Towards a Framework for Light-Dosimetry Studies: Quantification Metrics

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Abstract

Light-dosimetry aims to measure personal light exposure with wearable sensors, which is a complex multi-step procedure. The resulting data may be used to investigate non-visual effects of light in real-life settings, to validate laboratory findings and answer questions pertaining to implications in applied contexts. However, personal light exposure patterns are usually complex and can be quantified in many ways. Various measurement and analysis methods have been applied across previous studies, complicating comparability and interpretation of results. To improve the quality and comparability of light-dosimetry research, a framework with consensus guidelines for light-dosimetry procedures is needed. To provide the groundwork towards such a framework, we reviewed previous light-dosimetry studies to identify considerations regarding measurement and data quantification. Here, we review metrics for quantifying light-dosimetry data in terms of the characteristics known to modulate non-visual responses. Overall, various metrics have been employed across studies, with several metrics for each characteristic. We provide a description of each metric, discuss their properties, and provide example calculations for the application to light-dosimetry data. Moreover, we propose considerations for data quantification and possible research strategies for future studies. To facilitate exploration and use of the identified metrics, corresponding functions are provided in an openly accessible R-package.

Keywords: Non-visual, Dosimetry, Lighting, Circadian, Field studies, Daylight, Quantification

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1 Introduction

Light has a profound impact on many aspects of human life. Beyond giving rise to vision, light affects diverse physiological and behavioural functions, either directly or mediated by the circadian system,[1,2] and is therefore considered to play an important role in general health and wellbeing.[3] Much of what is known about these so-called *non-visual* effects of light has been established by extensive laboratory research, indicating that physiological and behavioural responses are modulated by different characteristics defining light exposure patterns, that is, their spectral composition, level, duration, timing, temporal dynamics and prior history, [4] as further elucidated below. However, laboratory stimuli are far removed from the complex dynamic light exposure patterns encountered in real-life: personal light exposure patterns are chaotic and highly complex signals resulting from the interaction between the light provided in our immediate environment and our behaviour within this environment. By measuring personal light exposure with wearable light sensors (i.e., light-dosimetry) together with non-visual responses in real-life settings, findings from controlled laboratory studies can be evaluated and complemented, and may help to answer questions pertaining to the implications of the non-visual effects of light in applied contexts, such as architecture and lighting design, therapeutical applications, shiftwork, transcontinental travel, and personal lifestyle.[5,6] Furthermore, light-dosimetry may help researchers and lighting designers to validate whether a design or intervention is impacting the subjects' actual light exposure as intended, and to identify potential for interventions.

To date, a considerable amount of light-dosimetry research has already been published, with growing efforts and interest in recent years. With an increasing amount of research, it becomes more and more important that data is collected according to common standards and exploited with a shared toolset. Such standardized procedures may be defined in a consensus framework, which may improve the quality of the generated data and make data FAIR (findable, accessible, interoperable, and reusable).[7] Such a framework is particularly important for a procedure such as light-dosimetry, which consists of multiple steps from measurement to data analysis, with each step warranting careful consideration.[8] Broadly, these steps consist of (1) selecting optical quantities, (2) calibrating dosimeters, (3) selecting a measurement setup, (4) processing the measured data, (5) calculating light exposure metrics, and (6) linking metrics to measured responses. Importantly, differences in the execution of each step may lead to substantial differences in the results, complicating their interpretation and comparison across studies.

Since to date no consensus guidelines for the light-dosimetry process exist, we set out to lay the groundwork towards establishing a framework for light-dosimetry applicable to real-life settings. To this end, we reviewed previously published light-dosimetry studies regarding methods for light measurement and data quantification. Given the wide scope of the topic, we separated the review in two parts: in a previously published paper,[9] we identified methodological considerations and knowledge gaps for measuring and preparing personal light exposure data (steps 1–4 above), while in the present paper, we review metrics employed by previous studies to quantify personal light exposure data in the context of research on the non-visual effects of light (steps 5–6 above). Note that, although our previous review paper focussing on measurement methodology is not necessary for understanding the work presented here, we would like to emphasize that for the establishment of a consensus framework, the entire dosimetry process needs to be considered.

The aim of the present review is to provide an overview of existing metrics for the quantification of light-dosimetry data, to discuss their potential relevance for research applications, and to highlight knowledge gaps and

possible ways in which the metrics can be used and evaluated in future research, which could ultimately enable them to be integrated into a dosimetry framework. Due to the already wide scope of this review, we did not attempt to systematically evaluate the identified metrics regarding their relevance for research into non-visual effects of light, although this would be an interesting complementary review and evaluation to conduct in the future as a follow-up to this paper.

2 Background

Light is a complex multidimensional stimulus that has been shown to modulate physiological and behavioural responses in laboratory settings in a way that depends on a combination of properties, notably: its spectral composition, level, duration, timing, temporal dynamics, and prior history.[4] We therefore decided to structure the present review of light-dosimetry metrics according to these six specific light exposure characteristics (*cf.* Sections 4.1 to 4.6). In the following two sections, we will briefly discuss these characteristics and associated findings that are relevant to the objectives of this review.

2.1 Light exposure characteristics modulating non-visual responses

2.1.1 Spectral composition

Non-visual responses have been shown to be modulated by input from all known retinal photoreceptor types.[10,11] However, this modulation seems to be dependent on the strength and temporal dynamics of the light stimulus as further discussed below. At longer timeframes and higher stimulus levels, as found in many real-world settings, evidence suggests that the spectral sensitivity of non-visual responses matches that of melanopsin (i.e., greatest sensitivity to short-wavelength light peaking at 480 nm).[12,13] Nevertheless, light exposure relative to all photoreceptors should be considered until the underlying mechanisms are better understood.[14]

2.1.2 Level, duration, and temporal dynamics

Many non-visual responses (e.g., melatonin suppression,[13,15] circadian phase shifting,[15,16] and alertness during nighttime[17]) have been related to stimulus level (e.g., corneal irradiance) and exposure duration in a dose-dependent manner (where dose is stimulus level multiplied by duration), with stronger responses for higher doses, following a sigmoidal function.

These dose-response relationships are strongly dependent on the duration of the light stimulus and its temporal pattern in a *non-linear* manner.[4] In particular, the effectiveness of a light stimulus at a given level decreases for longer stimulus durations.[18] Different non-visual responses (e.g., phase resetting, melatonin suppression, alertness) appear to have different temporal dynamics and duration-response functions.[19] Moreover, the spectral sensitivity of responses may change over time, with cone contributions diminishing after longer exposures and at higher light levels.[10] For example, during a 12h exposure to typical office lighting conditions, melatonin suppression is dominated by melanopsin.[20]

The findings for long-duration continuous stimuli are in line with the temporal dynamics of intrinsically photoreceptive ganglion cells (ipRGCs), integrating photic information over time.[21–23] At shorter time frames, however, non-visual response dynamics become more complex and do not follow normal photic integration,[24] as

demonstrated in studies showing that intermittent light pulses can be as effective as continuous longer exposures in circadian phase resetting.[25–27]

2.1.3 Timing

In addition to dose-dependent modulation, responses are modulated by the timing of light exposure relative to circadian rhythms and other biological processes (e.g., homeostatic sleep pressure). Phase resetting effects (i.e., the magnitude and direction of phase shifts) in the SCN, in particular, depend on timing, such that light in the biological morning phase advances, and light in the biological evening phase delays the circadian clock.[28–30] Similarly, modulation of so-called acute responses (i.e., the more immediate responses to a light stimulus) such as alertness, heart rate and body temperature seem to depend on the timing of light exposure, though findings about these relationships are currently inconclusive.[31,32]

2.1.4 Prior history

An important factor modulating non-visual responses to light is prior photic history. Accumulating evidence suggests that prior exposure to light on a scale of hours and days can reduce the sensitivity of light-induced responses, such as melatonin suppression,[33–36] circadian resetting,[33] and nocturnal alertness.[37] While these findings point towards long-term adaptation of the phototransduction system mainly mediated by intrinsic ipRGCs responses,[33] similar effects on melatonin suppression during much shorter time-frames suggest the existence of a secondary mechanism involving rod- and cone-driven adaptation and recovery.[38]

In addition to desensitising effects of prior light exposure, bright daytime light has also been found to enhance sleep, mood, and cognitive functions.[39–41] While these effects may simply reflect acute responses to bright light, recent evidence indicates that prior light exposure has persistent effects on a neurophysiological level. Specifically, a recent study in a diurnal mammal found enhancement of circadian amplitude by prior bright daytime light exposure, reflected by a higher daytime peak of the SCN's spontaneous electrical activity as well as an increased robustness of temperature and activity rhythms.[42] Likewise, in humans, a strong day-night contrast such as under natural conditions has been shown to reduce interindividual variability in phase of entrainment.[43,44]

2.2 Implications for light-dosimetry

While the findings described above have led to a better understanding of the intricate physiological mechanisms underlying the non-visual responses to light and have found their way into preliminary recommendations for lighting design and practice (e.g., [45–47]), it still remains unclear how these findings interact to affect responses across longer time frames and dynamic patterns such as encountered in real-life settings.[6] In laboratory studies, the modulation of non-visual responses to different light exposure characteristics are examined by exerting a tight control over the respective light stimulus. While stimuli vary depending on the research question, each stimulus is necessarily a specific instance of an arbitrary combination of all light exposure characteristics. As a result, any functional relationships (e.g., dose-response curves) are inherently linked to the specific instances of stimulus patterns used to derive them. What we do not know is to what extent these derived relationships generalise to other stimulus instances and ultimately to personal light exposure patterns, or, viewed differently, whether disentangling personal light exposure patterns into separate characteristics and relating them to measured responses reveals similar functional relationships. This issue is further complicated in real-life settings by inter-

individual differences in light sensitivity,[48,49] and by the numerous interactions observed between the non-visual responses themselves and other physiological and behavioural variables.[50]

Studying personal light exposure and non-visual responses in real-life settings may help to bridge current gaps in knowledge[6] and better understand the mechanisms underlying the non-visual responses to light.[5] However, it is far from straightforward to relate measured personal light exposure to measured responses. Specifically, an important question is how personal light exposure data should be *quantified*. That is, what metrics can or should be calculated from collected light data to characterise the light exposure patterns of an individual or group, or to examine the relationship between light and non-visual responses.[6]

To start answering this question, we assembled a comprehensive set of relevant light-dosimetry studies from which we identified metrics that have been developed and used over the recent decades of research in this field. We categorise the identified metrics based on the different characteristics modulating non-visual responses as reviewed above and discuss their potential relevance for research and possible ways to evaluate and compare the metrics in future studies.

3 Review method

3.1 Selection of studies

The selection of light-dosimetry studies was made by means of a forward and backward citation search method using the Web of Science citation database (forward and backward search) and the individual papers' reference list (forward search), within the period of January–March 2021. Two early dosimetry studies were chosen as a starting point,[51,52] since they were some of the first to study real-life light exposure patterns with wearable light meters (dosimeters) in the context of chronobiology. Based on these two studies, forward and backward citation was used to select studies that collected real-life personal light exposure data over at least 24 hours and that reported an analysis of the measured light data as a dependent or independent variable.

These selection criteria generally excluded intervention field studies where personal light exposure was measured but not analysed as a major independent or dependent variable, except for three studies.[49,53,54] Similarly, studies that measured personal light exposure in a context unrelated to the non-visual system (e.g., studies on visual acuity) were excluded, except for three myopia-related studies that used methodological approaches that have not been described by the other eligible studies.[55–57]

In total, 104 studies were deemed eligible and formed the set of dosimetry field studies reviewed here from which the list of metrics to discuss could be identified [35,43,44,49,51–150], together with a set of additional metrics based on four conceptual articles[151–155] specifically relevant to the scope of this review. A tabular overview of the selected studies and study characteristics is given in the supplementary data. For a more detailed description of the selection procedure please refer to our previously published review of methodological considerations in light-dosimetry.[9]

3.2 Light-dosimetry definition and terminology

The selected dosimetry studies were reviewed to identify metrics used to quantify the characteristics of measured personal light exposure data. In real-world settings, light exposure data collected with light-dosimetry typically consists of person-bound consecutive discrete light measurements over an extended period of several hours or

days (i.e., time series of light exposure data). The optical quantities of the data (e.g., photopic illuminance, spectral irradiance in different bandwidths, α-opic irradiance etc.) and the time interval between data points (i.e., epoch) each depend on the specific dosimeter model and its characteristics, as well as on the selected sampling settings of the dosimeter. Moreover, the collected data may in some cases need to be pre-processed before analysis, including the removal of invalid data points and noise, and/or (logarithmic) transformation to ensure adequate quantification (for details see our previously published paper[9]). The resulting dataset can then be analysed by calculating selected metrics of interest.

The metrics identified in the present review can be broadly differentiated in three classes: metrics that aggregate the data across a given time interval (that we will call *aggregate* metrics), metrics that are derived from a function fitted to the data (*parameter* metrics), and metrics that are calculated for each individual data point (*point* metrics). The sub-intervals of data that a metric is calculated for, depend on the metric itself and the analysis strategy. For each metric in this review, we will indicate its class (aggregate, parameter, or point) and whether it has been developed for a specific interval.

Furthermore, the term *light exposure data* will be used in the remainder of this review to indicate the time series of light data measured with a dosimeter, while the term *light level* will be used in a generic way, to indicate a value of any optical quantity (e.g., irradiance, luminance, illuminance, m-EDI etc.). In cases where only specific quantities are applicable, SI-compliant terms will be used.

4 Review of dosimetry metrics

In the following, quantification metrics identified in the reviewed studies are described and categorised based on the characteristics described in Section 2. For each category (i.e., within each subsection 4.*n*), a tabular overview of the respective metrics is provided (i.e., in Table *n*, respectively), including a brief description of each metric, its class, a pseudo-mathematical formula of the calculation procedure (where applicable), and the respective studies that used the metric.

To facilitate the exploration and use of the reviewed metrics, we also developed the R-package *lightdosimetry* (available on GitHub at github.com/steffenhartmeyer/lightdosimetry), which includes functions to calculate most of the metrics presented in this review.

4.1 Quantification of spectral composition

Metrics that were used to quantify characteristics related to spectral composition are shown in Table 1. Overall, three different metrics were identified: Spectral Contribution, Melanopic-Photopic Ratio, and Vis-nonvis.

The point metric Spectral Contribution quantifies the relative contribution of individual spectral irradiance components to the combined irradiance. One study analysed these contributions per season, for each hour during daytime,[138] and another study as a function of solar angle and before sleep onset,[106] showing how the spectral composition changes over the course of the day. The latter study additionally compared the distribution of light levels of different optical quantities, such as photopic illuminance and melanopic equivalent daylight illuminance (m-EDI), showing characteristic overlapping peaks during night time for light sources with similar photopic and melanopic activation.[106] Similarly, the point metric Melanopic-Photopic Ratio (M/P ratio) quantifies the spectral composition in terms of photopic vs. melanopic activation, and has been used to investigate the relative impact of

different light sources on melanopic light levels before bedtime.[66] Note that the term M/P ratio can refer to differently calculated metrics (cf.[155]). Therefore, the specific term [e.g., melanopic daylight equivalent ratio (m-DER)] or the calculation procedure should always be reported. Like the M/P ratio, the aggregate metric Vis-nonvis introduced by Hubalek *et al.*[96] quantifies the relationship between photopic illuminance and "circadian" irradiance c(λ).[156] This metric is calculated for a given time interval and increases with a decreasing amount of short-wavelength light.

In summary, the metrics presented above quantify spectral composition by integrating for different spectral quantities. They can be used to achieve a better understanding of what the spectral composition of personal light exposure patterns is and how it changes in relation to environmental factors. Note, however, that for the research of non-visual effects of light it may be sufficient to simply quantify light exposure data in terms of different optical quantities (ideally α-opic quantities[157]). Overall, 20 studies used quantities other than photopic illuminance (Figure 1A). This low number of studies may be due to a lack of dosimeters with sufficient spectral resolution, as discussed in our previously published review.[9]

4.2 Quantification of light level

Metrics that were used to quantify characteristics related to light level are shown in Table 2. Three types of metrics were identified: Standard descriptive metrics, Mean across the Brightest 10 Hours (M10m) and Darkest 5 Hours (L5m), and Rhythm Adjusted Mean (MESOR) derived from cosinor analysis.

Standard descriptive metrics have been used by most studies and include the Arithmetic Mean, Geometric Mean, Median, Percentiles, Maximum, Standard Deviation, and Inter-Quartile Range (IQR). These aggregate metrics can be calculated across any time interval of interest; therefore, their informativeness depends on the interval that is selected. In contrast, the aggregate metrics M10m and L5m, and the parameter metric MESOR quantify the central tendency of light levels specifically across the 24h day and are not applicable for selected subintervals.

Note that, while aggregating time series of light levels across a given interval provides information about the distribution of light levels an individual was exposed to during that interval, aggregating the data into regularly spaced intervals (e.g., hourly bins) may help to reduce noise in the data and analyse changes in light levels over longer timeframes. For instance, Martinez-Nicolas *et al.*[113], analysed the rate of change in consecutive log-transformed illuminance (averaged into 10 min bins) in relation to the rate of change in the corresponding wrist temperature.

Overall, we can say that the identified light level-related metrics aim to quantify the central tendency of light levels across a given interval, although light levels can also be directly related to responses of interest.

4.3 Quantification of duration

Metrics that were used to quantify duration-related characteristics are shown in Table 3. Overall, two metrics were identified: Time Above/Below Threshold (TAT(C)), and Time within Range (TAT(C_{min},C_{max})).These aggregate metrics calculate the total amount of time spent above or below a defined threshold light level C or within a range of light levels [C_{min}, C_{max}], respectively. Both metrics can be expressed in terms of absolute duration or as percentage of time (e.g., percentage of available sunlight hours). Note, that these metrics are calculated across a

given interval as the total amount of discrete time points where the threshold conditions are fulfilled, independent of the sequence of data points (cf. Pulses above Threshold in Section 4.5).

Across the 58 studies that used these metrics, various thresholds and ranges were used (Figure 1B), specified in terms of photopic illuminance by all studies. Some but not all studies provided a rationale for selecting specific thresholds, such as indication of environmental lighting conditions (e.g., 1000 lx, indicating daylight and/or light exposure outdoors), recommended light levels for light therapy (e.g., 2500 lx [158]), or thresholds for melatonin suppression, circadian resetting, and alertness (e.g., 80 lx, 100 lx, 550 lx [15,17]). Only few studies defined thresholds based on the collected data; for example, Woelders *et al.*[149], who selected a threshold of 615 lx to indicate daylight, since data recorded during solar darkness did not exceed this value. Three studies selected thresholds based on a sensitivity analysis.[119,125,142] In this method, TAT was calculated for a wide range of thresholds (e.g., 10–3000 lx [142]) and analysed to identify which thresholds correlated with measured responses (e.g., hyperactivity [142]).

Duration of light exposure is thus generally quantified relative to a given light level threshold or range, the latter allowing more differentiated analysis of time spent at specific light levels. The fact that the informativeness of these metrics depends on the selected threshold(s), highlights the importance of selecting thresholds based on a specific rationale or by means of a sensitivity analysis.

4.4 Quantification of timing

Metrics that were used to quantify timing-related characteristics are described in Table 4. Overall, eight metrics were identified (detailed below): Rhythm Acrophase, Centroid of Light Exposure (LE), Midpoint of Cumulative Exposure (CE), Mean Timing of Light above Threshold (MLiT(*C*)), Onset of M10, L5 (M10on, L5on), First and Last Timing of Light above Threshold (FLiT(*C*), LLiT(*C*)), Phase Angle, and Relative Timing.

The parameter metric Rhythm Acrophase and the aggregate metrics Centroid of LE, Midpoint of CE, and MLiT aim to estimate the timing of the peak or centre of gravity of the light exposure data within a given time interval (usually a 24h-day). Similarly, the aggregate metrics M10on and L5on quantify the on- and offset of the 10 hours timespan with the highest or lowest average light level, while the aggregate metrics FLiT and LLiT quantify the on- and offset of light levels above a specific threshold *C*. Moreover, Phase Angle quantifies the offset between any timing metric relative to a given timepoint, which has been calculated for MLiT relative to wake onset,[99] and for FLiT and LLiT relative to wake on- and offset.[143,146] Note that the metrics MLiT, FLiT and LLiT integrate information about light levels and are thus dependent on the selection of appropriate thresholds. As described for TAT in the previous section, sensitivity analysis can be used to select relevant thresholds, which has been employed for MLiT by four studies.[99,119,125,142]

An important consideration for quantifying timing-related characteristics is the reference timescale. Most studies represented the time series of light exposure data relative to the time of day; however, in the context of non-visual responses, usually the timing relative to internal time (e.g., the circadian rhythm) is of interest. Therefore, it may be useful to represent and quantify the light exposure data relative to a physiological or behavioural marker (Relative Timing). Amongst the 11 studies that represented the data in this way, eight studies related light to sleep on- and offset, three to dim light melatonin onset (DLMO), and one to core body temperature minimum (CBT_{min}). Light exposure data represented relative to individual internal time can then be analysed to assess its impact on the circadian system; for example, by quantifying light exposure data relative to individual phase response

curves.[109] In the absence of physiological markers such as DLMO or CBT_{min}, individual phase estimates based on measured sleep and wake times may be used.

Note that many studies calculated and compared timing metrics for the entire day and/or for sub-intervals, by which information about timing can be integrated in any of the metrics. However, due to the large variety of intervals used across studies, they are not reviewed here.

Metrics for light exposure timing have thus been found to quantify either the centre/peak of light exposure, or the on- and offset of a given exposure period. Amongst these methods, parameterised metrics exist that allow the calculation of exposure timing relative to specific light levels of interest and are suitable for sensitivity analyses. Note that for research on non-visual effects, it may be useful to calculate timing relative to individual physiological or behavioural markers, if available.

4.5 Quantification of temporal dynamics

Metrics that were used to quantify characteristics related to temporal dynamics are shown in Table 5. Overall, eight metrics were identified: Rhythm Amplitude, Relative Amplitude (RA), Light Quality Index (LQI), Rhythm Robustness, Interdaily Stability (IS), Intradaily Variability (IV), Frequency of Intensity Changes (FIC), and Pulses above Threshold.

The first six metrics quantify 24h-rhythm characteristics of the light exposure data. Specifically, the parameter metric Rhythm Amplitude, and the aggregate metrics RA and LQI quantify the contrast between the light and dark period, whereas the parameter metric Rhythm Robustness, and the aggregate metrics IV and IS, quantify the temporal variability within and across days. Note that Rhythm Amplitude and Rhythm Robustness (as well as MESOR and Rhythm Acrophase described in the previous sections) are derived from fitting a 24h-cyclic rhythm to the data, such as in cosinor-based methods, which are frequently used for the analysis of circadian rhythms.[159] Similarly, IS, IV, and RA were originally developed as non-parametric methods for the analysis of actigraphy data to assess the strength and disruption of rest-activity rhythms.[160]

The last two aggregate metrics quantify the intermittency of the light exposure data, with FIC calculating the number of times consecutive light levels cross a given threshold,[55] and Pulses above Threshold identifying continuous episodes (or pulses) of light above a given threshold and quantifying them in terms of their number, mean level, mean duration, total duration, and mean onset.[57,148] Due to their threshold parameterisation, Pulse metrics and FIC sensitivity analysis can be used to identify relevant threshold light levels,[148] similar to metrics such as TAT and MLiT.

In summary, temporal dynamics are quantified in terms of several characteristics, such as temporal variability and intermittency, as well as the contrast between given periods. It is important to note that some of the identified metrics were developed to specifically quantify 24h data and may thus not be suitable for shorter timeframes. Novel metrics such as Pulses above Threshold offer promising ways to characterise the intermittency of light exposure data within any timeframe while integrating information about light level and duration, which makes them suitable for sensitivity analyses.

4.6 Quantification of exposure history

Metrics that were used to quantify exposure history related characteristics are shown in Table 6. Overall, four metrics were identified: Cumulative Exposure (CE), Solar-normalised CE, Dose(C_{min},C_{max}), and Exponential Moving Average (EMA).

The aggregate metric Cumulative Exposure (CE) was used most frequently to quantify exposure history and is simply calculated as the integral of the light exposure data across a given interval (usually a 24h-day). In order to facilitate comparison of this metric across studies and seasons, one study additionally calculated the Solar-normalised CE, indicating the fraction of available daylight that subjects were exposed to.[55] As an alternative to CE, the aggregate metric Dose(C_{min},C_{max}) quantifies exposure history based on the cumulative exposure within several ranges of light levels, which has been used to compare the contribution of light at specific levels to the overall exposure history.[94]

A different approach was employed by Price *et al.*[121], who quantified exposure history in time with an Exponential Moving Average (EMA) filter, described in detail in a conceptual article.[161] Instead of expressing exposure history as the total amount of light an individual was exposed to over a given interval, this method mimics the response dynamics of the non-visual system. Unlike aggregate metrics such as CE or TAT, this point metric integrates information about prior light history at each point in time, which may be particularly relevant for assessing acute effects to light and for tracking internal time while undergoing continuous phase adjustment.

Overall, we found two different approaches for quantifying light exposure history. One approach is to aggregate light exposure data across a given interval resulting in an estimate of the total light dose received, where a more detailed differentiation can be achieved by calculating light dose for specific light levels. The second approach is to calculate light exposure history as a function of time considering previous exposures, thereby retaining temporal information.

4.7 Additional metrics

In addition to the metrics used in the reviewed dosimetry studies, four conceptual articles were identified that present relevant metrics for light dosimetry, described in Table 7. Barroso *et al.*[151] developed five metrics (Bright/Dark Threshold, Bright/Dark Mean Level, Circadian Contrast, Bright/Dark Cluster, Circadian Variation) intended to be used in light-dosimetry studies to quantify relevant light characteristics (i.e., level, duration, and temporal dynamics) for circadian research. Blesić *et al.*[152,153] used Wavelet Transform Spectral Analysis and Detrended Fluctuation Analysis to quantify behavioural patterns and exposure timescales for personal UV-exposure data, which may prove useful for quantification of light-dosimetry data in general. Fernández-Martinez *et al.*[154] introduced the Disparity Index, a measure of the temporal variability of time series, which was originally developed in the context of ecology and has recently been applied in a light-dosimetry study[162] to characterise exposure variability.

5 Application of metrics

To provide insights as to the type of outcomes one can expect from the different metrics discussed in Section 4, we calculated the identified metrics for two exemplary days of personal light exposure measurements. Note that

the exemplary calculations are for illustrative purposes only and are not intended to evaluate the metrics as to their relevance for research on the non-visual effects of light.

The exemplary data were collected with the Spectrace dosimeter, a novel wearable sensor recording spectral irradiance across 14 channels in the visible range, with automatic gain and integration time adjustment (see Webler *et al.*[163] for details). The data were retrieved from Spectrace recordings while being worn by one of the authors from waking up to going to bed over several days in August 2021 in Lausanne, Switzerland. Light exposure was measured on the chest (i.e., in a vertical plane just below shoulder height) with an epoch of 30 s and averaged into 1 min bins for the calculations presented here (using the geometric mean).

Two days with visually different exposure patterns were selected from the dataset (see Figure 2A). The first day (Day 1) is characterized by consistently low light exposure across the day with brief periods of bright light exposure in the early morning and late afternoon; the second day (Day 2) consists of a brief period of bright light exposure at midday and a long period of bright light exposure in the late afternoon and evening. Note that both days were workdays; therefore, bright light exposure coincides with time before or after work or the lunch break.

Metrics were calculated with light quantified as m-EDI (untransformed unless noted otherwise), for the periods where the wearer was awake (i.e., 05:44 – 21:23 and 05:08 – 23:37 for Day 1 and 2, respectively), except for metrics derived from cosinor analysis (MESOR, Rhythm Amplitude, Rhythm Robustness, Rhythm Acrophase), as well as M10, IS, and IV, given their requirement for 24h data. Metrics are visualized in Figure 2 and a tabular overview of the results is provided in Table 8.

5.1 Level

All metrics related to exposure level indicate a tendency for higher m-EDI together with a larger spread for Day 2 compared to Day 1 (Table 8). However, large differences between the metrics exist, especially between the Arithmetic Mean and the Geometric Mean, Median, and MESOR. Due to the strongly skewed distribution of light levels, the Arithmetic Mean substantially overestimates the central tendency of light levels, compared to the Geometric Mean and the Median. Note that the MESOR results in similar but lower values than the Median and Geometric Mean, as it is calculated from a cosinor function fitted to the log-transformed light data, which in this case does not adequately fit the data (R^2 = ~0.5).

These exemplary results highlight the difficulty of quantifying exposure level in a single metric. Particularly problematic is the fact that light exposure data are typically not normally distributed,[164] which, despite its frequent use, renders the Arithmetic Mean an inadequate measure to quantify the central tendency of measured light exposure data. In addition, light exposure often varies greatly, even across short timeframes, limiting the mean's informativeness. Therefore, it is recommended to use the Geometric Mean or the Median together with their respective measures of spread (i.e., Geometric SD and IQR, respectively), or to log-transform the data before aggregation (for a detailed discussion refer to our previously published review[9]). Although the MESOR has been used by many studies, its informativeness for quantifying exposure level is limited since it depends on the goodness of fit of the fitted rhythmic function (e.g., cosinor).

Note that for illustrative purposes the metrics were calculated across the period when the subject was awake. However, it may often be more meaningful to use these metrics to aggregate the data across specific sub-intervals

or regularly spaced intervals (i.e., binning) to integrate information about the timing of light exposure or analyse changes in light levels over longer timeframes.

5.2 Duration

The duration metric TAT was calculated for threshold levels between 20 lx and 2000 lx m-EDI (Figure 2D), as well as for the ranges 10-100 lx, 100-500 lx, and 500-1000 lx m-EDI (Table 8). Across all thresholds, TAT(C) was longer for Day 2 than Day 1, mainly due to a longer light exposure period. Moreover, by plotting TAT(C) as a function of threshold level, characteristic environments/lighting conditions can be identified in the changes in slope of the plotted curve; for instance, for Day 2 the plateau between 100 lx and 1000 lx m-EDI would differentiate between indoor and outdoor conditions. Time spent in characteristic lighting conditions can be further examined by calculating TAT(C_{min},C_{max}) for specific threshold ranges; for example, a longer exposure to low and high light levels combined with a shorter exposure to moderate light levels can thereby be identified for Day 2 when compared to Day 1.

As shown here, the calculation of exposure duration is not straightforward but strongly depends on the light levels under consideration. Note that TAT(C) for a single threshold informs about the time spent at any light levels above or below a specified light level of interest, limiting its informativeness. For example, TAT(100) and TAT(1000) are identical if no light levels between 100 lx and 1000 lx are recorded, leading to a plateau when plotting TAT(C) as a function of threshold. Therefore, to examine how much time was spent at specific light levels, TAT(C_{min},C_{max}) or the difference between TAT(C) for different thresholds can be calculated. This also shows that TAT(C) as a function of threshold can be used in a sensitivity analysis for measured responses; for example, calculating the correlation coefficients between TAT(C) and hyperactivity or sleep onset to determine the (range of) threshold(s) with the strongest association to the response.[142]

5.3 Timing

The metrics Acrophase, Midpoint of CE (Mid. CE), Centroid of LE (Cent. LE), and MLiT quantify the central tendency of light exposure timing; however, as they are calculated differently, they may vary significantly for different exposure patterns (Figure 2B, Table 8). For Day 1, Acrophase, Mid. CE, and Cent. LE, are similar and located close to the midpoint of the light exposure period as quantified by MLiT(10), due to the relatively consistent light levels across the day. Contrastingly, for Day 2, Acrophase, Mid. CE, and especially Cent. LE are shifted later, given to the long period of relatively bright light exposure in the late afternoon. For both days, the central tendency of the timing of bright light exposure periods is better captured by MLiT(1000), due to the threshold parameterisation. Moreover, the analysis of different threshold values for MLiT, FLiT and LLiT shows how the timing of light intensities is distributed across the day (Figure 2E).

The metrics shown here allow to estimate the central tendency of light exposure timing or the on- and offset of light exposure periods. While for non-parametric metrics the results depend on the specific calculation procedure, parameterised metrics such as MLiT allow a more finely tuned quantification of the timing at specific exposure intensities. However, a significant shortcoming of most timing metrics included here is that they ignore intermittent exposures. For example, MLiT(1000) may be identical for a day with 1 h of bright light exposure in the morning and late afternoon (e.g., commuting times) and a day with a single bright exposure period around noon, yet the effects on the circadian system might be very different. An alternative may be to divide the exposure

period in meaningful subintervals for which the timing metrics are calculated, or to quantify intermittency with metrics such as Pulses above Threshold (see next Section 0 Exposure Dynamics).

On a technical note, while timing may be represented on a 24 h scale, it is important that the calculation of the metrics is performed on time encoded as an incremental variable (e.g., epoch time) to correctly calculate timing across intervals that span midnight (e.g., 2022/01/01 08:00 – 2022/01/02 02:00). Moreover, often it may be more meaningful to represent light exposure with respect to *internal time* (i.e., relative to a physiological or behavioural phase marker), especially when comparing between participants or groups (*cf.* Wilson *et al.*[148]). To transform metrics calculated in clock time into relative time, the timing of the internal phase marker (e.g., DLMO, CBT_{min}) simply needs to be subtracted (with time encoded as an incremental variable, see above). For example, relative to a hypothetical DLMO at 20:00, MLiT(1000) at 16:10 equals DLMO-3.83 and LLiT(20) at 00:43 (+1 day) equals DLMO+4.72.

5.4 Dynamics

Several metrics related to the exposure dynamics were calculated and are shown in Table 8. Rhythm Amplitude and LQI reflect the difference in contrast in light levels across the day between both days, with a higher contrast for Day 2. The variability metrics IV, Disparity Index, and Circadian Variation indicate higher variability of light levels for Day 1 compared to Day 2, which is in line with consistently more and shorter Pulses above Threshold for Day 1 (Figure 2D and F). However, while for Day 1 there is higher intermittency at lower thresholds, FIC shows that for Day 2 intermittency increases again at higher thresholds (Figure 2F).

These exemplary results highlight the different ways in which the temporal dynamics of the exposure patterns can be quantified; yet – and reassuringly – the overall results are relatively consistent. Of note is the metric Pulses above Threshold, which quantifies multiple aspects of the pattern dynamics, integrating information about the light level, duration, timing, and intermittency. Moreover, pulses can be fine-tuned by specifying a minimum pulse length, and the duration and proportion of interruptions (i.e., light below threshold) allowed within a pulse (here ≥2 min, ≤8 min, and <25%, respectively; see Wilson *et al.*[148]), which helps to smooth noise in the data and mimics non-visual response kinetics. Note that without specification of these parameters, for a given threshold, Number of Pulses is identical to half of FIC, and Total Pulse Time is identical to TAT(*C*), highlighting the versatility of this metric.

5.5 Exposure History

Exemplary calculations for exposure history are shown in (Table 8). As expected, CE is much higher for Day 2 compared to Day 1. However, calculating light doses for specific ranges of light levels (Dose(C_{min},C_{max})) shows that light doses at lower light levels are higher for Day 1 compared to Day 2 and vice versa. While these metrics aggregate light dose across time, Exponential Moving Average (EMA) quantifies light dose at each point in time (Figure 2C), mimicking the response dynamics of the non-visual system with a sluggish response onset and a persistent response after stimulus offset. For the present calculation the data for each day was looped to determine the EMA value at the start of the time series. Note that EMA for raw data results in higher dose levels and more abrupt changes in dose than EMA for log-transformed data.

The difference in EMA dose levels for aggregated raw or log-transformed data reiterates the problems with aggregating non-normally distributed light exposure data (see Section 0 Exposure Intensity, and our previously

published review [9]) and should also be considered when calculating CE. Furthermore, it should be noted that EMA provides an interesting basis for the calculation of any of the other metrics, similar to smoothing the data beforehand.[9]

5.6 Summary

The calculation of metrics for these two exemplary datasets shows interesting similarities and differences between the various metrics and thus highlights some of their advantages and disadvantages. An important consideration, when quantifying light exposure patterns, is the skewed log-normal distribution and the large range of light levels. Therefore, metrics that are based on an aggregation of light levels are biased by their distribution, which, to some extent, is an issue for all non-parametric metrics presented here. An elegant solution to this issue is the parameterisation of metrics with a certain threshold level or range (e.g., TAT, MLiT, Pulses above Threshold), allowing to quantify overall light dose, timing, and intermittency without aggregating light levels directly. In addition, parameterised metrics facilitate the exploration of exposure patterns by allowing a visualisation of the metrics as a function of light level. On the other hand, the informativeness of threshold-parameterised metrics depends on the chosen threshold(s). The latter therefore need to be selected carefully, either based on a-priori evidence or by means of a sensitivity analysis. Moreover, it is important to note that most of the metrics presented in this review aggregate the data across a specified time interval; therefore, the informativeness of a metric depends on the selected interval. In the exemplary calculation, the data were aggregated across the period when the subject was awake; however, more specific sub-intervals may be chosen depending on the research question.

6 Discussion

Our review shows that many different metrics have been used by previous studies to quantify light exposure data, yet often only a small subset of metrics was explored within each study. The overview of metrics we provide, may enable a more holistic exploration of collected data within and across studies; on the one hand, to better understand the mechanisms underlying non-visual effects of light, and, on the other hand, to evaluate which metrics may be more relevant for a particular research question or context.

The wide range of metrics that exists, allows to disentangle complex personal light exposure patterns into many different aspects; however, some metrics are redundant or may not be relevant, making it unclear which metrics are most suited for light-dosimetry research. Which metrics should be considered in a particular research context depends also on the type of response; for example, intermittency or dose in time may be more relevant for the analysis of acute effects, whereas metrics quantifying light dose across the course of a day may be more relevant for effects on circadian rhythms. Moreover, an integral problem to the quantification of personal light exposure patterns, emphasized several times throughout this review, is the high temporal variability, wide range, and skewed distribution of light levels. For instance, these properties of light exposure patterns make it likely that aggregating light exposure across long intervals into a mean value will not be effective, especially because it disregards any temporal information. A better solution may be offered by threshold-parameterised metrics such as TAT; however, TAT disregards how the time spent above a certain threshold is distributed across the considered interval. In effect, most metrics are complementary to each other, highlighting the importance of using, exploring, and evaluating them all together in light-dosimetry research.

Several evaluation strategies are possible (see Table 9 for an overview of proposed strategies) and studies focussing specifically on the evaluation of quantification metrics and novel ways of how they could be applied to further research on non-visual effects are already underway. Notably, a very recent study by Peeters *et al.*[165] systematically evaluated the metrics TAT and MLiT and t*h*eir interaction in a range of sensitivity analyses against sleep parameters and subjective alertness in office workers, indicating a promising way to compare non-visual response relationships in the real-world to those in the laboratory, especially for large datasets. Other approaches to evaluate metrics may be to calculate and compare metrics for large datasets with different categorical variables (e.g., sample groups, seasons, locations etc.) and identify which metrics differentiate groups and which metrics are redundant or inconsistent. Furthermore, to understand what specific characteristics of light exposure are driving non-visual effects in real-life settings, a possible approach may be to compare metrics between light exposure patterns of individuals with similar or different responses. That is, investigating in which ways light exposure patterns that lead to the same response are similar and in which ways they are different. This approach could also be employed to better understand the predictions of computational models of the non-visual system, since a major drawback of such models is that they do not explain what is important about the pattern that led to the predicted response. In the long-term, findings from the evaluation of metrics could be combined into recommendations for a minimum toolset for quantifying light-dosimetry data.

Finally, we would like to emphasize that the quantification of light exposure data is one of the last steps in the light-dosimetry process (or *dosimetry chain* [8]), building on accurate measurement and preparation of the data, which we discussed in detail in our previously published review.[9] Hence, any efforts of evaluating selected metrics together with analyses of non-visual responses will be diminished if the measured data are inaccurate or not representative in the first place.

7 Conclusion

In this review, we present and discuss metrics employed in previous studies for the quantification of personal light exposure patterns, thereby complementing a parallel effort by the authors towards building the groundwork for a framework for light-dosimetry studies. A framework for light-dosimetry studies should indeed encompass the entire process from measurement to data preparation to quantification and analysis. The groundwork has been laid, now it is up to the scientific community to build upon this and take lighting research in the field to the next level.

This review is the first to provide a comprehensive overview of relevant metrics for light-dosimetry in the context of research into the non-visual effects of light, highlighting the wide range of metrics available. As part of a consensus framework, the identified metrics may help to explore non-visual effects of light in the real-world and verify findings of controlled laboratory studies, ultimately driving our understanding to inform any aspect of our lives with light, be it in architecture and lighting design, therapy and medicine, shiftwork, or general personal lifestyle. With this review effort, we hope to make the field of light-dosimetry more accessible and encourage high-quality research and further innovation.

Declaration of conflicting interests

The authors declare no potential conflicts of interest with respect to the research, authorship and/or publication of this paper.

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References

1. Chellappa SL, Steiner R, Blattner P, Oelhafen P, Götz T, Cajochen C. Non-visual effects of light on melatonin, alertness and cognitive performance: can blue-enriched light keep us alert? *PLOS ONE* 2011; 6: e16429.
2. Roenneberg T, Daan S, Merrow M. The art of entrainment. *Journal of Biological Rhythms* 2003; 18: 183–194.
3. Lunn RM, Blask DE, Coogan AN, Figueiro MG, Gorman MR, Hall JE, et al. Health consequences of electric lighting practices in the modern world: a report on the National Toxicology Program's workshop on shift work at night, artificial light at night, and circadian disruption. *Science of The Total Environment* 2017; 607–608: 1073–1084.
4. Prayag AS, Münch M, Aeschbach D, Chellappa SL, Gronfier C. Light modulation of human clocks, wake, and sleep. *Clocks & Sleep* 2019; 1: 193–208.
5. de Kort P Yvonne. Opinion: on becoming smart. *Lighting Research and Technology* 2021; 53: 4–4.
6. Münch M, Wirz-Justice A, Brown SA, Kantermann T, Martiny K, Stefani O, et al. The role of daylight for humans: gaps in current knowledge. *Clocks & Sleep* 2020; 2: 61–85.
7. Wilkinson MD, Dumontier M, Aalbersberg IjJ, Appleton G, Axton M, Baak A, et al. The FAIR Guiding Principles for scientific data management and stewardship. *Scientific Data* 2016; 3: 160018.
8. Price LLA. Opinion: The dosimetry chain. *Lighting Research and Technology* 2015; 47: 896–896.
9. Hartmeyer SL, Webler FS, Andersen M. Towards a framework for light-dosimetry studies: methodological considerations: *Lighting Research and Technology*. 2022;0(0). doi:10.1177/14771535221103258
10. Gooley JJ, Rajaratnam SMW, Brainard GC, Kronauer RE, Czeisler CA, Lockley SW. Spectral responses of the human circadian system depend on the irradiance and duration of exposure to light. *Science Translational Medicine* 2010; 2: 31ra33-31ra33.
11. Thapan K, Arendt J, Skene DJ. An action spectrum for melatonin suppression: evidence for a novel non-rod, non-cone photoreceptor system in humans. *The Journal of Physiology* 2001; 535: 261–267.
12. Brown TM. Melanopic illuminance defines the magnitude of human circadian light responses under a wide range of conditions. *Journal of Pineal Research* 2020; 69: e12655.
13. Prayag AS, Najjar RP, Gronfier C. Melatonin suppression is exquisitely sensitive to light and primarily driven by melanopsin in humans. *Journal of Pineal Research* 2019; 66: e12562.
14. Lucas RJ, Peirson SN, Berson DM, Brown TM, Cooper HM, Czeisler CA, et al. Measuring and using light in the melanopsin age. *Trends in Neurosciences* 2014; 37: 1–9.
15. Zeitzer JM, Dijk D-J, Kronauer RE, Brown EN, Czeisler CA. Sensitivity of the human circadian pacemaker to nocturnal light: melatonin phase resetting and suppression. *The Journal of Physiology* 2000; 526: 695–702.
16. Boivin DB, Duffy JF, Kronauer RE, Czeisler CA. Dose-response relationships for resetting of human circadian clock by light. *Nature* 1996; 379: 540–542.
17. Cajochen C, Zeitzer JM, Czeisler CA, Dijk D-J. Dose-response relationship for light intensity and ocular and electroencephalographic correlates of human alertness. *Behavioural Brain Research* 2000; 115: 75–83.

18. Chang A-M, Santhi N, Hilaire MS, Gronfier C, Bradstreet DS, Duffy JF, et al. Human responses to bright light of different durations. *The Journal of Physiology* 2012; 590: 3103–3112.
19. Prayag AS, Jost S, Avouac P, Dumortier D, Gronfier C. Dynamics of non-visual responses in humans: as fast as lightning? *Frontiers in Neuroscience*; 2019; 13.
20. Moore-Ede M, Heitmann A, Guttkuhn R. Circadian potency spectrum with extended exposure to polychromatic white led light under workplace conditions. *Journal of Biological Rhythms* 2020; 35: 405–415.
21. Dacey DM, Liao H-W, Peterson BB, Robinson FR, Smith VC, Pokorny J, et al. Melanopsin-expressing ganglion cells in primate retina signal colour and irradiance and project to the LGN. *Nature* 2005; 433: 749–754.
22. Nelson DE, Takahashi JS. Sensitivity and integration in a visual pathway for circadian entrainment in the hamster (Mesocricetus auratus). *The Journal of Physiology* 1991; 439: 115–145.
23. Wong KY. A retinal ganglion cell that can signal irradiance continuously for 10 hours. *Journal of Neuroscience* 2012; 32: 11478–11485.
24. Vidal L, Morin LP. Absence of normal photic integration in the circadian visual system: response to millisecond light flashes. *Journal of Neuroscience* 2007; 27: 3375–3382.
25. Gronfier C, Wright KP, Kronauer RE, Jewett ME, Czeisler CA. Efficacy of a single sequence of intermittent bright light pulses for delaying circadian phase in humans. *American Journal of Physiology - Endocrinology And Metabolism* 2004; 287: E174–E181.
26. Rimmer DW, Boivin DB, Shanahan TL, Kronauer RE, Duffy JF, Czeisler CA. Dynamic resetting of the human circadian pacemaker by intermittent bright light. *American Journal of Physiology - Regulatory, Integrative and Comparative Physiology* 2000; 279: R1574–R1579.
27. Zeitzer JM, Ruby N, Fisicaro R, Heller C. Response of the human circadian system to millisecond flashes of light. *PLOS ONE* 2011; 6: e22078.
28. Khalsa SB, Jewett ME, Cajochen C, Czeisler CA. A phase response curve to single bright light pulses in human subjects. *The Journal of Physiology* 2003; 549: 945–952.
29. St Hilaire MA, Gooley JJ, Khalsa SBS, Kronauer RE, Czeisler CA, Lockley SW. Human phase response curve to a 1 h pulse of bright white light: PRC to 1 h light pulses in humans. *The Journal of Physiology* 2012; 590: 3035–3045.
30. Rüger M, Hilaire MAS, Brainard GC, Khalsa S-BS, Kronauer RE, Czeisler CA, Lockley SW. Human phase response curve to a single 6.5 h pulse of short-wavelength light. *The Journal of Physiology* 2013; 591: 353.
31. Rüger M, Gordijn MCM, Beersma DGM, de Vries B, Daan S. Time-of-day-dependent effects of bright light exposure on human psychophysiology: comparison of daytime and nighttime exposure. *American Journal of Physiology - Regulatory, Integrative and Comparative Physiology* 2006; 290: R1413–R1420.
32. Souman JL, Tinga AM, te Pas SF, van Ee R, Vlaskamp BNS. Acute alerting effects of light: a systematic literature review. *Behavioural Brain Research* 2018; 337: 228–239.
33. Chang A-M, Scheer FAJL, Czeisler CA. The human circadian system adapts to prior photic history. *The Journal of Physiology* 2011; 589: 1095–1102.
34. Hébert M, Martin SK, Lee C, Eastman CI. The effects of prior light history on the suppression of melatonin by light in humans. *Journal of Pineal Research* 2002; 33: 198–203.
35. Rufiange M, Beaulieu C, Lachapelle P, Dumont M. Circadian light sensitivity and rate of retinal dark adaptation in indoor and outdoor workers. *Journal of Biological Rhythms* 2007; 22: 454–457.
36. Smith KA, Schoen MW, Czeisler CA. Adaptation of human pineal melatonin suppression by recent photic history. *Journal of Clinical Endocrinology & Metabolism* 2004; 89: 3610–3614.
37. Chang A-M, Scheer FAJL, Czeisler CA, Aeschbach D. Direct effects of light on alertness, vigilance, and the waking electroencephalogram in humans depend on prior light history. *Sleep* 2013; 36: 1239–1246.
38. Lee S-I, Kinoshita S, Noguchi A, Eto T, Ohashi M, Nishimura Y, et al. Melatonin suppression during a simulated night shift in medium intensity light is increased by 10-minute breaks in dim light and decreased by 10-minute breaks in bright light. *Chronobiology International* 2020; 37: 897–909.
39. Riemersma-van der Lek RF. Effect of bright light and melatonin on cognitive and noncognitive function in elderly residents of group care facilities: A randomized controlled trial. *JAMA* 2008; 299: 2642.

40. Münch M, Nowozin C, Regente J, Bes F, De Zeeuw J, Hädel S, et al. Blue-enriched morning light as a countermeasure to light at the wrong time: Effects on cognition, sleepiness, sleep, and circadian phase. *Neuropsychobiology* 2016; 74: 207–218.
41. Ancoli-Israel S, Gehrman P, Martin JL, Shochat T, Marler M, Corey-Bloom J, et al. Increased light exposure consolidates sleep and strengthens circadian rhythms in severe Alzheimer's disease patients. *Behavioral Sleep Medicine* 2003; 1: 22–36.
42. Bano-Otalora B, Martial F, Harding C, Bechtold DA, Allen AE, Brown TM, et al. Bright daytime light enhances circadian amplitude in a diurnal mammal. *Proceedings of the National Academy of Sciences* 2021; 118: e2100094118.
43. Stothard ER, McHill AW, Depner CM, Birks BR, Moehlman TM, Ritchie HK, et al. Circadian entrainment to the natural light-dark cycle across seasons and the weekend. *Current Biology* 2017; 27: 508–513.
44. Wright KP, McHill AW, Birks BR, Griffin BR, Rusterholz T, Chinoy ED. Entrainment of the human circadian clock to the natural light-dark cycle. *Current Biology* 2013; 23: 1554–1558.
45. Underwriters Laboratory [UL]. Design guide- lines for promoting circadian entrainment with light for day-active people. UL Design Guideline 24480, Edition 1, 2019.
46. International Well Building Institute [IWBI]. WELL Building Standard v2, Q1-Q2 2022 version. Section L03: Circadian Lighting Design. Retrieved 25 October 2022, from https://v2.well-certified.com/v/en/light/feature/3.
47. Brown TM, Brainard GC, Cajochen C, Czeisler CA, Hanifin JP, Lockley SW, et al. Recommendations for daytime, evening, and nighttime indoor light exposure to best support physiology, sleep, and wakefulness in healthy adults. PLOS Biology 2022; 20: e3001571.
48. Chellappa SL. Individual differences in light sensitivity affect sleep and circadian rhythms. *Sleep* 2021; 44: zsaa214.
49. Phillips AJK, Vidafar P, Burns AC, McGlashan EM, Anderson C, Rajaratnam SMW, et al. High sensitivity and interindividual variability in the response of the human circadian system to evening light. *Proceedings of the National Academy of Sciences* 2019; 116: 12019–12024.
50. Cajochen C, Reichert C, Maire M, Schlangen LJM, Schmidt C, Viola AU, et al. Evidence that homeostatic sleep regulation depends on ambient lighting conditions during wakefulness. *Clocks & Sleep* 2019; 1: 517–531.51. Okudaira N, Kripke DF, Webster JB. Naturalistic studies of human light exposure. American Journal of Physiology-Regulatory, Integrative and Comparative Physiology 1983; 245: R613–R615.
52. Savides TJ, Messin S, Senger C, Kripke DF. Natural light exposure of young adults. Physiology and Behavior 1986; 38: 571–574.
53. Peeters ST, Smolders KCHJ, de Kort YAW. What you set is (not) what you get: how a light intervention in the field translates to personal light exposure. Building and Environment 2020; 185: 107288.
54. Zeitzer JM, Friedman L, Yesavage JA. Effectiveness of evening phototherapy for insomnia is reduced by bright daytime light exposure. Sleep Medicine 2011; 12: 805–807.
55. Alvarez AA, Wildsoet CF. Quantifying light exposure patterns in young adult students. Journal of Modern Optics 2013; 60: 1200–1208.
56. Ulaganathan S, Read SA, Collins MJ, Vincent SJ. Measurement duration and frequency impact objective light exposure measures. Optometry and Vision Science 2017; 94: 588–597.
57. Read SA, Vincent SJ, Tan C-S, Ngo C, Collins MJ, Saw S-M. Patterns of daily outdoor light exposure in Australian and Singaporean children. Translational Vision Science and Technology; 2018; 7(3): 8.
58. aan het Rot M, Moskowitz DS, Young SN. Exposure to bright light is associated with positive social interaction and good mood over short time periods: a naturalistic study in mildly seasonal people. Journal of Psychiatric Research 2008; 42: 311–319.
59. Adamsson M, Laike T, Morita T. Annual variation in daily light exposure and circadian change of melatonin and cortisol concentrations at a northern latitude with large seasonal differences in photoperiod length. Journal of Physiological Anthropology 2016; 36: 6.
60. Akacem LD, Wright KP, LeBourgeois MK. Bedtime and evening light exposure influence circadian timing in preschool-age children: a field study. Neurobiology of Sleep and Circadian Rhythms 2016; 1: 27–31.
61. Asai Y, Obayashi K, Oume M, Ogura M, Takeuchi K, Yamagami Y, et al. Farming habit, light exposure, physical activity, and depressive symptoms. a cross-sectional study of the HEIJO-KYO cohort. Journal of Affective Disorders 2018; 241: 235–240.
62. Auger RR, Burgess HJ, Dierkhising RA, Sharma RG, Slocumb NL. Light exposure among adolescents with delayed sleep phase disorder: a prospective cohort study. Chronobiology International 2011; 28: 911–920.

63. Böhmer MN, Valstar MJ, Aarts MPJ, Bindels PJE, Oppewal A, Someren EJW, et al. Shedding light on light exposure in elderly with intellectual disabilities. Journal of Intellectual Disability Research 2021; 65: 361–372.
64. Borugian MJ, Gallagher RP, Friesen MC, Switzer TF, Aronson KJ. Twenty-four-hour light exposure and melatonin levels among shift workers. Journal of Occupational and Environmental Medicine 2005; 47: 1268–1275.
65. Boubekri M, Cheung IN, Reid K. Impact of windows and daylight exposure on overall health and sleep quality of office workers: a case-control pilot study. Journal of Clinical Sleep Medicine 2014; 10: 603–611.
66. Cain SW, McGlashan EM, Vidafar P, Mustafovska J, Curran SPN, Wang X, et al. Evening home lighting adversely impacts the circadian system and sleep. Scientific Reports 2020; 10: 19110.
67. Campbell SS, Kripke DF, Gillin JC, Hrubovcak JC. Exposure to light in healthy elderly subjects and alzheimer's patients. Physiology and Behavior 1988; 42: 141–144.
68. Cole RJ, Kripke DF, Wisbey J, Mason WJ, Gruen W, Hauri PJ, et al. Seasonal variation in human illumination exposure at two different latitudes. Journal of Biological Rhythms 1995; 10: 324–334.
69. Crowley SJ, Molina TA, Burgess HJ. A week in the life of full-time office workers: work day and weekend light exposure in summer and winter. Applied Ergonomics 2015; 46: 193–200.
70. Darling AL, Hart KH, Arber S, Berry JL, Morgan PL, Middleton BA, et al. 25-Hydroxyvitamin D status, light exposure and sleep quality in UK dwelling South Asian and Caucasian postmenopausal women. The Journal of Steroid Biochemistry and Molecular Biology 2019; 189: 265–273.
71. Daugaard S, Garde AH, Bonde JPE, Christoffersen J, Hansen ÄM, Markvart J, et al. Night work, light exposure and melatonin on work days and days off. Chronobiology International 2017; 34: 942–955.
72. Daugaard S, Markvart J, Bonde JP, Christoffersen J, Garde AH, Hansen ÅM, et al. Light exposure during days with night, outdoor, and indoor work. Annals of Work Exposures and Health 2019; 63: 651–665.
73. Dumont M, Benhaberou-Brun D, Paquet J. Profile of 24-h Light exposure and circadian phase of melatonin secretion in night workers. Journal of Biological Rhythms 2001; 16: 502–511.
74. Dumont M, Lanctôt V, Cadieux-Viau R, Paquet J. Melatonin production and light exposure of rotating night workers. Chronobiology International 2012; 29: 203–210.
75. Emens JS, Yuhas K, Rough J, Kochar N, Peters D, Lewy AJ. Phase angle of entrainment in morning- and evening-types under naturalistic conditions. Chronobiology International 2009; 26: 474–493.
76. Esaki Y, Kitajima T, Obayashi K, Saeki K, Fujita K, Iwata N. Daytime light exposure in daily life and depressive symptoms in bipolar disorder: a cross-sectional analysis in the APPLE cohort. Journal of Psychiatric Research 2019; 116: 151–156.
77. Espiritu RC, Kripke DF, Ancoli-Israel S, Mowen MA, Mason WJ, Fell RL, et al. Low illumination experienced by San Diego adults: association with atypical depressive symptoms. Biological Psychiatry 1994; 35: 403–407.
78. Eto N, Okada K, Obana A, Okazaki S, Nishiwaki Y. Use of an eyeglass-type measuring device to assess exposure of the eye to light among urban office workers. Toho Journal of Medicine 2016; 2: 86–94.
79. Feigl B, Ojha G, Hides L, Zele AJ. Melanopsin-driven pupil response and light exposure in non-seasonal major depressive disorder. Frontiers in Neurology 2018; 9.
80. Figueiro MG, Rea MS. Evening daylight may cause adolescents to sleep less in spring than in winter. Chronobiology International 2010; 27: 1242–1258.
81. Figueiro MG, Hamner R, Higgins P, Hornick T, Rea MS. Field measurements of light exposures and circadian disruption in two populations of older adults. Journal of Alzheimer's Disease: JAD 2012; 31: 711–715.
82. Figueiro MG, Steverson B, Heerwagen J, Kampschroer K, Hunter CM, Gonzales K, et al. The impact of daytime light exposures on sleep and mood in office workers. Sleep Health 2017; 3: 204–215.
83. Flanagan SC, Cobice D, Richardson P, Sittlington JJ, Saunders KJ. Elevated melatonin levels found in young myopic adults are not attributable to a shift in circadian phase. Investigative Ophthalmology and Visual Science 2020; 61: 45–45.
84. Gibbs M, Hampton S, Morgan L, Arendt J. Predicting circadian response to abrupt phase shift: 6-sulphatoxymelatonin rhythms in rotating shift workers offshore. Journal of Biological Rhythms 2016; 22: 368–370.

85. Goulet G, Mongrain V, Desrosiers C, Paquet J, Dumont M. Daily light exposure in morning-type and evening-type individuals. Journal of Biological Rhythms 2007; 22: 151–158.
86. Grandner MA, Kripke DF, Langer RD. Light exposure is related to social and emotional functioning and to quality of life in older women. Psychiatry Research 2006; 143: 35–42.
87. Grundy A, Sanchez M, Richardson H, Tranmer J, Borugian M, Graham CH, et al. Light intensity exposure, sleep duration, physical activity, and biomarkers of melatonin among rotating shift nurses. Chronobiology International 2009; 26: 1443–1461.
88. Grundy A, Tranmer J, Richardson H, Graham CH, Aronson KJ. The influence of light at night exposure on melatonin levels among Canadian rotating shift nurses. Cancer Epidemiology, Biomarkers and Prevention 2011; 20: 2404–2412.
89. Guillemette J, Hébert M, Paquet J, Dumont M. Natural bright light exposure in the summer and winter in subjects with and without complaints of seasonal mood variations. Biological Psychiatry 1998; 44: 622–628.
90. Gumenyuk V, Roth T, Drake CL. Circadian phase, sleepiness, and light exposure assessment in night workers with and without shift work disorder. Chronobiology International 2012; 29: 928–936.
91. Hall AL, Davies HW, Koehoorn M. Personal light-at-night exposures and components of variability in two common shift work industries: uses and implications for future research. Scandinavian Journal of Work, Environment and Health 2018; 44: 80–87.
92. Harb F, Hidalgo MP, Martau B. Lack of exposure to natural light in the workspace is associated with physiological, sleep and depressive symptoms. Chronobiology International 2015; 32: 368–375.
93. Hebert M, Dumont M, Paquet J. Seasonal and diurnal patterns of human illumination under natural conditions. Chronobiology International 1998; 15: 59–70.
94. Heil DP, Mathis SR. Characterizing free-living light exposure using a wrist-worn light monitor. Applied Ergonomics 2002; 33: 357–363.
95. Higgins PA, Hornick TR, Figueiro MG. Rest-activity and light exposure patterns in the home setting: a methodological case study. American Journal of Alzheimer's Disease and Other Dementias 2010; 25: 353–361.
96. Hubalek S, Brink M, Schierz C. Office workers' daily exposure to light and its influence on sleep quality and mood. Lighting Research and Technology 2010; 42: 33–50.
97. Jean–Louis G, Kripke DF, Ancoli–Israel S, Klauber MR, Sepulveda RS, Mowen M-A, et al. Circadian sleep, illumination, and activity patterns in women: influences of aging and time reference. Physiology and Behavior 2000; 68: 347–352.
98. Jean-Louis G, Kripke DF, Elliott JA, Zizi F, Wolintz AH, Lazzaro DR. Daily illumination exposure and melatonin: influence of ophthalmic dysfunction and sleep duration. Journal of Circadian Rhythms 2005; 3: 13.
99. Joo EY, Abbott SM, Reid KJ, Wu D, Kang J, Wilson J, et al. Timing of light exposure and activity in adults with delayed sleep-wake phase disorder. Sleep Medicine 2017; 32: 259–265.
100. Kawinska A, Dumont M, Selmaoui B, Paquet J, Carrier J. Are modifications of melatonin circadian rhythm in the middle years of life related to habitual patterns of light exposure? Journal of Biological Rhythms 2005; 20: 451–460.
101. Keller LK, Grünewald B, Vetter C, Roenneberg T, Schulte-Körne G. Not later, but longer: sleep, chronotype and light exposure in adolescents with remitted depression compared to healthy controls. European Child and Adolescent Psychiatry 2017; 26: 1233–1244.
102. Kim SJ, Lim YC, Kwon HJ, Lee JH. Association of rest–activity and light exposure rhythms with sleep quality in insomnia patients. Chronobiology International 2020; 37: 403–413.
103. Koller M, Kundi M, Stidl H-G, Zidek T, Haider M. Personal light dosimetry in permanent night and day workers. Chronobiology International 1993; 10: 143–155.
104. Koller M, Härma M, Laitinen JT, Kundi M, Piegler B, Haider M. Different patterns of light exposure in relation to melatonin and cortisol rhythms and sleep of night workers. Journal of Pineal Research 1994; 16: 127–135.
105. Kripke DF, Jean-Louis G, Elliott JA, Klauber MR, Rex KM, Tuunainen A, et al. Ethnicity, sleep, mood, and illumination in postmenopausal women. BMC Psychiatry 2004; 4: 8.
106. Lee EE, Amritwar A, Hong LE, Mohyuddin I, Brown T, Postolache TT. Daily and seasonal variation in light exposure among the Old Order Amish. International Journal of Environmental Research and Public H*ealth* 2020; 17: 4460.

107. Liu L, Marler MR, Parker BA, Jones V, Johnson S, Cohen-Zion M, et al. The relationship between fatigue and light exposure during chemotherapy. Supportive Care in Cancer 2005; 13: 1010–1017.

108. Lowden A, Lemos NAM, Gonçalves BSB, Öztürk G, Louzada F, Pedrazzoli M, Moreno CR. Delayed sleep in winter related to natural daylight exposure among Arctic day workers. Clocks and Sleep 2018; 1: 105–116.

109. Maren SV der, Moderie C, Duclos C, Paquet J, Daneault V, Dumont M. Daily profiles of light exposure and evening use of light-emitting devices in young adults complaining of a delayed sleep schedule. Journal of Biological Rhythms 2018; 33: 192–202.

110. Martin J, Jeste DV, Caliguiri MP, Patterson T, Heaton R, Ancoli-Israel S. Actigraphic estimates of circadian rhythms and sleep/wake in older schizophrenia patients. Schizophrenia Research 2001; 47: 77–86.

111. Martin JS, Hébert M, Ledoux É, Gaudreault M, Laberge L. Relationship of chronotype to sleep, light exposure, and work-related fatigue in student workers. Chronobiology International 2012; 29: 295–304.

112. Martin JS, Gaudreault MM, Perron M, Laberge L. Chronotype, light exposure, sleep, and daytime functioning in high school students attending morning or afternoon school shifts: an actigraphic study. Journal of Biological Rhythms 2016; 31: 205–217.

113. Martinez-Nicolas A, Ortiz-Tudela E, Madrid JA, Rol MA. Crosstalk between environmental light and internal time in humans. Chronobiology International 2011; 28: 617–629.

114. Martinez-Nicolas A, Madrid JA, Rol MA. Day–night contrast as source of health for the human circadian system. Chronobiology International 2014; 31: 382–393.

115. Nioi A, Roe J, Gow A, McNair D, Aspinall P. Seasonal differences in light exposure and the associations with health and well-being in older adults: an exploratory study. Health Environments Research and Design Journa 2017; 10: 64–79.

116. Obayashi K, Saeki K, Iwamoto J, Okamoto N, Tomioka K, Nezu S, et al. Positive effect of daylight exposure on nocturnal urinary melatonin excretion in the elderly: a cross-sectional analysis of the HEIJO-KYO study. The Journal of Clinical Endocrinology and Metabolism 2012; 97: 4166–4173.

117. Obayashi K, Saeki K, Iwamoto J, Okamoto N, Tomioka K, Nezu S, et al. Effect of exposure to evening light on sleep initiation in the elderly: a longitudinal analysis for repeated measurements in home settings. Chronobiology International 2014; 31: 461–467.

118. Papantoniou K, Pozo OJ, Espinosa A, Marcos J, Castaño-Vinyals G, Basagaña X et al. Circadian variation of melatonin, light exposure, and diurnal preference in day and night shift workers of both sexes. Cancer Epidemiology, Biomarkers and Prevention 2014; 23: 1176–1186.

119. Pattinson CL, Allan AC, Staton SL, Thorpe KJ, Smith SS. Environmental light exposure Is associated with increased body mass in children. PLOS ONE 2016; 11: e0143578.

120. Phillips AJK, Clerx WM, O'Brien CS, Sano A, Barger LK, Picard RW, et al. Irregular sleep/wake patterns are associated with poorer academic performance and delayed circadian and sleep/wake timing. Scientific Reports 2017; 7: 3216.

121. Price LLA, Udovicic L, Khazova M. Circadian light exposures of shift working nurses. In: *Proceedings of the 29th Quadrennial Session of the CIE*, Washington DC, USA, 14-22 June 2019: paper no. PP30, pp.838–845. Vienna, CIE.

122. Rabstein S, Burek K, Lehnert M, Beine A, Vetter C, Harth V, et al. Differences in twenty-four-hour profiles of blue-light exposure between day and night shifts in female medical staff. Science of The Total Environment 2019; 653: 1025–1033.

123. Rea MS, Brons JA, Figueiro MG. Measurements of light at night (LAN) for a sample of female school teachers. Chronobiology International 2011; 28: 673–680.

124. Refinetti R. Chronotype variability and patterns of light exposure of a large cohort of United States residents. The Yale Journal of Biology and Medicine 2019; 92: 179–186.

125. Reid KJ, Santostasi G, Baron KG, Wilson J, Kang J, Zee PC. Timing and intensity of light correlate with body weight in adults. PLOS ONE 2014; 9: e92251.

126. Ruiz FS, Beijamini F, Beale AD, Gonçalves B da SB, Vartanian D, Taporoski TP, et al. Early chronotype with advanced activity rhythms and dim light melatonin onset in a rural population. Journal of Pineal Research 2020; 69: e12675.

127. Scheuermaier K, Laffan AM, Duffy JF. Light exposure patterns in healthy older and young adults. Journal of Biological Rhythms 2010; 25: 113–122.

128. Silva A, Simón D, Pannunzio B, Casaravilla C, Díaz Á, Tassino B. Chronotype-dependent changes in sleep habits associated with dim light melatonin onset in the antarctic summer. Clocks and Sleep 2019; 1: 352–366.
129. Smit AN, Broesch T, Siegel JM, Mistlberger RE. Sleep timing and duration in indigenous villages with and without electric lighting on Tanna Island, Vanuatu. Scientific Reports 2019; 9: 17278.
130. Shochat T, Martin J, Marler M, Ancoli-Israel S. Illumination levels in nursing home patients: effects on sleep and activity rhythms. Journal of Sleep Research 2000; 9: 373–379.
131. Shochat T, Santhi N, Herer P, Flavell SA, Skeldon AC, Dijk D-J. Sleep timing in late autumn and late spring associates with light exposure rather than sun time in college students. Frontiers in Neuroscience 2019; 13: 882.
132. Smolders KCHJ, de Kort YAW, van den Berg SM. Daytime light exposure and feelings of vitality: results of a field study during regular weekdays. Journal of Environmental Psychology 2013; 36: 270–279.
133. Staples VSL, Archer SN, Arber S, Skene DJ. Daily light exposure profiles in older non-resident extreme morning and evening types. Journal of Sleep Research 2009; 18: 466–471.
134. Stone JE, Sletten TL, Magee M, Ganesan S, Mulhall MD, Collins A, et al. Temporal dynamics of circadian phase shifting response to consecutive night shifts in healthcare workers: role of light–dark exposure. The Journal of Physiology 2018; 596: 2381–2395.
135. Sun J-L, Wu S-C, Chang L-I, Chiou J-F, Chou P-L, Lin C-C. The Relationship between light exposure and sleep, fatigue, and depression in cancer outpatients: test of the mediating effect. Cancer Nursing 2014; 37: 382–390.
136. te Lindert BHW, Itzhacki J, van der Meijden WP, Kringelbach ML, Mendoza J, Van Someren EJW. Bright environmental light ameliorates deficient subjective 'liking' in insomnia: an experience sampling study. Sleep 2018; 41: zsy022.
137. Thorne H, Hampton S, Morgan L, Skene DJ, Arendt J. Differences in sleep, light, and circadian phase in offshore 18:00–06:00 h and 19:00–07:00 h shift workers. Chronobiology International 2008; 25: 225–235.
138. Thorne HC, Jones KH, Peters SP, Archer SN, Dijk D-J. Daily and seasonal variation in the spectral composition of light exposure in humans. Chronobiology International 2009; 26: 854–866.
139. Tsai S-Y, Barnard KE, Lentz MJ, Thomas KA. Twenty-four hours light exposure experiences in postpartum women and their 2–10-week-old infants: an intensive within-subject design pilot study. International Journal of Nursing Studies 2009; 46: 181–188.
140. Tsai S-Y, Thomas KA, Lentz MJ, Barnard KE. Light is beneficial for infant circadian entrainment: an actigraphic study. Journal of Advanced Nursing 2012; 68: 1738–1747.
141. Tsuzuki K, Mori I, Sakoi T, Kurokawa Y. Effects of seasonal illumination and thermal environments on sleep in elderly men. Building and Environment 2015; 88: 82–88.
142. Ulset VS, Czajkowski NO, Staton S, Smith S, Pattinson C, Allen A, et al. Environmental light exposure, rest-activity rhythms, and symptoms of inattention and hyperactivity: An observational study of Australian preschoolers. Journal of Environmental Psychology 2021; 73: 101560.
143. van Duijnhoven J, Aarts M, Kort H. Personal lighting conditions of office workers: an exploratory field study. Lighting Research & Technology. 2021; 53(4): 285–310.
144. Vinzio S, Ruellan A, Perrin A-E, Schlienger J-L, Goichot B. Actigraphic assessment of the circadian rest–activity rhythm in elderly patients hospitalized in an acute care unit. Psychiatry and Clinical Neurosciences 2003; 57: 53–58.
145. Wallace-Guy GM, Kripke DF, Jean-Louis G, Langer RD, Elliott JA, Tuunainen A. Evening light exposure: implications for sleep and depression. Journal of the American Geriatrics Society 2002; 50: 738–739.
146. Wams EJ, Woelders T, Marring I, van Rosmalen L, Beersma DGM, Gordijn MCM, Hut RA. linking light exposure and subsequent sleep: a field polysomnography study in humans. Sleep 2017; 40: 12.
147. Wang EJ, Kripke DF, Stein MT, Parry BL. Measurement of illumination exposure in postpartum women. BMC Psychiatry 2003; 3: 5.
148. Wilson J, Reid KJ, Braun RI, Abbott SM, Zee PC. Habitual light exposure relative to circadian timing in delayed sleep-wake phase disorder. Sleep 2018; 41: 11.
149. Woelders T, Beersma DGM, Gordijn MCM, Hut RA, Wams EJ. Daily light exposure patterns reveal phase and period of the human circadian clock. Journal of Biological Rhythms 2017; 32: 274–286.

150. Youngstedt SD, Leung A, Kripke DF, Langer RD. Association of morning illumination and window covering with mood and sleep among post-menopausal women. Sleep and Biological Rhythms 2004; 2: 174–183.
151. Barroso A, Simons K, de Jager P. Metrics of circadian lighting for clinical investigations. *Lighting Research and Technology* 2014; 46: 637–649.
152. Blesić SM, Stratimirović ĐI, Ajtić JV, Wright CY, Allen MW. Novel approach to analysing large data sets of personal sun exposure measurements. *Journal of Exposure Science & Environmental Epidemiology* 2016; 26: 613–620.
153. Blesić SM, du Preez DJ, Stratimirović DI, Ajtić JV, Ramotsehoa MC, Allen MW, et al. Characterization of personal solar ultraviolet radiation exposure using detrended fluctuation analysis. *Environmental Research* 2020; 182: 108976.
154. Fernández-Martínez M, Vicca S, Janssens IA, Carnicer J, Martín-Vide J, Peñuelas J. The consecutive disparity index, D: a measure of temporal variability in ecological studies. *Ecosphere* 2018; 9: e02527.
155. Miller NJ, Irvin A. M/P ratios – Can we agree on how to calculate them? – Illuminating Engineering Society, https://www.ies.org/fires/m-p-ratios-can-we-agree-on-how-to-calculate-them/ (2019, accessed 14 May 2021).
156. Gall D. Circadiane Lichtgrössen und deren messtechnische Ermittlung. *Licht* 2002; 54: 1292–1297.
157. CIE. *System for metrology of optical radiation for ipRGC-influenced responses to light*. CIE S 026/E:2018, Vienna, Austria, 2018.
158. Tuunainen A, Kripke DF, Endo T. Light therapy for non-seasonal depression. *The Cochrane Database of Systematic Reviews* 2004; 2.
159. Cornelissen G. Cosinor-based rhythmometry. *Theoretical Biology & Medical Modelling* 2014; 11: 16.
160. Van Someren EJW, Swaab DF, Colenda CC, Cohen W, McCall WV, Rosenquist PB. Bright light therapy: improved sensitivity to its effects on rest-activity rhythms in Alzheimer patients by application of nonparametric methods. *Chronobiology International* 1999; 16: 505–518.
161. Price LLA. On the role of exponential smoothing in circadian dosimetry. *Photochemistry and Photobiology* 2014; 90: 1184–1192.
162. Kompier ME, Smolders KCHJ, Kramer RP, van Marken Lichtenbelt WD, de Kort YAW. Contrasting dynamic light scenarios in an operational office: effects on visual experience, alertness, cognitive performance, and sleep. *Building and Environment* 2022; 212: 108844.
163. Webler FS, Chinazzo G, Andersen M. Towards a wearable sensor for spectrally-resolved personal light monitoring. *Journal of Physics: Conference Series* 2021; 2042: 012120.
164. Dobb R, Martial F, Elijah D, Storchi R, Brown TM, Lucas RJ. The impact of temporal modulations in irradiance under light adapted conditions on the mouse suprachiasmatic nuclei (SCN). *Scientific Reports* 2017; 7: 10582.
165. Peeters ST, Smolders KCHJ, Kompier ME, de Kort YAW. Let me count the light: accounting for intensity, duration and timing of light when predicting sleep and subjective alertness in field studies. *LEUKOS* 2022; 0: 1–21.

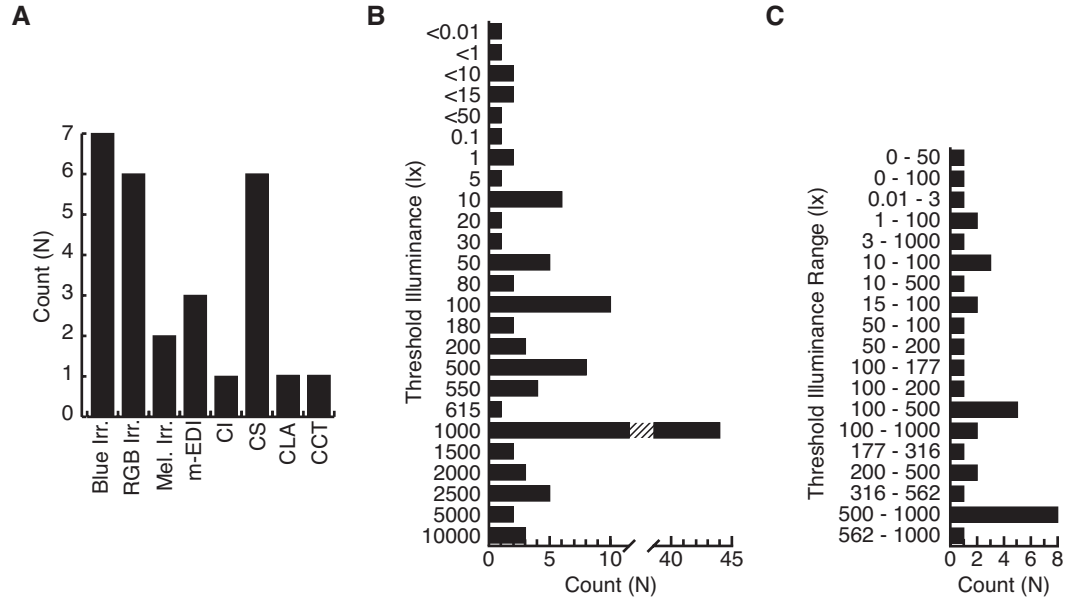

Figure 1. A) Quantities other than photopic illuminance that were used across studies (Blue Irr. = short-wavelength irradiance, RGB Irr. = short-, medium-, and long-wavelength irradiance, Mel. Irr. = melanopic irradiance, m-EDI = melanopic equivalent daylight illuminance CI = irradiance weighted by $c(\lambda)^{156}$, CS = Circadian Stimulus, CLA = Circadian Light, CCT = correlated colour temperature); **B)** Photopic illuminance thresholds for the calculation of TAT(C) and for **C)** TAT(C_{min},C_{max}) across studies (TAT = Time above Threshold). Thresholds that were used to calculate the time below threshold are indicated with a "<" operator.

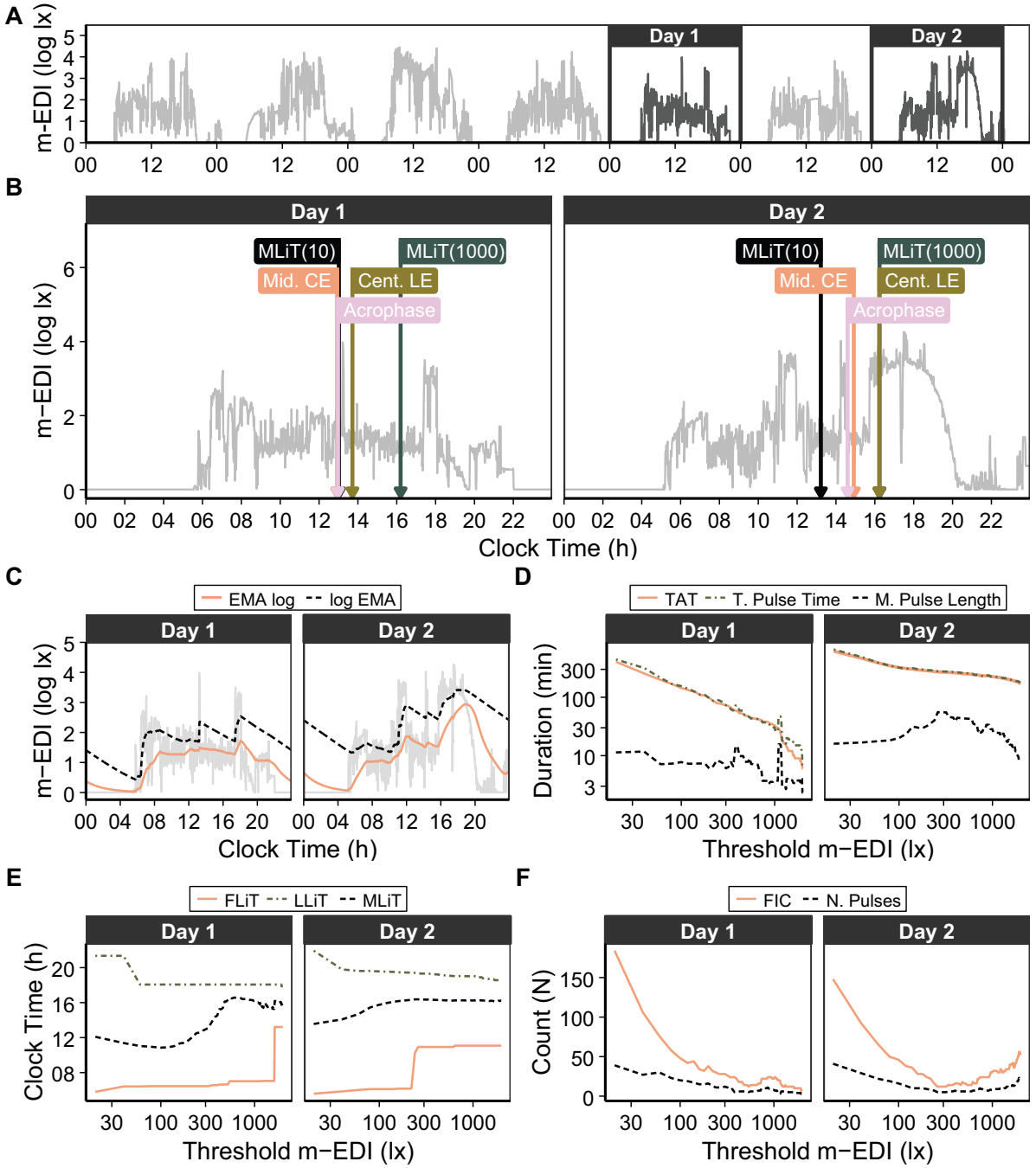

Figure 2. Calculation of metrics for example data: **A)** context of exemplary days (Day 1 and Day 2); **B)** comparison of timing-related metrics (MLiT = mean light timing above threshold, Mid. CE = midpoint of cumulative exposure, Cent. LE = centroid of light exposure, Acrophase = cosinor acrophase); **C)** exponential moving average (EMA) light dose with log-transformation before (EMA log) and after (log EMA) quantification; **D–F)** duration-, timing-, and temporal dynamics-related metrics as a function of threshold level (TAT = time above threshold, T. Pulse Time = total pulse time, M. Pulse Length = mean pulse length, FLiT = first light timing above threshold, LLiT = last light timing above threshold, FIC = frequency of intensity changes, N.Pulses = number of pulses). Note that only metrics are displayed that allowed for meaningful exemplary visual comparisons.

Table 1. Metrics quantifying the spectral composition.

Metric	Class	Description	Pseudo formula	Studies (reference number)
Spectral Contribution	Point	Contribution of individual spectral irradiance components (e.g., 450–500 nm) relative to the total energy across the visible spectrum. Example: Change in spectral contribution as a function of solar angle.[106]	spectral irradiance / SUM(spectral irradiance)	106,138
Melanopic-Photopic Ratio (M/P)	Point	Melanopic vs. photopic activation. Example: Mean M/P (m-DER) as function of mean m-EDI for different light sources.[66]		66
Vis-nonvis	Aggregate	Relationship between photopic illuminance and circadian irradiance (CI) across time interval.	log(MEDIAN(illuminance)) – log(MEDIAN(CI))	96

Note: CI = irradiance weighted by $c(\lambda)$[156].

Table 2. Metrics quantifying characteristics related to light level.

Metric	Class	Description	Studies (reference number)
Arithmetic Mean, Geometric Mean, Median, Percentiles, Maximum, Standard Deviation, IQR	Aggregate	Measures of central tendency and spread.	35,43,49,52,54,55,60,62,63,66,68,71,72,76,78–80,82,84,86–88,90–92,96–99,101,103–108,110,115–118,121–123,126,129–131,134–136,138–141,143–147,149,150
Mean of M10 (M10m), Mean of L5 (L5m)	Aggregate	Mean across brightest continuous 10h (M10) and darkest continuous 5h (L5). Note: The brightest/darkest period is defined as the 10h/5h period with the highest/lowest mean light level, respectively. Usually calculated for 24h data.	81,108,114
MESOR	Parameter	Rhythm-adjusted mean of fitted cosinor function. Note: Requires data to cover the period of the fitted rhythm (e.g., 24h). Looping the data may help to achieve a better fit. Usually calculated with log-transformed light levels.	77,86,92,97,98,105,130,139,145,147,150

Table 3. Metrics quantifying duration-related characteristics.

Metric	Class	Description	Pseudo formula	Studies (reference number)
TAT(C)	Aggregate	Total amount of time or percentage of time above/below threshold light level C. Note: Sometimes referred to as TALT in the literature.	TAT(C) = COUNT(light ≥ C) × epoch TAT(<C) = COUNT(light ≤ C) × epoch	43,44,49,52,54–58,61,67–73,76,77,79,83,85,89,91,94–96,101–104,107,110–113,115,117,119,122,124,125,127,130,132,133,135,140–144,148,149
TAT(C_{min},C_{max})	Aggregate	Total amount of time or percentage of time within range of light levels [C_{min}, C_{max}].	COUNT(C_{min} ≤ light < C_{max}) × epoch	63,93,94,100,110,113,127,132,139

Table 4. Metrics quantifying timing-related characteristics.

Metric	Class	Description	Pseudo formula	Studies (reference number)
Rhythm Acrophase	Parameter	Timing of the peak (acrophase) of a fitted rhythm (e.g., cosinor). See MESOR in Table .		77,86,92,97,98,101,102,105,124,130,139,140,146,150
Centroid of LE	Aggregate	Mean of timepoints weighted in proportion to corresponding light levels. Note: Calculated by [120] as the mean hour weighted by the corresponding mean hourly illuminance.	SUM(time × light) / SUM(light)	120
Midpoint of CE	Aggregate	Timepoint at which of 50% of the total daily cumulative exposure is reached. Note: Calculated by [131] with log-transformed illuminance.	time[50%CE]	131
Mean timing of light above threshold (MLiT(*C*))	Aggregate	Mean of timepoints at which corresponding light levels are below or above a given threshold *C*.	MEAN(time[light ≥ C])	83,99,119,125,148
Onset of M10 and L5 (M10on, L5on)	Aggregate	Onset of brightest continuous 10h (M10) and darkest continuous 5h (L5). See M10m, L5m in Table .		108
First/last timing of light above threshold (FLiT(*C*), LLiT(*C*))	Aggregate	First and last timepoint at which light levels are above/below a given threshold *C*.	FLiT(C) = time[light ≥ C][1] LLiT(C) = time[light ≥ C][end]	69,143,146
Phase Angle	Aggregate	Time from beginning of interval (e.g., wake onset) to timing metric; time from timing metric to end of interval (e.g., wake offset). Examples: - Phase Angle of FLiT and LLiT relative to wake on- and offset [143,146] - Phase Angle of MLiT to wake onset [99]	| metric – time[1] | | metric – time[end] |	99,143,146
Relative Timing	Point	Representation of light exposure relative to physiological/behavioural time (e.g., sleep on-/offset, DLMO, CBT_{min}).		64,67,73,82,99,106,108,109,120,126,131,148

Table 5. Metrics quantifying temporal dynamics related characteristics.

Metric	Class	Description	Pseudo formula	Studies (reference number)
Rhythm Amplitude	Parameter	Amplitude of a fitted rhythm (e.g., cosinor). See MESOR in Table .		77,92,97,102,109,130,139,140
Relative Amplitude (RA)	Parameter	Relative amplitude between M10 and L5. See M10m, L5m in Table .	(M10m – L5m) / (M10m + L5m)	102,113,114
Light Quality Index (LQI)	Aggregate	Index quantifying the contrast between light and dark periods. Note: Ranges between -1 and 1, with -1 indicating exposure to <10 lx and 1 indicating exposure to >500 lx (photopic illuminance).	(TAT(500) – TAT(<10)) / (TAT(500) + TAT(<10))	113
Rhythm Robustness	Parameter	Goodness of fit of a fitted rhythm (e.g., cosinor), equivalent to R^2. See MESOR in Table .		102,139,140
Interdaily Stability (IS)	Aggregate	Variability of 24h light exposure patterns across multiple days. Note: Calculated as the ratio of the variance of the average daily pattern to the total variance across all days. Typically calculated for mean hourly light levels.[160] Ranges between 0 (Gaussian noise) and 1 (Perfect Stability).	VAR(mean daily pattern) / VAR(all days)	95,102,113,114
Intradaily Variability (IV)	Aggregate	Variability of consecutive light levels within a 24h day. Note: Calculated as the ratio of the variance of the differences between consecutive light levels to the total variance across the day. Typically calculated for mean hourly light levels.[160] Higher values indicate more fragmentation.	VAR(consecutive differences) / VAR(day)	95,102,113,114
Frequency of Intensity Changes (FIC(*C*))	Aggregate	Number of times consecutive light levels cross threshold *C*. Note: Calculated by [55] with photopic illuminance threshold of 1000 lx.		55
Pulses(*C*) Above Threshold	Aggregate	Clustering of continuous episodes (pulses) with light above threshold *C*. The following metrics were calculated across identified pulses: - Number of Pulses [57,148] - Mean Pulse Intensity [148] - Mean Pulse Length [148] - Total Pulse Time [148] - Mean Pulse Onset [148] Clustering Criteria: - Interruptions ≤8min and <25% of pulse length [148] - Pulse length ≥5min [57]		57,148

Table 6. Metrics quantifying characteristics related to exposure history.

Metric	Class	Description	Pseudo formula	Studies (reference number)
Cumulative Exposure (CE)	Aggregate	Integral of light exposure over given interval.	SUM(light)	54,55,59,64,96,99, 103,106,131,141,143
Solar-normalized CE	Aggregate	Ratio of cumulative personal light exposure to cumulative solar radiation.	SUM(light) / SUM(solar)	55
Dose(C_{min},C_{max})	Aggregate	Dose of light exposure within range of levels [C_{min}, C_{max}].	$TAT(C_{min},C_{max}) \times (C_{max} - C_{min})/2$	94
EMA dose	Point	Light exposure smoothed with an exponential weighted moving average. Note: The amount of smoothing can be adjusted with the parameter β. Calculated by [121] with $\beta = \log(2)/90$, approximating a decay half-life of 90 minutes. An appropriate initial value at t = 0 can be estimated by looping the data (see [161]).	$EMA_t = EMA_{t-1} + \beta \times (light_t - EMA_{t-1})$	121

Table 7. Other relevant quantification methods and metrics proposed by studies not included in the review.

Study (reference number)	Description
151	Bright/Dark Threshold (T_B, T_D): Max/min threshold where TAT > 6h/8h. Bright/Dark Mean Level (M_B, M_D): 20% trimmed mean of light above T_B / below T_D. Circadian Contrast: Difference between M_B and M_D. Bright/Dark Cluster (C_B, C_D): Longest continuous interval above T_B / below T_D. Circadian Variation: Average hourly coefficient of variation.
152,153	Wavelet Transform Spectral Analysis and Detrended Fluctuation Analysis: Quantification of behavioural patterns and exposure timescales.
154	Disparity Index: Measure of temporal variability of time series. Higher values indicate more variability.

Table 8. Metrics calculated for two exemplary days (Day 1 and Day 2) in August 2021 in Lausanne, Switzerland. Unless otherwise noted, metrics were calculated for the periods when the subject was awake.

Metric	Day 1	Day 2
Exposure Level		
Mean ± SD (lx)	121 ± 501	723 ± 1,830
GeoMean ± SD (lx)	19 ± 7	22 ± 37
Median (lx)	16	25
IQR (lx)	35	228
Maximum (lx)	9,648	18,077
M10m (lx) [b]	151	1,323
MESOR (lx) [a b]	8	18
Exposure Duration		
TAT(10,100) (min)	508	417
TAT(100,500) (min)	96	70
TAT(500,1000) (min)	15	27
TAT(1000) (min)	33	225
TAT(1000) (% daylength)	4%	27%
Exposure Timing		
Mid. CE (hh:mm) [a]	12:56	14:55
Cent. LE (hh:mm)	13:43	16:13
Acrophase (hh:mm) [b]	12:58	14:35
MLiT(10) (hh:mm)	13:01	13:13
MLiT(1000) (hh:mm)	16:11	16:14
M10on (hh:mm) [b]	08:05	09:58
FLiT(500) (hh:mm)	06:39	10:56
LLiT(500) (hh:mm)	18:04	19:07
FLiT(500) Angle (min)	55	348
LLiT(500) Angle (min)	199	270
Exposure Dynamics		
Rhythm Amplitude (lx) [a b]	7	16
LQI	-0.89	-0.47
Rhythm Robustness [a b]	0.48	0.49
IV [a b]	0.55	0.46
Disparity Index	0.55	0.48
FIC(1000)	26	28
N. Pulses(200)	16	9
Pulse(200) Mean (lx)	771	1,386
M. Pulse(200) Length (min)	6	32
T. Pulse(200) Time (min)	96	291
M. Pulse(200) Onset (hh:mm)	10:07	12:18
Exposure History		
CE (lx-min)	113,486	802,706
Dose(10,100) (lx-min)	22,860	18,765
Dose(100,500) (lx-min)	19,200	14,000
Dose(500,1000) (lx-min)	3,750	6,750
Dose(1000,3000) (lx-min)	29,000	152,000
Metrics in Barrosso *et al.*[151]		
T_B (lx)	24	72
T_D (lx)	0.21	0.55
M_B (lx)	96	1,677
M_D (lx)	0.01	0.01
C_B (min)	56	132
C_D (min)	455	313
Circadian Variation	5.21	2.93

[a] Calculated with log-transformed light levels. Metrics related to exposure levels were back transformed to standard scale for easier comparability.

[b] Calculated for the entire 24 h period.

Note: SD = standard deviation, GeoMean = geometric mean, IQR = interquartile range, M10m = mean of brightest 10 h, MESOR = rhythm adjusted mean, TAT = time above threshold, Mid.CE = midpoint of cumulative exposure, Cent. LE = centroid of light exposure, MLiT = mean light timing above threshold, M10on = onset of brightest 10 h, FLiT = first light timing above threshold, LLiT = last light timing above threshold, LQI = light quality index, IV = intradaily variability, FIC = frequency of intensity changes, N. Pulses = number of pulses, M. Pulse Length = mean pulse length, T. Pulse Time = total pulse time, M. Pulse Onset = mean pulse onset, CE = cumulative exposure, T_B = bright threshold, T_D = dark threshold, M_B = bright mean level, M_D= dark mean level, C_B = bright cluster, C_D = dark cluster.

Table 9. Possible strategies for evaluating light-dosimetry metrics in future studies.

- Sensitivity analyses of parameterised metrics against measured responses to identify dose-response relationships.
- Compare distribution of metrics across data of diverse samples, to identify metrics with a wide range of outcome values, indicating metrics that can differentiate groups/individuals.
- Compare distribution of metrics between groups of individuals with similar measured responses.
- Compare distribution of metrics between groups of light exposure time series that lead to similar predicted responses.
- In the long term: define minimum toolset to quantify/describe personal light exposure data.