M/P illuminance ratio and any of the design variables (material M/P reflectance or glazing M/P transmittance). In Lark, CDAT, and ALFA there moderate ($r > 0.4$) to strong positive ($r > 0.8$) correlations between M/P and the design variables. ALFA had the strongest correlation between material M/P reflectance and M/P. Lark had the strongest correlation between glazing M/P transmittance and M/P. However, the differences between the correlation coefficients of Lark, CDAT, and ALFA were small. Figure 4 visualizes how the distribution of M/P illuminance ratio differs across material M/P reflectance and glazing M/P transmittance.

Table 3: Spearman's rank correlation coefficients of simulated M/P and design variables.

	Simulation Method			
	Mardaljevic et al. (2013)	Lark	CDAT	ALFA
Material M/P Reflectance	≈ 0	.70**	.66**	.74**
Glazing M/P Transmittance	≈ 0	.40**	.38**	.39**

** is significant at 0.01 level
* is significant at 0.05 level

Table 4: Spearman's rank correlation coefficients of simulated M-P with design variables.

	Simulation Method			
	Mardaljevic et al. (2013)	Lark	CDAT	ALFA
Material M/P Reflectance	-.06	.55**	.53**	.59**
Glazing M/P Transmittance	.02	.45**	.35**	.40**

** is significant at 0.01 level
* is significant at 0.05 level

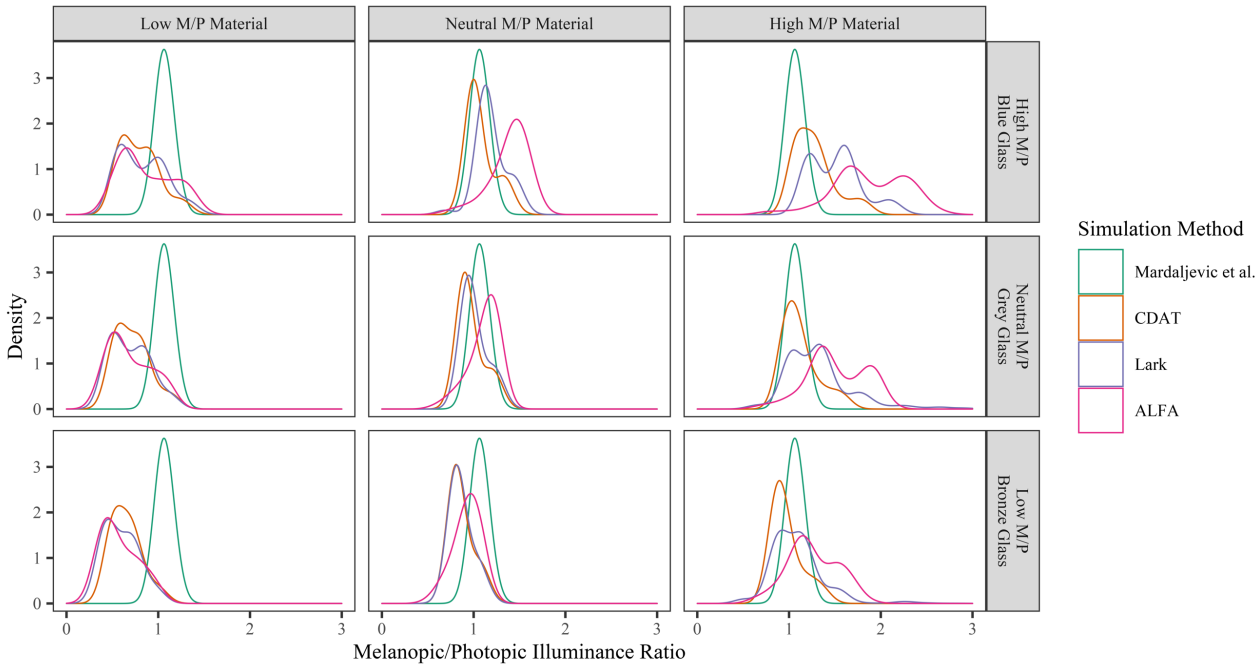

Figure 4: Distribution of Melanopic/Photopic (M/P) Illuminance Ratio for Light Simulation Methods.

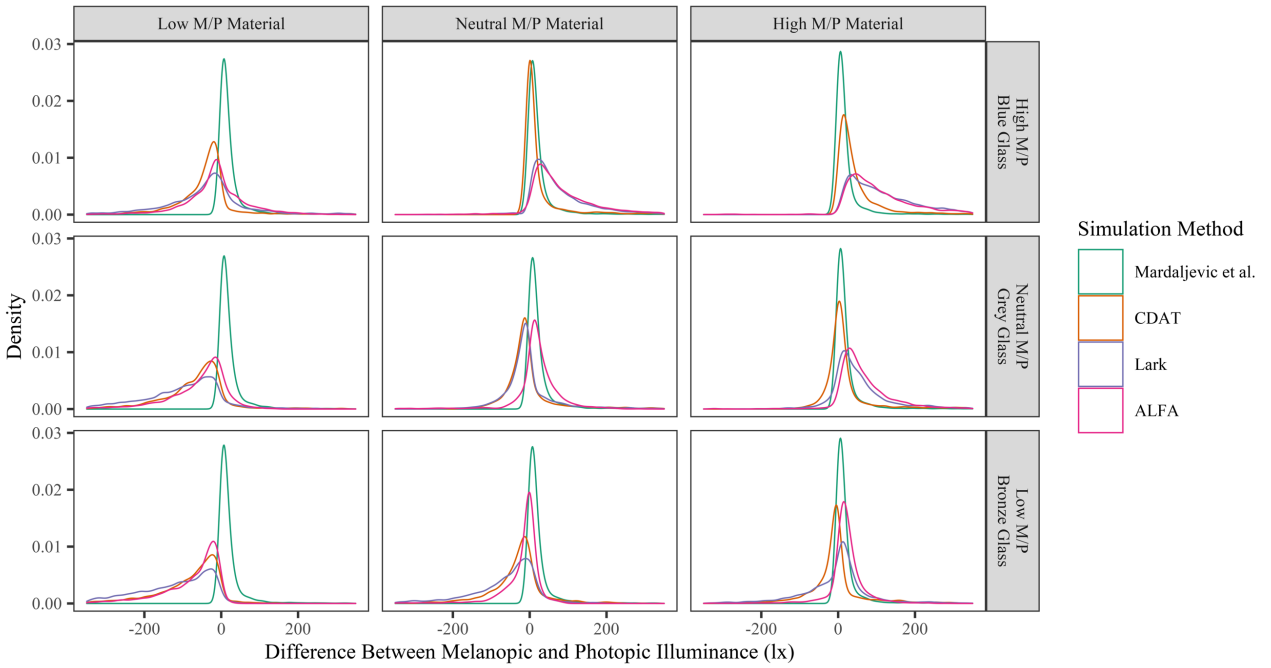

Figure 5: Distribution of the Difference Between Melanopic and Photopic Illuminance for Light Simulation Methods.

When exploring the relationship of the difference between melanopic and photopic lux (M-P) with the design variables in Table 4, glazing type or material type were not correlated with M-P in the Mardaljevic et al. (2013) method. In Lark, CDAT, and ALFA, M-P was moderately correlated to material and glazing type. Similar to M/P, material type was most strongly correlated with M-P in ALFA, while glazing type was most correlated and M-P in Lark. Again, the difference was small between Lark, CDAT, and ALFA. Figure 5 visualizes how the distribution of M-P differs across material M/P reflectance and glazing M/P transmittance.

Circadian Health Evaluation

Because we found nvRD to be the most correlated with the design factors we tested, we also compared it to the predicted non-visual effects from the novel workflow. As see in Table 5, nvRD were moderately to strongly ($0.4 < r < 0.76$) correlated with simulated phase shift, subjective sleepiness (KSS), and melatonin suppression. The strength of relationship also varies between the type of circadian response. The strongest relationship is between nvRD and the phase shift of peak melatonin. The weakest relationship is between nvRD and subjective sleepiness. Naturally, this relationship becomes weaker when nvRD

is condensed into a pass-fail metric (whether nvRD ≥ 4.2 or not). However, the relative strength of the relationship between circadian responses is similar with subjective sleepiness possessing the weakest relationship with nvRD as a pass-fail metric.

Table 5: Correlation of raw nvRD score (Pearson) and threshold nvRD (Spearman's rank order) with Tekieh et al (2020) circadian system responses.

	Phase Shift	Sleepiness (KSS)	Melatonin Suppression
nvRD (raw)	-0.76**	-0.88**	0.61**
nvRD (threshold)	-0.20**	-0.20**	0.13**

** is significant at 0.01 level
* is significant at 0.05 level

In terms of the relationship between circadian health design metrics and our design parameters (Table 6), N-VE scores for all periods were correlated with material M/P reflectance. However, the effect size of this relationship was not practical ($r < 0.2$). N-VE scores had no significant relationship with glazing M/P transmittance. CF were not significantly correlated with material type, and was positively correlation with glazing type but did not exhibit a practical effect. nvRD was positively correlated with material M/P reflectance and glazing M/P transmittance, with a slightly stronger relationship with glazing M/P transmittance than material M/P reflectance. The circadian symptoms (phase shift, sleepiness, and melatonin suppression) predicted using the novel workflow with Tekieh et al.'s (2020) biological model all had a positive correlation with material M/P reflectance and glazing M/P transmittance, although M/P material reflectance did not exhibit a practical effect (again, $r < 0.2$). Glazing type seemed to have a stronger relationship with the simulated symptoms than material type, but the effect size was barely practical. There was a small difference between the direct symptoms, but melatonin suppression had the weakest relationship with the design variables. Overall, nvRD score and the simulated symptoms had the strongest relationship with the design variables. Figure 6 displays box plots of the distribution for each circadian health metric with each design parameter setting.

Discussion and Conclusion

Compared to the other models, the M/P and M-P results of Mardaljevic et al. (2014) were less sensitive to design changes like material and glazing. We predict that this is the result of our methodology because we chose materials and glazing with similar visible reflectance or transmittance. The primary difference between the three material palettes and three glazing types was colour. Because the Mardaljevic et al. (2014) method does not weight by RGB channel, the M-P results were not affected, and M/P results were minimally affected by the colour of the architectural space. Mardaljevic et al. does show the increased circadian effects of more daylight based on unpublished data. As demonstrated here, ignoring the effects that interior surfaces and glazing may have on the spectral qualities of light can be a limitation,

Table 6: Spearman's rank correlation coefficients of circadian health metrics and design variables.

	"resetting" N-VE	"alerting" N-VE	"avoidance" N-VE	CF	nvRD	Phase Shift	Sleepiness (KSS)	Melatonin Suppression
Material M/P Reflectance	-0.09**	-0.09**	-0.09**	.06	.15**	-.14**	-.16**-	.08**
Glazing M/P Transmittance	.03	.03	.02	.12**	.21**	-.23**	-.23**	.17**

** is significant at 0.01 level
* is significant at 0.05 level

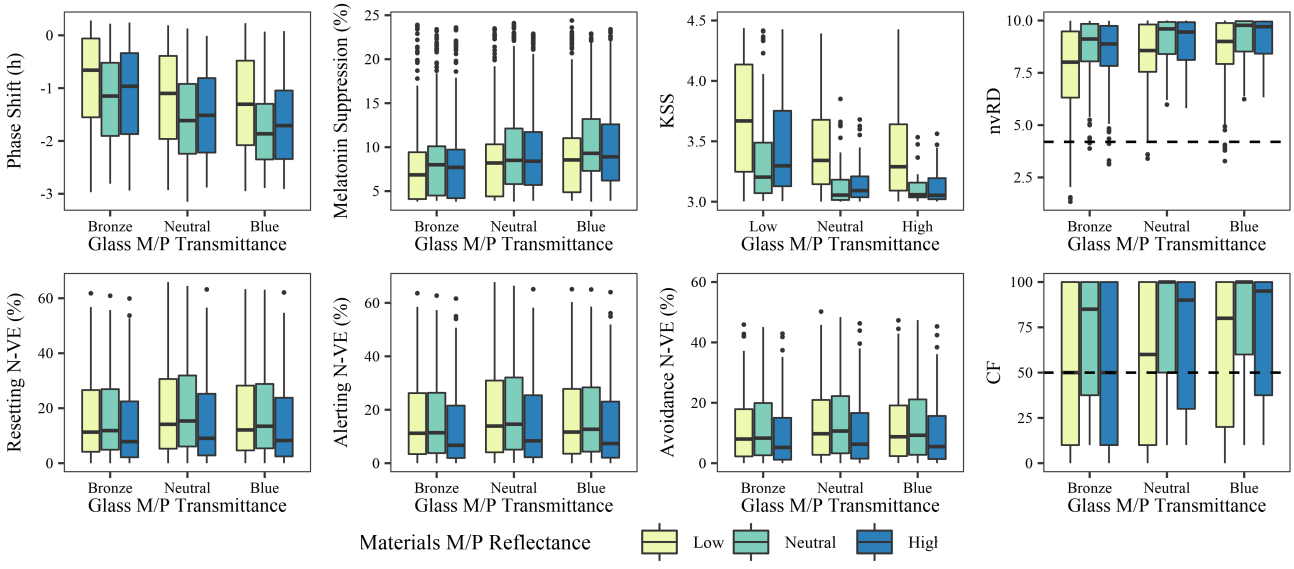

Figure 6: Distributions of Non-Image Forming Lighting Metrics.

especially when comparing between spaces with similar visible material reflectance and glazing transmittance. This limitation transferred to the N-VE response to material palette changes that resulted in no relationship or an extremely weak negative relationship with M/P material reflectance and transmittance.

ALFA, Lark, and CDAT simulations showed similar results in terms of sensitivity to material reflectance spectrum and glass transmittance spectrum. ALFA was the most sensitive to material palette changes, followed by Lark and then CDAT. The succession is in line with the number of colour channels utilized in each method: ALFA utilizes 81-colour channels, Lark is 9-colour channels, and CDAT uses the 3-colour channel version of Lark. Geisler-Moroder and Dür (2009) found that the brightness and colours simulated in spaces with many interreflections were more accurate and distinct when using a method with more colour channels. Thus, the small differences between ALFA, Lark, and CDAT may be because increasing the number of colour channels prevents colours from mixing with each interreflection. Another possible explanation may be due to the method's utilization of an ambient cache. Unlike the other methods, ALFA does not utilize an ambient cache so there is less interpolation between sensor points.

Further research should aim to validate the assumptions made in each method regarding sky colour against physical measurements. One factor that was difficult to control in our simulations was sky color spectrum as ALFA's is physics-based, Lark relies on user input, and CDAT and the Mardaljevic et al. (2013) method rely on sky classification methods.

In terms of translating simulated light into circadian health metrics, this study demonstrates how previous approaches may not capture lights effect on health metrics. This study found that phase shifting, subjective sleepiness, and melatonin suppression do not respond the same way to design changes. This concept is also demonstrated by the varying correlation strength between nvRD and simulated biological symptoms. These results are sensible because the circadian system is complex with many different symptoms that respond independently to light. A singular circadian health design metric like the nvRD or CF may not be appropriate. Because circadian symptoms differ in their response to light, quantifying the likelihood that a lighting design will have a circadian effect as a single metric cannot capture light's effect on the circadian system. This brings into question the practicality of metrics that determine the likelihood of a circadian response rather than each symptom of the NIF system. The relationship between NIF symptoms and nvRD became weaker when nvRD was condensed into a pass-fail metric.

Due to the circadian system's sensitivity to timing, categorizing the day into distinct periods may be a step towards circadian health design metrics that relate to biological symptoms. For example, the "resetting" and "avoidance" N-VE periods may have a stronger effect on melatonin suppression because the "alerting" period is during a time when melatonin is already naturally low. Nevertheless, each circadian response has its own natural cycle so determining how each circadian response is being affecting in each period of Anderson et al (20120) and Mardaljevic et al. (2013) is still obscure. For example, strong light in the "resetting" period leads to a phase advance whereas strong light in the "avoidance" period may cause a phase delay. Thus, a designer may predict that the models in this study cause a phase advance because there are strong N-VEs in the "resetting" period. Our novel method corroborates this prediction and is able to specify the phase advance in hours over a week of exposure.

Simulating biological symptoms grants a more nuanced understanding of a building's effect on a human occupant's circadian system and may allow designers to make special considerations depending on the program of the project. For example, designers may want alertness for an office building or proper circadian entrainment in a long-term occupancy project.

A limitation to this study is the absence of electric lighting. Due to the timing of light exposure, artificial light at night may cause phase shifting that is greater than the results of this study which focused on daylighting only. The "avoidance" period is particularly important when considering modern-day artificial lighting. For example, in this study's purely daylit model, each distinct period is strongly and similarly correlated with single period metrics like the CDAT's CF (Konis, 2019) and both methods offer similar information. However, strong nighttime light may lead to a drastically larger "avoidance" N-VE. The CDAT would simplify nighttime light to a greater circadian response overall without specifying the negative impact of light at night. Further research should aim to explore how circadian design methods respond to simulating artificial light. Another limitation is the models were not validated against physical measurements in the real world. Thus, the models were discussed in relation to each other and their accuracy may only be discussed speculatively based on previous research. A future direction would be to validate the lighting and circadian health results using physical measurements from the real world.

Despite these limitations, the study highlights discrepancies between light simulation methods which are the foundation for simulating the circadian health of occupants. It also demonstrates the usefulness of utilizing circadian system models from medical research (Abeysuriya et al., 2018; Postnova et al., 2018; Tekieh et al., 2020) for a more refined and direct understanding of building design that promotes circadian health.

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