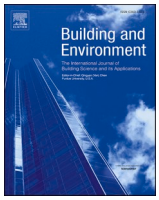
Wearable monitoring for evaluating non-visual effects of light on health and well-being: a systematic review

Building and Environment 284 (2025) 113482

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv



Wearable monitoring for evaluating non-visual effects of light on health and well-being: a systematic review

Francesco Salamone [a], Sergio Altomonte [b], Claudia Naves David Amorim [c], Giovanni Ciampi [d,*], Ludovico Danza [a], Aicha Diakite-Kortlever [e], Veronica Garcia-Hansen [f], Mandana S. Khanie [g], Marshal Maskarenj [b], Anna Pellegrino [h], Michelangelo Scorpio [d], Natalia Sokol [i], Natalia Giraldo Vasquez [j], Sergio Sibilio [d]

[a] Construction Technologies Institute, National Research Council of Italy (ITC-CNR), Via Lombardia 49, San Giuliano Milanese, 20098, Milano, Italy
[b] Université catholique de Louvain, Architecture et Climat, Louvain Research Institute for Landscape, Architecture, Built Environment, 1340, Louvain-la-Neuve, Belgium
[c] University of Brasília, Faculty of Architecture and Urbanism, Laboratory of Environmental Control and Energy Efficiency LACAM, Campus Universitário Darcy Ribeiro, Ala Norte 70, 910-900, Brasília, Brazil
[d] Department of Architecture and Industrial Design, University of Campania Luigi Vanvitelli, Via San Lorenzo Abazia di San Lorenzo, 81031, Aversa, Italy
[e] Technische Universität Berlin, Chair of Lighting Technology, 10587 Berlin, Germany
[f] School of Architecture and Built Environment, Queensland University of Technology, 2 George Street, Brisbane, Queensland, Australia
[g] Institute for Environmental Design and Engineering (IEDE), The Bartlett, Faculty of the Built Environment, University College London, London, WC1H 0NN, UK
[h] Department of Energy "Galileo Ferraris", Politecnico di Torino, 10129, Turin, Italy
[i] Faculty of Architecture, Gdansk University of Technology, 80-233, Gdansk, Poland
[j] International Centre for Indoor Environment and Energy, Department of Environmental and Resource Engineering, Technical University of Denmark, 2800, Kongens Lyngby, Denmark

ARTICLE INFO

Keywords:
Non-visual effects of light
Wearables
Light exposure monitoring
Physiological monitoring
Human activity monitoring
Users' feedback
Health and well-being
Circadian rhythms
Systematic review

ABSTRACT

The impact of light on circadian rhythms, alertness, and well-being is widely recognized. Advancements in lighting research emphasize the importance of understanding these effects, mainly by measuring personal light dose, considering timing, intensity, duration, and spectrum. Therefore, new monitoring devices have been developed to measure individual light exposure and improve light dose analysis on circadian rhythms. Currently available devices include wearable sensors and low-cost, open-source, solutions that are adaptable and widely applicable. These wearables, when used alongside other measurement tools and standardized protocols, offer a comprehensive means to study light exposure in real-world conditions. However, despite the growing availability of these technologies, there is a lack of systematic evaluation regarding their accuracy, reliability, and applicability in both research and practical settings. This review explores recent developments in wearable technologies for monitoring the non-visual effects of light on humans. Emphasizing the role of circadian rhythms, it discusses how light exposure influences alertness, mood, and overall health and well-being. A range of monitoring devices is evaluated, highlighting variations in functionality and way of wearing, while identifying data reliability and standardization gaps. This review paper aims to emphasize the importance of integrating different measurement tools, combining environmental monitoring (e.g., light exposure), physiological assessments (e.g., heart rate, body temperature), and personal feedback (e.g., subjective reports on alertness and well-being). The review results highlight a more holistic approach to studying the impact of light on humans. Furthermore, it proposes future research directions and practical applications to enhance health outcomes through personalized light management strategies.

1. Introduction

The non-visual aspects of light, including its effects on circadian rhythms, alertness, and overall well-being, have gained increased attention in research and practical applications [1–7]. Daylight plays a pivotal role in synchronizing the circadian rhythms, which are essential

* Corresponding authors.
E-mail addresses: francesco.salamone@cnr.it (F. Salamone), giovanni.ciampi@unicampania.it (G. Ciampi), michelangelo.scorpio@unicampania.it (M. Scorpio).

https://doi.org/10.1016/j.buildenv.2025.113482
Received 21 February 2025; Received in revised form 24 June 2025; Accepted 23 July 2025
Available online 29 July 2025

for regulating sleep-wake cycles, work performance, mood, and other physiological functions [6]. The importance of these non-visual effects is underscored by studies reporting that disruptions to circadian rhythms can lead to health issues such as sleep disorders, mood disturbances, and impaired cognitive function [8,9]. In addition, inappropriate timing in light exposures affects sleep quality [10] and contributes to adverse health outcomes, including increased risk of neurological disorders, metabolic dysregulation, and cardiovascular diseases [11,12]. Specific wavelengths and intensity, and spatial distribution of light, as well as duration and timing, influence the circadian system differently, emphasizing the need for precise monitoring of light exposures [13].

Monitoring devices have been developed to measure light exposure and analyze its non-visual effects [14–18]. These tools range from sophisticated commercial tools to low-cost, open-source solutions that are easily adaptable and replicable across diverse settings [14–21]. Wearable sensors, developed to track light exposure, have leveraged technological advancements [14–18]. Low-cost, open-source approaches offer flexibility in design and application, making them especially valuable for research and practice [20,21]. Van Duijnhoven et al. [22, 23] analyzed the characteristics and usability of over 50 wearable light loggers through expert meetings and iterative discussions. Their findings highlighted the diversity in design, functionality, and availability of these devices. However, technical improvements and enhanced data reliability remain necessary.

Developing a framework for using devices to measure light exposure - while integrating the objective environmental data they provide with information from other instruments that monitor subjective individual parameters, physiological responses, and feedback from a human-centered perspective – is essential for ensuring consistent and reliable data collection, especially in the absence of widely accepted industry standards [20,22]. These innovations hold the potential to bridge current light and daylight management systems with human-centered controls that provide personalized solutions towards improved comfort and health [24–26] while also reducing energy consumption and environmental impacts [27,28].

In practice, devices for measuring the non-visual effects of light are often used alongside wearable sensors that can simultaneously measure multiple physical and physiological parameters, or environmental monitoring systems, to provide a comprehensive analysis of light exposure. Data analysis in this field typically combines objective data (e.g., environmental light intensity and spectral distribution) with subjective data (e.g., individual physiological responses and user feedback), for a holistic understanding of how light influences non-visual pathways. Studies have frequently investigated real-life contexts [2,5,11,17, 18,24–26,29–38], including healthcare settings [1,2,9,11,18] workplaces [17,34], educational environments [8,17], and controlled laboratory conditions [16,39,40].

Given recent advancements in wearable and nearable devices (i.e., smart devices embedded with sensors and wireless communication capabilities which are placed in the proximity of the users) capable of capturing individual light exposures, this review systematically analyzes the current frameworks and methodologies available for measuring the non-visual aspects of light. It evaluates their effectiveness, adaptability, and application across various contexts while identifying gaps in current knowledge and proposing directions for future research and development [41].

While van Duijnhoven et al. [22] provide a comprehensive matrix of monitoring devices for environmental parameters, there remains a critical need for a deeper analysis of wearable-based frameworks, i.e., a methodological or technical system that utilizes wearable devices to gather and interpret data, often in real time, for a specific application such as health or physiological monitoring, environmental sensing, and behavioral, performance or perception analysis [42–44], and the insights gained from their application. This review emphasizes opportunities to leverage wearable devices as monitoring systems for the non-visual effects of light in practical applications. Additionally, it explores how wearable devices can monitor light exposure, integrate physiological responses and human activities and feedback, and deepen the understanding of the effects of circadian exposures on overall health and well-being.

The review also discusses limitations and challenges associated with wearable technologies, particularly regarding accuracy and user compliance. It highlights recent advancements in sensor technology, including improvements in accuracy, miniaturization, and usability, which make wearable devices more practical and accessible for everyday use.

The following research questions have driven this review:

- What is the context for the use of wearables to study non-visual effects? What types of spaces and participants are primarily considered for measuring the non-visual aspects of light, and why?
- What are the main functionalities of tools for measuring the non-visual effects of light?
- How are these tools designed? Do they leverage low-cost, open-source approaches to support replicability, adaptability, and usability across diverse contexts?
- What additional devices are commonly used alongside these tools, and what types of data (objective or subjective) are primarily utilized in the analysis?

The systematic methodology for collecting relevant papers is detailed in Section 2. Section 3 provides an overview of the gathered articles. Section 4 organizes the results into three subsections: subSection 4.1 reviews studies on the primary characteristics of wearables used to monitor environmental parameters that quantify the non-visual effects of light on humans; subSection 4.2 discusses articles utilizing wearables to monitor physiological responses and human activities; and subSection 4.3 examines user feedback for assessing subjective perceptions of health and well-being during testing. Section 5 focuses on the discussion, and Section 6 presents the main conclusions and recommendations for future research.

2. Methodology

The methodology used for collecting relevant papers involved three steps: 1) identifying the database for the query, 2) defining the query, and 3) identifying additional studies from other sources.

Elsevier's Scopus search engine was selected from various available databases (e.g., PubMed, Web of Science, Google Scholar). Scopus includes resources from the Institute for Scientific Information (ISI) and focuses on physical and social sciences articles indexed from 1966 onwards [45]. This database is suitable for our research since we aim to examine the physiological and psychological effects of light on humans, including sleep-wake cycles, immune and metabolic functions [3], alertness, mood, and overall performance. This research topic has gained significant attention since the discovery of Intrinsically Photoreceptive Retinal Ganglion Cells (ipRGCs) in the human retina at the turn of the century [46,47].

Scopus offers flexible search capabilities, including both basic and advanced search functions. The advanced search allows for customized and specific queries using coding operators. A detailed search guide is available in [48]. The query was designed to align with the research goal outlined in the introduction. Fig. 1 shows its structure.

The TITLE-ABS-KEY field code shown in grey was used to ensure that only documents containing the selected words in the titles, the abstracts, and the keywords were collected. Specifically, the KEY field involves a combined search that includes the author's assigned keywords (AUTHKEY) and the controlled vocabulary terms (INDEXTERMS) assigned by Scopus's professional indexers. While researchers may sometimes give limited attention to defining the AUTHKEY, keywords are crucial for communicating scientific results [49]. In this sense, the INDEXTERMS are added by Scopus professional indexers based on different

TITLE-ABS-KEY ((monitoring OR wearable) AND (light OR daylight) AND ("non image forming" OR "non visual" OR circadian OR health) AND ("built environment" OR (light W/3 effect)) AND (EXCLUDE (DOCTYPE , "cr"))

Fig. 1. Scopus' query structure consisting of 5 sections.

vocabularies [50]. In rapidly evolving research fields, this approach can reveal a highly clustered set of new keywords [51].

The following sections characterize the query:

- the first set of keywords ("monitoring OR wearable", in red in Fig. 1) covers the monitoring activity;
- the second set of keywords ("light OR daylight" in orange in Fig. 1) is connected to the first set with the AND operator and identifies the monitored macro area of lighting-related aspects;
- the third set of words (""non image forming" OR "non visual" OR circadian OR health", in green in Fig. 1), connected to the second set with the AND operator, considers the human-centric perspective related to this area of research;
- the fourth set of words (""built environment" OR light W/3 effect", in blue in Fig. 1), connected to the third set with the AND operator, is related to the macro area of interest;
- the fifth set of words (in black in Fig. 1), connected to the previous four sets, identifies the type of documents to be excluded: "cr"=conference review.

The timeframe for publications was not specified in the query structure, which prevented a biasing in selection due to arbitrarily set year constraints. Similarly, no geographical location limits were applied. In June 2025, this configured query returned 263 papers. Following the identification criteria featured in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) diagram, which is commonly used in review studies to ensure reproducibility and transparency of selection criteria [52], 27 additional studies were then included in the initial dataset, the co-authors have identified these studies through other sources. Fig. 2 illustrates the flow diagram of the review process, detailing how manuscripts were acquired and analyzed. As shown, the final number of papers ($N = 23$) resulted from two phases of the screening process, where duplicates were removed (only one in our case) in the first phase, following which, works that did not perfectly match the research topic were excluded based on their titles and the abstracts. Finally, the eligibility of the remaining papers was determined through full-text reading.

It is important to note that only one paper was considered duplicated after the initial identification phase, so the total number of papers considered in the screening was 250. To minimize the potential biases in the screening process and in eligibility assessment (since these decisions were primarily made by only one co-author) [53,54], all the co-authors

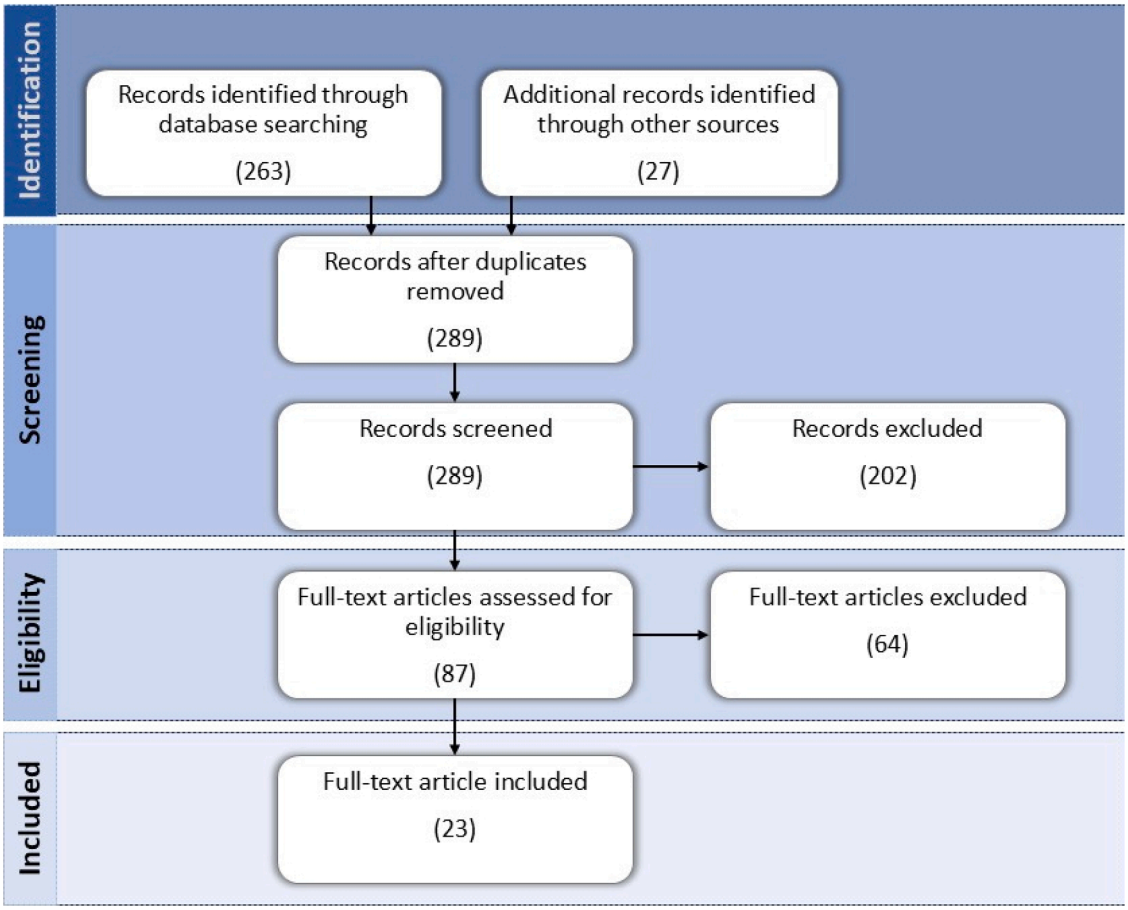


Fig. 2. PRISMA flow diagram (June 2025).

performed a comprehensive data extraction and reached a consensus over discrepancies through discussion [54]. Of the 23 manuscripts that were finally selected, 78 % were indexed on Scopus, while 22 % were derived from other sources.

3. General overview of studies

To verify the effectiveness of the selection process as described above, an Explanatory Data Analysis (EDA) was performed using titles and abstracts of the selected documents. The text of each title and abstract was tokenized, and all punctuation marks, stop words, and words shorter than 3 letters in length were removed. A lemmatization process was then applied, converting words to their base forms. Unlike stemming, which simply removes the last few letters and can result in incorrect meaning (e.g., 'caring' becomes 'car'), lemmatization considers context to convert words to their meaningful base forms (e.g., 'caring' becomes 'care') [55,20].

Next, bigrams and trigrams were formed, representing two or three words that frequently occurred together in the selected text (e.g., real-time monitoring, laboratory conditions). Finally, the EDA was performed using the 'wordcloud' package for Python, displaying the importance of each word based on its frequency of occurrence with varying font sizes. Fig. 3 shows the 50 most frequent words in the titles and abstracts, demonstrating that the screening process and eligibility assessment were correctly performed and that the selected papers were consistent with the research aim.

Among the most frequent words are light, sleep, light exposure, effect, lighting, circadian, spectral, exposure, and participant.

The Annual Growth Rate starting from 2009, i.e., the year of the first selected publication on this topic, was found to be 23.25 %. Fig. 4 shows the cumulative occurrences of articles published in the three most predominant journals (of the 17 selected journals).

Among the 23 peer-reviewed scientific articles analyzed, Lighting Research and Technology stands out as the preferred journal, having the highest concentration of articles published on the considered topic.

4. Results

Within the studies reported in the selected papers, the participants' ages range from 10 to 80 years. The number of participants is highly variable between studies (with a minimum of 3 subjects and a maximum of 4057), as shown in Fig. 5. In most cases, it is not specified how the sample size, defined as the number of participants tested, was determined, or whether it meets the minimum requirements to validate the hypothesis (i.e. power analysis). Additionally, 33 % of studies lack a clearly defined hypothesis statement, though the research objectives are specified in all cases.

In roughly half the cases [2,8,11,17,18,31,32,34,35,39,56], the state of health of participants is not consistently detailed. In five cases [9,29,36–38], participants are reported as healthy. In [24], out of 80 participants, half were classified as myopic. In [25], 14 participants had Tourette's Disorder, and 20 healthy participants served as a control group. In [26], all participants had Primary Biliary Cholangitis. In [57], half (17) of the participants were diagnosed with dementia, and the other half were caregivers living with patients. In [30], the authors noted that, while the health status was not fully defined, the 887 participants generally displayed good cognitive function. In [33], all 11 participants were affected by dementia. In [58] the authors analyzed health-related data from Hispanic Community Health Study/Study of Latinos (HCHS/SOL), which included 2147 participants, and from the Multi-Ethnic Study of Atherosclerosis (MESA), which included 1910 participants.

Fig. 5 also demonstrates the variation in evaluation period across studies, ranging from 1 hour (60 min) to over 6 weeks (62,400 min) per participant.

Fig. 5 reveals that, in most of the selected studies, the tests were conducted in real-life contexts, except for [39], which used a climatic chamber. In some cases, [2,11,25] and [26], even though the study was conducted in a real context, the participants were asked to wear special glasses or were given specific lighting conditions, which is the reason for the distinction between the first two legend entries (i.e., "real-life" and "real-life intervention"). Among the studies set in real-life environments, 40 % did not clearly specify the testing environment, whereas in the remaining 60 %, the environment used for testing was well-defined. For instance, in [35], the bedroom served as the testing space because the study examined how the spectrum of light exposure affects sleep quality through non-visual pathways. The cross-sectional study was conducted from February to May 2022 in the greater Copenhagen area (Denmark), involving 96 students. Similarly, [25] used the bedroom to investigate circadian delays and sleep disturbances in adults (average age 30) with Tourette's Disorder, and compared these to healthy controls (HC) as baseline while investigating whether short-wavelength wearable morning light therapy could advance the circadian phase and improve sleep and clinical symptoms. Hartmeyer et al. [56] involved 20 participants who were monitored over two workweeks (4–5 days/week), with at least 2160 min of light exposure data per person. The measurements were conducted in a real office environment in central London equipped with a daylight-responsive LED lighting system and a glazed façade that allows access to daylight.

Another specific home environment, the living room, was used in

Fig. 3. Exploratory Analysis with wordcloud of the most used terms in the title and abstract of the selected papers.

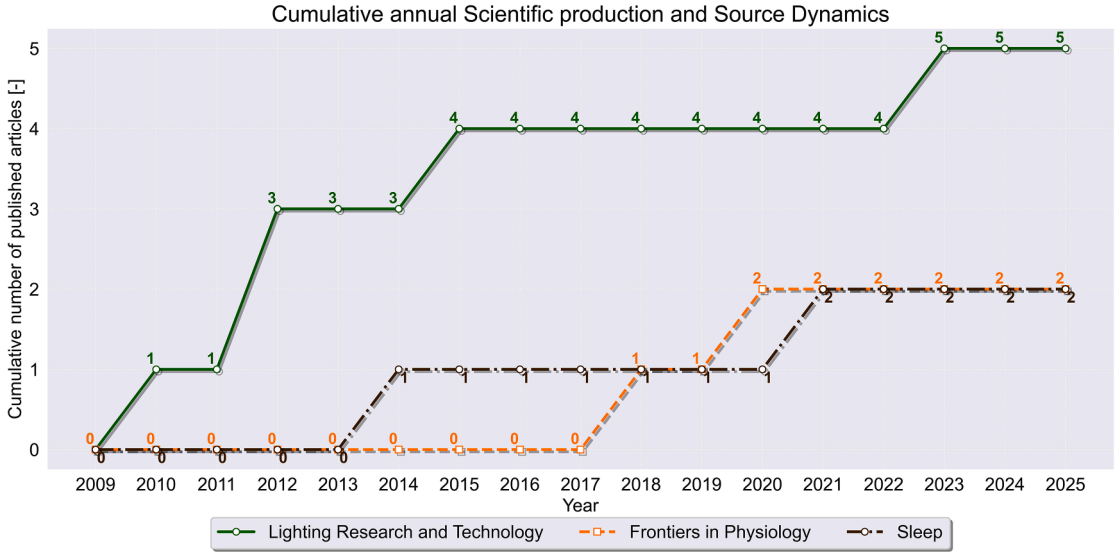


Fig. 4. Cumulative annual Scientific production and Source Dynamics.

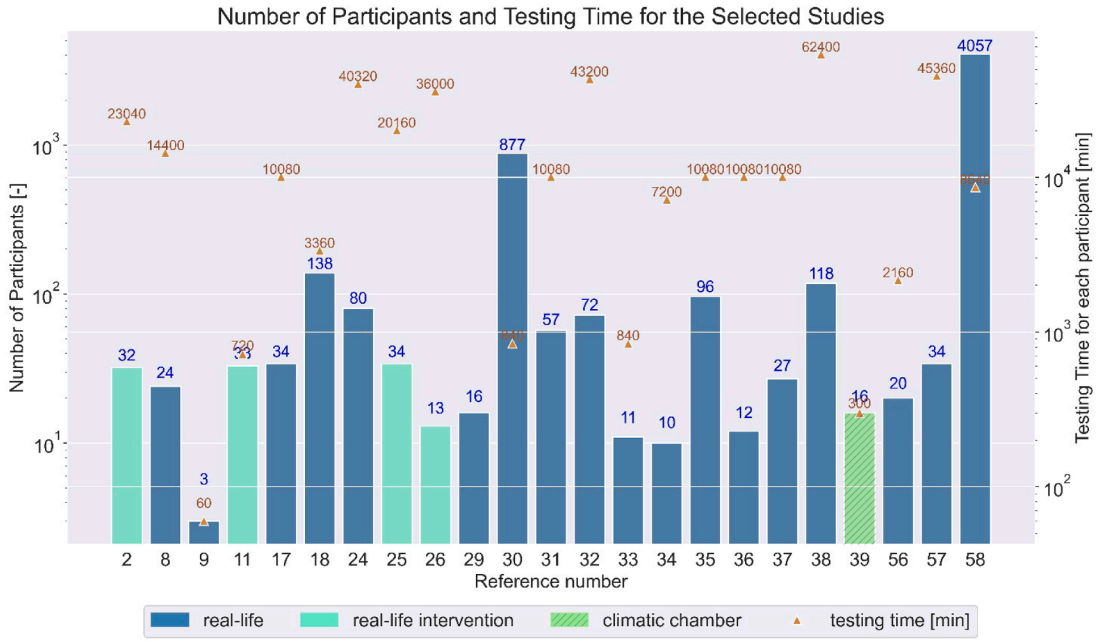


Fig. 5. Number of participants (also shown with a blue number on each bar), test time in minutes (also shown in brown on each marker point) and type of environment for the selected studies (color-coded in the bar).

[57] to test whether adults (average age 66) with dementia and their caregivers could detect differences in chromaticity shift (CS) under two different lighting conditions. Van Lieshout-van Dal et al. [33] also used the home as the general environment to investigate the influence of a dynamic lighting system on individuals with dementia.

A hospital study [11] examined the effectiveness of morning light therapy combined with short-wavelength filter glasses at night on the sleep quality, timing, and mood of medical inpatients. Also, in a hospital, [2] assessed the daytime spectral sensitivity in terms of alertness, performance, and waking EEG in healthy young adults (average age 24) exposed to different light wavelengths. In [9], the study used an ambulatory space, while [18] employed a hospital as the natural work environment for nurses to examine the differences in behavioral circadian entrainment and disruption between day-shift and rotating-shift nurses.

Additionally, case-specific environments were considered in some studies, e.g. [29,24,8,30] and [34]. In [29], a dormitory was used to explore the effects of natural daylight on sleep quality, alertness, mood, and fatigue. The studies [24] and [30] are the only two studies focused on both indoor and outdoor spaces. In [24], the authors investigated the effects of different types of light, particularly dim light, on myopia in children aged 10 to 15. In [30], light exposure timing of community-dwelling older men was studied to assess whether enhances sleep-wake consolidation. The study analyzed natural light exposure patterns and their associations with sleep-wake fragmentation, physical and mental health, and cognition, aiming to support non-invasive interventions, like light therapy, for healthy aging.

In [8], a classroom was used as part of an intervention study on the effects of a dynamic lighting system on high school students in Reykjavik (Iceland). The study investigated how these types of data can be

analyzed, what insights they provide into individuals' spectral light exposure, and how they could be used to assess lighting interventions. Lastly, [34] evaluated, in an office environment, the effects of intense morning or afternoon light exposure on subjective sleepiness, vitality, mood, fatigue, sleep on office workers, and their light appraisals.

The study carried out by Wallace et al. [58] included 4057 adults from two large U.S. cohort studies (2147 from Hispanic Community Health Study/Study of Latinos (HCHS/SOL) and 1910 from Multi-Ethnic Study of Atherosclerosis (MESA)). The white light exposure (lux) and physical activity (triaxial movement) of each participant were continuously monitored using wrist-worn devices called Actiwatch Spectrum for six days, yielding approximately 8640 min (144 h) of light exposure data. The study took place in free-living conditions across eight diverse geographic regions, capturing both indoor and outdoor settings during participants' daily routines.

In Appendix A, a comprehensive summary of the selected manuscripts is provided. They are organized into three subsections, corresponding to distinct fields: environmental, physiological, and subjective monitoring, as detailed below. Each research study chosen covers at least two of these three fields of analysis, with each subsection encompassing 81 % of the total selected studies.

4.1. Quantifying the impact of non-visual effects of light on humans through personal and environmental monitoring

This subsection provides a comprehensive overview of the hardware and software systems employed across the selected studies, focusing on their ability to monitor key parameters such as irradiance, spectral distribution, photopic illuminance, melanopic equivalent daylight illuminance (mEDI) and circadian stimulus (CS/Cla) of personal light exposure.

The Actiwatch, available in different versions, was used in various studies: the Spectrum [59,60], used in [31,36,39] and [58], which is also available under the name "Spectrum+" or Spectrum Pro", has a light sensor with a wavelength range of 400–700 nm and can measure the irradiance, photon flux, and photopic illuminance; the "2″ version, used in [24] and [30], is equipped with a light sensor that monitors wavelength in the range of 400–900 nm and can measure irradiance, photon flux, and photopic illuminance; the "L" [61] version, used in [17] and [31], is equipped with a sensor capable of monitoring wavelengths between 330–720 nm and is used to measure illuminance. In addition to the "L" version of the Actiwatch, a version called "RGB", as mentioned in [17], is equipped with three photodiodes with dye-based red, green, and blue (RGB) filters. Wallace et al. [58], performed large-scale environmental monitoring using wrist-worn devices that recorded ambient light exposure across multiple geographic regions. The analysis revealed significant variation in light exposure patterns based on season, location, and demographics, indicating that many participants experienced insufficient bright light during the day and elevated exposure at night. The Actiwatch is capable of measuring a broad spectrum of light intensities, from very dim (scotopic) to bright daylight (photopic), making it useful for diverse lighting conditions. However, the Actiwatch 2 tends to underestimate actual light levels, which can affect measurement accuracy [62].

The Daysimeter, known for its high photometric accuracy, was another frequently used device. It demonstrated superior spatial sensitivity and a photopic response more closely aligned with the V(λ) function compared to the Actiwatch Spectrum [63]. Miller et al. in [18] used the Daysimeter to monitor circadian light-dark stimuli (CS/CLa), while Figueiro et al. in [36] used this device to compare its data quality against the Actiwatch Spectrum for measuring circadian light and activity. Similarly, Itzhacki et al. in [37] used Daysimeters to evaluate the effects of light intensity on subjective preferences by measuring multiband spectral data and illuminance. The LYS sensors were employed in the studies of Van Lieshout-van Dal et al. [33] and of Khanie et al. [35] to assess daily light exposure. These sensors were worn near the eyes to investigate their effects on individuals with dementia [33] and on students' sleep quality [35], respectively. The lightweight LYS button seems to require device-specific calibration due to variability in light measurement accuracy. It is also sensitive to orientation, with rotation affecting results. However, its measurement error is smaller at lower light levels, as shown in comparisons with the reference-calibrated sensor [64].

Hartmeyer et al. [56], used wearable light-dosimeters (AS7265x spectral sensors from AMS) to quantify personal light exposure in an office setting and to assess how a daylight-responsive lighting system influenced non-visual light input at eye level. The results highlighted that actual exposure depended not only on the lighting design but also on individual behaviors, workstation location, and proximity to windows, underscoring the importance of real-world measurements for evaluating non-visual effects. In addition to commercial systems, new prototypes have been developed to characterize the quality and quantity of light in environments. Stampfli et al. [9] developed a light dosimeter (Lido) to take automatic measurements at pre-set intervals near a person's face. The available hardware photosensors were calibrated to approximate the s/m/l cone-opic, rhodopic, and melanopic spectral sensitivity curves, and a software suite was developed for the evaluations. Lido includes custom mountings and software for data analysis, but is reportedly unreliable below 5 lx, which limits its use in the evening [9]. Hartmeyer et al. [8] used the Spectrace dosimeter prototype, which has 14 spectral channels in the visible range, to register different types of light spectra that high-school students were exposed to in classrooms. Smartphone and smartwatch sensors, including ambient light and noise monitors, were utilized in the study of Gabinet and Portnov [32] to explore the effects of artificial light and noise on sleep. Additionally, Peeters et al. [34] used a brooch with a light logger, and Cain et al. [38] studied the impact of home lighting on sleep and circadian cycles, using a wearable device with a mini-spectrometer, SPECCY [15], to monitor light exposure. Sloane et al. [57] used a circadian light meter to assess incident circadian stimulus in an intervention study, with Actiwatch-L worn on participants' wrists to track sleep and circadian rhythms.

Overall, these studies highlight the diversity of devices and approaches used to comprehensively monitor environmental lighting and its impact on human health and behavior. Table B.1 in Appendix B provides a detailed overview of the devices used for environmental and personal dose monitoring, including their placement, validation status, form factor and size, associated software and the main stimulus variables [65] monitored along with information on their measurement accuracy. This evaluation highlights the diversity in design and functionality, as well as the varying levels of accuracy and standardization across the monitoring tools.

As highlighted in Table B.1, although wearable devices are widely used in the current literature for field testing, detailed information regarding their measurement accuracy is often unavailable. This highlights the urgent need to establish a standardized calibration protocol before deploying such instruments in field studies.

All hardware used for environmental and personal dose monitoring is commercially available or has been developed for research purposes without an open-source license.

4.2. Physiological and human activities monitoring to assess the non-visual effects of light

The studies monitored various physiological parameters and human activities using wearable devices, which can be grouped by the devices employed:

The Actiwatch series was widely used to measure activity and sleep patterns. For instance, the Actiwatch-L was used in the study of Thorne et al. [17] along with the "RGB" version to track activity and light exposure simultaneously, while the study of Sloane et al. [57] used Actiwatch-L to evaluate sleep latency, duration, and efficiency. The

Philips Actigraph family also includes the Actiwatch 2 used in the study of Lok et al. [30] and Landis [24], while the Actiwatch Spectrum, also known as the Actiwatch Spectrum Pro or Plus, was included in 5 of the selected studies [25,31,34,38], and [58]. Ricketts et al. [25] used the wearable device in combination with the company's proprietary software, Actiware version 6.0.9, to determine sleep efficiency (total sleep time divided by time in bed multiplied by 100), among other measures. During the test, saliva samples were also collected at 30-minute intervals to determine dim light melatonin-onset (DLMO), which is "the single most accurate marker for assessing the circadian pacemaker" [66]. The main problem reported with determining DLMO from saliva samples was that each sample had to be stored in ice at −20 °C during the testing phase and then sent for batch analysis by radioimmunoassay analysis of melatonin concentration [25]. A similar approach was also used in the studies of Cain et al. [38] and Huang et al. [31] with a strict sleep-wake schedule monitoring with the Actiwatch Spectrum and assessing salivary melatonin levels with hourly samples [38] or 30-minute samples [31].Wallace et al. [58], used the Actiwatch Spectrum as a wrist-worn device to continuously measure ambient white light exposure (in lux) and activity levels over a period of six consecutive days. Participants wore the device on the wrist, with the sensor facing upward in the same plane as the back of the hand. Light data were collected in 30-second epochs, allowing for detailed tracking of light exposure patterns throughout the day and night. They demonstrated the value of wearable light dosimetry combined with activity tracking to assess how real-world office lighting conditions influence individual light exposure patterns relevant to circadian regulation and sleep-wake behavior. Peeters et al. [34] used the Actiwatch Spectrum as an objective measure of sleep and wake time along with other sensors used for environmental assessment, as detailed in Section 4.1 and Table B.1 (Appendix B).

The Daysimeter, a versatile tool for circadian studies, developed for the first time in 2005 with a series of upgrades and described in section 3.1 [20], was also considered in the study of Itzhacki et al. [37] and Miller et al. [18]. The Daysimeter allows the measurement of rest/activity patterns through three orthogonally oriented solid-state accelerometers.

Hartmeyer et al. [56] used the wearable light dosimeter Spectrace prototype to measure personal light exposure at the chest level, positioned on the outer layer of clothing and worn continuously during waking hours across two workweeks. Participants were asked to maintain the same desk location throughout the study, and the device was worn while they carried out their normal office routines. The results showed that large-scale monitoring of light exposure and physical activity using wrist-worn devices enables the identification of population-level patterns associated with non-visual effects of light, such as disrupted circadian rhythms and insufficient daytime light exposure.

Jawbone is another type of wearable used in the studies selected. In the study by Dong and Zhang [29] the Jawbone UP3 was used to quantify bedtime, deep sleep time, rapid-eye-movement sleep time, and sleep onset time. The Jawbone UP3 also has three heart rate monitoring sensors that record data during active and resting periods, but these data were not included in this study. A Jawbone wearable was also considered in the study of Formentin et al. [11], the UP24 model, which is the predecessor of the UP3. It was used to identify sleep/wake activity by recording movements with an accelerometer.

Other devices include the SOMNO watch wearable, an FDA-approved device for measuring sleep parameters, used in the study of Turco et al. [26] for sleep/wake detection, or more generally, activity data. Sleep/wake detection was also considered in the study of Hartmeyer et al. [8], with the Spectrace, and in [35] where a FitBit actiwatch was used to track sleep quality along with an iButton to determine the temperature of the skin (T_{skin}). In this rather uniform context, two contributions [2] and [9] stand out due to the use of different sensors. Rahman et al. [2] used a Temec Vitaport-3 digital recorder to measure EEG, electrooculogram (EOG), and a two-lead electrocardiogram (ECG). Stampfli [9] used a Pupil Core eye tracker [67].

Table B.2 in Appendix B summarizes the hardware and software used and the parameters considered. Fig. 6 displays the above-mentioned hardware. Considering that different versions of Spectrace were developed, but no details on which version was used in [8] were reported, we decided to exclude this device from the figure below.

All hardware used to monitor physiological and human activity is commercially available or has been developed for research purposes without an open-source license.

4.3. Subjective assessment of health and well-being

This section presents selected studies that have investigated the potential relation between light and its possible influence on mood, alertness, and overall well-being. To study this relationship, it is essential to acquire user feedback and subjective perception. The selected studies are grouped based on the specific scales used.

The Karolinska Sleepiness Scale (KSS) [68] was used in studies by Dong and Zhang [29], Peeters et al. [34], Formentin et al. [11], and Rahman et al. [2] to assess levels of sleepiness. The KSS categorizes sleepiness into ten levels, ranging from "extremely alert" to "extremely sleepy", and was frequently combined with other subjective measures, such as alertness, mood, and vitality.

The Pittsburgh Sleep Quality Index (PSQI) [69], used in studies by Sloane et al. [57], Turco et al. [26], Ricketts et al. [25]., Formentin et al. [11], Thorne et al. [17], Gabinet and Portnov [32] and Cain et al. [38], provided a comprehensive assessment of sleep quality and disturbances. This index includes several subscales that evaluate areas such as sleep latency, duration, and efficiency, offering a detailed picture of participants' sleep patterns. The Epworth Sleepiness Scale (ESS) [70] was utilized in studies by Sloane et al. [57], Ricketts et al. [25], and Cain et al. [38], to measure daytime sleepiness. This scale uses a 4-point range to gauge levels of sleepiness, complementing the sleep quality assessments provided by the PSQI.

A daily sleep diary was used by Hartmeyer et al. [56], to collect subjective sleep parameters. The diary collected information on bedtime, preparation time and wake-up times, sleep latency, awakenings during sleep, total Wake After Sleep Onset (WASO) duration, and a 5-point scale for sleep quality and recovery feelings. Time in bed was calculated as the duration from bedtime to getting out of bed. In contrast, total sleep time was computed by subtracting total WASO duration and sleep latency from sleep onset to wake onset. Participants completed the survey upon waking using the MyCap application [71].

Turco et al. [26], Cain et al. [38], Thorne et al. [17] and Formentin et al. [11] used the Horne-Östberg Chronotype Questionnaire (HÖ) [72], also known as "Morningness-Eveningness questionnaire" [73], to determine participants' chronotypes, classifying them as morning or evening types. This information proved valuable in research exploring the relationship between light exposure and circadian alignment.

Mood was assessed using both Visual Analog Scales (VAS) and Likert Scales, have been employed in several studies. VAS, used in studies by Formentin et al. [11] and Itzhacki et al. [37], helped assess mood states and preferences. For instance, a study [37] used VAS to measure "liking" and "wanting" responses, with endpoints ranging from 0 (not at all) to 100 (very much). Instead, 5-point, 7-point, and 9-point Likert scales were used by Dong and Zhang [29], Peeters et al. [34], and Krüger et al. [39], to evaluate mood, vitality, and light appraisals.

Health and Functioning Scales have also been utilized. For example, the 36-item Short Form Health Survey (SF-36) [74], employed in the study by Turco et al. [26], provided an evaluation of health-related quality of life. Other studies, such as those by Lok et al. [30] and Sloane et al. [57], used additional scales like the Physical Activity Scale for the Elderly (PASE) [75], Geriatric Depression Scale (GDS) [76], and Quality of Life in Alzheimer's Disease (QoL-AD) [77] to assess various health-related parameters.

Other Sleep and Mood Scales included the Insomnia Severity Index

Fig. 6. Exemplary selection of the hardware used for physiological and human activities monitoring.

(ISI) [78], which was used in the study by Cain et al. [38] to assess insomnia severity using a 5-point categorical scale. Additionally, Ricketts et al. [25]. employed the Yale Global Tic Severity Scale (YGTSS) [79] to examine the effects of light therapy on tic severity and associated sleep issues.

Cognitive assessment was also incorporated in several studies; for instance, the Mini-Mental State Examination (MMSE) was considered by van Lieshout-van Dal et al. in [33] and by Figueiro et al. in [36], while the Baddeley Reasoning Test was employed in a study by Khanie et al. [35].

Finally, Experience Sampling Methods were used in the study by Itzhacki [37] to track mood and emotional states in real-time. Participants provided mood reports at quasi-random intervals throughout the day, using VAS, with endpoints of 0 (not) and 100 (very much), to capture fluctuations in mood.

Table B.3 in Appendix B summarizes all scales used in the selected studies for acquiring users' feedback and the associated subjective parameters.

5. Discussion

The current review allows us to answer the main questions presented in the introduction and to introduce the following key points of discussion:

5.1. User considerations: contextual use and participant-centered design for future research direction

In investigating the non-visual effects of light, prior research has primarily focused on various real-life contexts and employed diverse participant groups to assess outcomes related to circadian rhythm, mood, alertness, and health conditions. The spaces studied include personal spaces like bedrooms, where studies examine how light exposure affects sleep quality and circadian delays (e.g., for those with Tourette's Disorder), and common living areas, such as the living room, where responses to changes in light chromaticity by participants with dementia and their caregivers were evaluated. In hospital and medical settings, light exposure's impact on patient sleep, alertness, and mood is often studied, reflecting the relevance of light's non-visual effects on health and well-being in clinical care.

Participants in these studies range widely in age, health conditions, and sample size. Studies include individuals with specific health conditions, such as dementia, Tourette's Disorder, and Primary Biliary Cholangitis, alongside healthy participants or control groups, to evaluate how light may alleviate symptoms or improve life quality in diverse groups. Additionally, specific workspaces like classrooms and offices were selected to measure light's impact on students and office workers' alertness, mood, and fatigue. Studies in classrooms, for instance, assessed how dynamic lighting interventions could support learning and well-being among students, while office studies have focused on how morning or afternoon light exposure influences workplace mood and vitality.

This broad investigation across diverse settings and participants emphasizes the non-visual impact of light on sleep, mood, and alertness, showing its potential therapeutic and functional benefits across different demographics and environmental contexts.

Focusing on blue-enriched light for cognitive stimulation [80,81] and yellow-enriched light for sleep promotion [80,82], future research could explore the non-visual effects of light in populations with specific sensitivities or heightened responsiveness to lighting conditions. For example, young children are especially responsive to visual stimuli; bright colors and dynamic lighting can strongly influence their behavior and mood. This responsiveness underscores the importance of understanding how quality of light exposure is developmentally appropriate and supportive of their cognitive and emotional needs. Similarly, individuals with Autism Spectrum Disorder (ASD), Attention Deficit Hyperactivity Disorder (ADHD), or Sensory Processing Disorder (SPD) may have heightened sensitivity to certain light types and intensities, which can affect their comfort and behavior [83]. Other populations, such as those with migraines, epilepsy, anxiety disorders, or older adults experiencing visual or cognitive changes, may also benefit from wearable-driven studies on non-visual light effects. Wearable devices offer a promising avenue for investigating how light affects these diverse groups in real-world settings. Including control groups in such studies, as observed in some of the work reviewed here, can strengthen internal validity by enabling more accurate comparisons between experimental and baseline conditions.

This review highlights that wearables facilitate research in real-life settings by allowing participants to move freely while being monitored over extended periods. This method is particularly beneficial when occupant feedback is required, as it reduces certain biases. For instance, participants might alter their behavior or responses if they know researchers or technicians are observing them, a phenomenon known as the Hawthorne effect [84]. Although this effect has not been extensively

studied in building physics, it could have a “disruptive influence” [85] on responses in living labs or climate chambers. Therefore, despite the limited variable control in real-life contexts, using wearables to keep participants in their natural environments without direct researcher involvement may help minimize this bias. Additionally, the increasing use of wearable light loggers in free-living conditions has enabled personalized data collection in everyday environments, offering new opportunities to improve health outcomes by tailoring lighting to individual circadian needs. Capturing light exposure outside the lab is essential for understanding the non-visual effects of light from an overall perspective. This real-time monitoring of light exposure is crucial for capturing inter-daily variations in light exposure and for developing integrative lighting systems [86] that can enhance comfort, productivity, and overall health and well-being.

5.2. Standardization challenges: framework validation, data comparability and experimental limitations

Across the various studies, wearables have been reported to play a crucial role in collecting objective data (such as light intensity, movement, and physiological responses) to achieve insights into the effects of light on human health. While several studies have integrated subjective measures of well-being (e.g., through sleep diaries or mood scales), the connection between objective light exposure data and subjective experience remains underexplored. Future research should focus on more integrated approaches that link objective data with user-reported outcomes, ensuring that findings reflect the complex interplay between environmental light exposure and human health [42,43], and enabling analysis through machine learning methods [44].

In this sense, in the selected studies, subjective data were mainly collected through questionnaires and standardized scales, like the Pittsburgh Sleep Quality Index and the Epworth Sleepiness Scale. No particular attention was given to how to avoid recall bias [87] which is one of the challenges that the Ecological Momentary Assessment (EMA) [88], a set of methods and design principles for the collection of data closer to real-time in participants’ natural real-world environments, was designed to address. The use of wearables and specific app (e.g. Cozie app [89] or MyCap application [71] as used by Hartmeyer et al. [56]) could help to perform the EMA and mitigate the bias effect. This can also allow digital data to be acquired for large-scale implementation in a smarter way than by transcribing feedback on data written with a pencil on a piece of paper or diary. Following this approach, the length of the rating scales could also be revised, introducing scales with a maximum of 5 points for ease of choice of response on a wearable device, smaller than, for example, the 9-point Karolinska Sleepiness Scale. Furthermore, when using wearables, it is more than desirable to include user satisfaction with the devices, using simplified versions of established instruments [5] such as the Wearable Acceptability Range (WEAR) Scale [90] or the System Usability Scale (SUS) [91], thus allowing the perceived impact, comfort, and user acceptability of wearables to be considered. Despite some standardized guidelines are available [65,92,93], another challenge is the lack of standardization across studies [94], which makes it very difficult to generalize findings or compare results from different research contexts. There is a need for standardizing the protocols for measuring light exposure, since research teams in this field come from diverse disciplines. In this case, the use of a specifically developed checklist [95] or templates [96] should be considered, as they can help ensure that all necessary details are included in reports. Additionally, significant variations in measurements can occur depending on sensor placement, such as the wrist, chest, or eye, as highlighted in the selected studies (Section 4.1 and Table B.1 in Appendix B). Different positions of the sensor capture light exposure differently due to variations in orientation, shading, and environmental interactions [97]. For example, wrist- or chest-mounted devices may overestimate light exposure during tasks if compared with the eye-level position [97]. Eye-level sensors seem to underestimate light intensity measurement but, on the other hand, most accurately reflect the light entering the visual field and impacting non-visual photoreceptors, which are critical for circadian regulation. These positional and environmental discrepancies make it challenging to directly compare results from different wearable devices, as they may measure distinct aspects of light exposure. In addition, the design of wearable light loggers must strike a balance between measurement accuracy and user comfort and usability [98]. Without standardized protocols and metrics, studies risk producing inconsistent or incomparable data, limiting the reliability of conclusions and hindering the development of universally applicable guidelines. Therefore, establishing standards for sensor placement, environmental details, and data interpretation is essential to ensure consistency, accuracy, and meaningful comparisons in light exposure research. In this context, while incorporating a pupil-core eye tracker can provide valuable information about the effective light entering the eye and triggering non-visual photoreceptor responses, especially considering that pupil diameter tends to be more stable under high irradiance conditions [9] making accurate eye tracking particularly important in low-light environments (typically in the evening), its use may be limited to controlled settings such as offices. In more challenging environments like hospitals or intensive care units, where patients may have their eyes closed and staff face demanding workflows, adding such devices may not be feasible. Most attention should also be paid to reporting statistical parameters, such as statistical power and effect size. Notably, only a few papers provide information on effect size, as detailed in Table B.3. Standardized procedures for reporting statistical parameters would significantly improve the assessment of the statistical rigor of research findings and enhance comparability among studies. As evidenced by Section 4.2, some wearables used for monitoring physiological parameters and/or human activities were commercially ready-to-use devices. While certified medical devices are preferable because their use can streamline approval by recognized Institutional Review Boards (IRBs), which is crucial for extensive trials involving human participants (it must be noted that the Medical Devices Directive MDD 93/42/EEC has been replaced by the Medical Device Regulation MDR 2017/745). However, certain commercial instruments not certified as medical devices have also been used in some studies, raising concerns about their ability to accurately quantify and classify sleep [99]. Such limitations may affect the reliability and validity of the findings.

This review also highlights a significant gap: the limited use of open-source tools, as most identified devices are proprietary, restricting researchers’ ability to modify them to meet specific experimental requirements or integrate them with other open platforms. Making these technologies more accessible, customizable, and adaptable to diverse research environments could greatly enhance studies on the non-visual effects of light. Open-source frameworks would foster greater collaboration among researchers, promoting the sharing of designs, methodologies, and data. This collaborative approach would also allow communities to continuously improve device functionality by refining wearables based on shared knowledge. The open-source approach would allow researchers to create a common framework for light exposure monitoring, ensuring consistency and comparability across studies. This would be particularly beneficial for studies conducted in different geographic or socio-economic contexts where access to proprietary technology might be limited. While the potential of open-source solutions is vast, it is necessary to ensure that these devices meet high standards of accuracy and reliability, and in this case, the collaboration between academic institutions and technology developers could bridge this gap by refining and validating these tools.

In the project MELIDOS [100,101], it is indicated that some light loggers may consider "low-cost" and "Do It Yourself" (DIY) options. Guidolin’s study [102] emphasizes the use of wearable light loggers that can be employed in real-world settings, which suggests that there may be opportunities for low-cost implementations. The study highlights the importance of capturing personal light exposure in free-living

conditions, which can potentially be achieved with simpler and more accessible devices [102]. The focus on wrist-worn light loggers implies that these devices can be designed or adapted using readily available materials, making them suitable for DIY projects. Furthermore, the study's intention to include a diverse demographic indicates that such loggers could be made affordable to ensure broad participation [102]. Stefani's work [103] also provides insights into the usability and acceptance of wearable light loggers. The evaluation of user compliance with the Lido light dosimeter indicates that, while there are challenges associated with existing devices, the high compliance rate suggests that simpler, more user-friendly designs could be developed [103]. This opens the door for DIY solutions that prioritize comfort and ease of use, potentially allowing individuals to create their own light loggers using basic components [103]. Moreover, the findings from Stefani's research indicate that the accuracy of wrist-worn devices can be affected by their placement and obstructions, suggesting that DIY loggers could be designed with these factors in mind to enhance performance [103]. By focusing on user-centered design, individuals could create low-cost light loggers that are tailored to their specific needs and environments. In conclusion, the discussions surrounding wearable devices imply that there is potential for developing such solutions. The emphasis on usability, compliance, and the need for real-world applications supports the idea that accessible, affordable, light logging devices can be created by individuals or small groups interested in monitoring their light exposure.

Another important issue that deserves a mention is that while in controlled environments (such as living labs or climatic chambers), it is possible to regulate all environmental variables, in real-life research studies, facilitated by the use of wearables, these variables cannot be fully controlled, even though it is well established that the environment as a whole significantly influences how we feel and behave [104]. As highlighted in Section 4.3, various scales were employed to gather user feedback on mood, emotional state, and physical and mental health satisfaction. However, it is evident that one cannot depend solely on the monitoring and subsequent analysis of data regarding the visual and non-visual effects of light, as in the cases examined. Thus, while the effects of individual environmental characteristics referring to the four main psychophysical domains (visual, thermal, acoustics, and air quality) are well understood, their combined effects remain ambiguous due to the complex, non-linear interactions involved in processing sensory cues [104]. Additionally, the inability to control environmental variables in real-world contexts further complicates the analysis. These limitations emphasize the critical need for multi-environmental wearables monitoring systems capable of capturing and analyzing the dynamic interplay of environmental factors. Such systems are essential for advancing our understanding and guiding the development of effective environmental design strategies in real-life applications to improve health and well-being.

5.3. Real-World and clinical integration of wearable monitoring: opportunities and strengths

The application of wearable light and physiological monitoring extends beyond academic research and holds promising potential for integration into clinical and real-world environments. In clinical settings, wearable technologies can facilitate continuous, non-invasive monitoring of patients, providing valuable real-time data on light exposure, sleep-wake cycles, and mood-related indicators. This integration can be especially beneficial for managing conditions influenced by circadian rhythms, such as sleep disorders, depression, bipolar disorder, and neurodegenerative diseases like Alzheimer's. For instance, personalized light exposure recommendations derived from wearable data could support therapeutic interventions, including light therapy or sleep hygiene strategies, and help clinicians make data-driven adjustments to treatment plans. In psychiatric or geriatric care, where patients may be unable to communicate their experiences clearly, wearable monitoring can serve as an objective complement to caregiver reports, providing insights into behavioral patterns, episodes of agitation, or responses to environmental stimuli. In this context, combining light logging with motion or heart rate tracking could create a comprehensive profile of a patient's physiological and environmental interaction, which is essential for diagnosing and managing complex conditions.

Outside clinical environments, wearable monitoring offers scalable opportunities for public health, occupational health, and educational settings. For example, schools and workplaces could adopt wearable devices to assess how lighting conditions impact alertness, performance, and well-being throughout the day. Real-time feedback from wearables can interact with adaptive lighting systems to adjust illumination based on the time of day or user status, thereby optimizing comfort and productivity. Similarly, in elder care facilities or assisted living environments, continuous light exposure monitoring could help align artificial lighting with residents' circadian rhythms, promoting better sleep and mood regulation.

Integration into real-world settings also demands user-friendly and cost-effective solutions. Devices must be unobtrusive, comfortable, and intuitive, especially for populations with limited digital literacy or mobility impairments. In this regard, user-centered design, as discussed earlier, is vital to ensure acceptability and long-term compliance. Moreover, ensuring interoperability with electronic health records (EHRs) or mobile health applications can further enhance the utility of wearable data, allowing clinicians or caregivers to track trends, set alerts for deviations, and provide proactive interventions.

Nonetheless, ethical and privacy concerns must be addressed, especially when wearable devices are used in continuous monitoring. Clear consent protocols, data anonymization, and secure data management frameworks must be implemented to maintain trust and protect sensitive personal information.

Effectively, the integration of wearable light monitoring into clinical and everyday settings can lead to a systemic shift – from occasional and periodic self-reports, to continuous, real-world, and personalized data – enabling a more effective prevention, tailored treatments, and enhanced quality of life across diverse populations.

5.4. Long-Term data reliability and consistency in wearable monitoring

As wearable monitoring becomes more common in research and practice, ensuring long-term data reliability is increasingly important. While short-term studies often show high compliance and accurate measurements, extended use introduces challenges that can compromise data quality (such as device wearability, sensor drift, and user fatigue). Sensors exposed to everyday environmental conditions may lose calibration over time, leading to gradual shifts in measurement accuracy. Without regular checks or reference validation, these small errors can accumulate and distort results, especially in studies that track subtle health or behavioral changes over weeks or months. User compliance also tends to decline over time, particularly if the device is uncomfortable, unattractive, or interferes with daily life. People may remove it or forget to wear it, creating gaps in the data. Engagement strategies, like reminders or showing users their own progress, can help maintain motivation, especially in clinical or older populations where additional support may be necessary. To safeguard data quality, it is useful to build in validation tools, such as comparing light exposure to movement data, using backup sensors, or applying algorithms that detect suspicious patterns like extended periods of inactivity. These approaches can flag and correct for missing or unreliable data. Finally, ethical considerations become even more critical with prolonged monitoring. The longer data is collected, the more sensitive it becomes, especially when it involves location tracking or physiological metrics. Robust privacy measures are crucial for maintaining participant trust and protecting personal information. Therefore, an effective long-term use of wearables depends not only on the technology, but also on its thoughtful design, user support, and careful data handling throughout the study.

6. Conclusions

In conclusion, our systematic review has yielded the following findings:

- Prior research has investigated the non-visual effects of light in various real-life contexts, such as assessing impacts on circadian rhythm, mood, alertness, and health conditions.
- Studies have been conducted in personal spaces (e.g., bedrooms), common living areas (e.g., living rooms), and medical settings, highlighting the relevance of light's effects on health and well-being. Studies in classrooms and offices have examined how light influences alertness, mood, and fatigue, particularly through dynamic lighting interventions.
- The studies have involved a wide range of participants, from those with specific health conditions (e.g., dementia, Tourette's Disorder) to healthy controls, while evaluating the potential therapeutic benefits of light.
- Wearable technologies facilitate real-life data collection, helping minimize biases (e.g., the Hawthorne effect) and allowing for personalized light exposure monitoring. However, variability in light exposure measurements due to sensor placement complicates comparisons across studies, underscoring the need for standardized protocols. Furthermore, the absence of open-source tools restricts research adaptability: the necessity of developing low-cost, user-friendly light loggers has been highlighted, promoting accessibility for diverse demographics.
- There is a need to integrate better objective light exposure data with subjective user reports to enhance understanding of light's effects on health and well-being.
- Concerns exist regarding the accuracy of non-medical wearables in measuring physiological responses and/or human activity, suggesting a preference for certified medical devices in research.
- Real-life studies face challenges in controlling environmental variables, emphasizing the need for multi-environmental monitoring systems to analyze the interactions of sensory cues effectively. Understanding the interplay of environmental factors through advanced monitoring systems is crucial for creating effective strategies to improve health and well-being in real-world applications.

Institutional review board statement

Not applicable.

Informed consent statement

Not applicable.

Data availability

Not applicable.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors utilized ChatGPT to enhance the language and correct grammatical errors in the manuscript during its preparation. Following this, the authors reviewed and edited the content as necessary and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Francesco Salamone: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Data curation, Conceptualization. **Sergio Altomonte:** Writing – review & editing, Writing – original draft, Data curation. **Claudia Naves David Amorim:** Writing – review & editing, Writing – original draft, Data curation. **Giovanni Ciampi:** Writing – review & editing, Writing – original draft, Validation, Methodology, Data curation, Conceptualization. **Ludovico Danza:** Writing – review & editing, Writing – original draft, Data curation. **Aicha Diakite-Kortlever:** Writing – review & editing, Writing – original draft, Data curation. **Veronica Garcia-Hansen:** Writing – review & editing, Writing – original draft, Data curation. **Mandana S. Khanie:** Writing – review & editing, Writing – original draft, Data curation. **Marshal Maskarenj:** Writing – review & editing, Writing – original draft, Data curation. **Anna Pellegrino:** Writing – review & editing, Writing – original draft, Data curation. **Michelangelo Scorpio:** Writing – review & editing, Writing – original draft, Validation, Methodology, Data curation, Conceptualization. **Natalia Sokol:** Writing – review & editing, Writing – original draft, Data curation. **Natalia Giraldo Vasquez:** Writing – review & editing, Writing – original draft, Data curation. **Sergio Sibilio:** Writing – review & editing, Writing – original draft, Validation, Methodology, Data curation, Conceptualization.

Declaration of competing interest

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

Acknowledgements

This work was conducted within the framework of IEA EBC - Annex 90 / SHC Task 70 – "Low Carbon, High Comfort Integrated Lighting" (https://task70.iea-shc.org/ or https://annex90.iea-ebc.org/). Claudia Amorim would like to thank the National Council for Scientific and Technological Development – CNPq (310529/2023–9) and Foundation for Research Support of the Federal District-FAPDF (00193–00002281/2022–01). Natalia Sokol's work was partly funded by the Gdańsk University of Technology's Argentum Triggering Research Grant: 23/1/2022/IDUB/I3b/Ag. Natalia Giraldo Vasquez would like to thank The Danish Energy Authority (EUDP) for funding the participation in IEA SHC Task 70- Low Carbon, High Comfort Integrated Lighting. Marshal Maskarenj would like to acknowledge the FNRS - Fonds de la Recherche Scientifique (Belgium) for postdoctoral fellowship n. 40000322 for project SCALE (Shading Control Algorithms from Luminance-based Evaluations), and scientific collaborator fellowship n. 40024409 for project SPARKLE (Spectral Profiles for Agent-based Responsive networK of Lighting Energy). Anna Pellegrino would like to acknowledge the EU – NextGen for funding the project MIRABLE (2022ZNJHHY), within the call "PRIN 2022″ (D.D of MUR n. 104, 2 Feb 2022), in the PNRR funding framework, Mission 4 Component 2 Investment 1.1. Veronica Garcia-Hansen would like to acknowledge the WiSTEM2D award by Johnson & Johnson. The contribution from researchers affiliated with the ITC—CNR was funded by the European Union - NextGenerationEU and by the Ministry of University and Research (MUR), National Recovery and Resilience Plan (NRRP), Mission 4, Component 2, Investment 1.5, project "RAISE - Robotics and AI for Socio-economic Empowerment" (ECS00000035). The contribution from researchers affiliated with the University of Campania Luigi Vanvitelli was funded by the research project titled "UrbanSense - Cittadini come sensori: promuovere l'inclusione attraverso lo sviluppo e l'applicazione di un sistema indossabile multifunzionale per una città citizen-oriented", CUP: B23C24000370005, within the call of the European Union - NextGenerationEU, National Recovery and Resilience Plan (NRRP), Mission 4, Component 2, Investment 1.5, projectRAISE - SPOKE 1 "Urban Technologies for Inclusive Engagement - Ambienti e servizi urbani accessibili ed inclusivi"".

Appendix A

Table A.1
summary of selected studies (The main subsections each study covers are marked with the symbol "•" in the last three columns).

Reference	Authors	Title	Study objective	Key findings	Section 4.1	Section 4.2	Section 4.3
[2]	S.A. Rahman, E.E. Flynn-Evans, D. Aeschbach, G.C. Brainard, C.A. Czeisler, S.W. Lockley	Diurnal spectral sensitivity of the acute alerting effects of light	To assess the effects of blue and green monochromatic light on alertness and performance	Blue and green light exposure affected alertness, with controlled environmental conditions critical for data reliability		•	•
[8]	B. Baldursdottir, G. Agustsson, I. Gudjonsson, M. Andersen, H. Valdimarsdottir, S. Hartmeyer	Insights into spectrally resolved light-dosimetry data	To assess the impact of a dynamic lighting system in classrooms on high school students	Light dosimetry differentiated light diets, with dynamic bright lighting influencing melanopic metrics more than static subdued lighting	•	•	
[9]	J.R. Stampfli, B. Schrader, C. di Battista, R. Häfliger, O. Schälli, G. Wichmann, C. Zumbühl, P. Blattner, C. Cajochen, R. Lazar, M. Spitschan	The Light-Dosimeter: A new device to help advance research on the nonvisual responses to light	To develop a light dosimeter to measure light exposure and its impact on pupil diameter	Pupil diameter was more stable at high irradiance and fluctuated significantly at low irradiance	•	•	
[11]	C. Formentin, S. Carraro, M. Turco, L. Zarantonello, P. Angeli, S. Montagnese	Effect of Morning Light Glasses and Night Short-Wavelength Filter Glasses on Sleep-Wake Rhythmicity in Medical Inpatients	To investigate the effects of blue-enriched and filtered glasses on alertness and sleep	Blue-enriched and blue-filtered glasses influenced alertness and evening relaxation, respectively		•	•
[17]	H.C. Thorne, K.H. Jones, S.P. Peters, S.N. Archer, D.J. Dijk	Daily and seasonal variation in the spectral composition of light exposure in humans	Investigating how light's spectral composition affects circadian rhythms	Seasonal and daily light variations affect circadian rhythms. Blue light therapy may benefit mood and sleep in low-light seasons	•	•	•
[18]	D. Miller, A. Bierman, M.G. Figueiro, E.S. Schernhammer, M.S. Rea	Ecological measurements of light exposure, activity and circadian disruption	Evaluating circadian lighting exposure in nurses with varying work schedules	Day-shift nurses experienced less circadian disruption. Rotating shifts led to significant circadian misalignment	•	•	
[24]	E.G. Landis, V. Yang, D.M. Brown, M.T. Pardue, S.A. Read	Dim light exposure and myopia in children	Evaluating the relationship between light exposure and myopia in children	Myopic children had less exposure to scotopic and outdoor photopic lighting. Broad light exposure is critical	•	•	•
[25]	E.J. Ricketts, H.J. Burgess, G. E. Montalbano, M.E. Coles, J. F. McGuire, H. Thamrin, D.L. McMakin, J.T. McCracken, M. A. Carskadon, J. Piacentini, C. S. Colwell	Morning light therapy in adults with Tourette's disorder	To study light therapy's effect on Tourette syndrome and circadian rhythms	Light therapy impacted circadian markers, but saliva sampling required strict storage protocols for accuracy		•	•
[26]	M. Turco, N. Cazzagon, I. Franceschet, C. Formentin, G. Frighetto, F. Giordani, N. Cellini, G. Mazzotta, R. Costa, B. Middleton, D.J. Skene, A. Floreani, S. Montagnese	Morning bright light treatment for sleep-wake disturbances in primary biliary cholangitis: A pilot study	To examine the impact of bright light therapy on Seasonal Affective Disorder (SAD)	Bright light therapy improved SAD symptoms when used daily for 15 days		•	•
[29]	Y. Dong, X. Zhang	Study on the effect of awakening daylight in dormitories on morning alertness, mood, fatigue and sleep quality of college students	To investigate the impact of daylight exposure in college dorms on alertness, mood, fatigue, and sleep quality	Daylight exposure before waking, especially in summer, improved cognition, mood, and sleep quality	•	•	•
[30]	R. Lok, S. Ancoli-Israel, K.E. Ensrud, S. Redline, K.L. Stone, J.M. Zeitzer	Timing of outdoor light exposure is associated with sleep-wake consolidation in community-dwelling older men	Investigating outdoor light exposure timing and its impact on sleep-wake fragmentation, health, and cognition in older men.	Bright light in the afternoon improved sleep-wake cycle stability. Poorer outcomes (sleep, lifestyle, health) were noted in individuals with fragmented sleep	•	•	•
[31]	Y. Huang, C. Mayer, P. Cheng, A. Siddula, H.J. Burgess, C. Drake, C. Goldstein, O. Walch, D.B. Forger, D.B. Forger	Predicting circadian phase across populations: A comparison of mathematical models and wearable devices	Predicting circadian phase using non-invasive wearable data	Natural light exposure and activity data provide insights into circadian rhythms, particularly under varied work schedules	•	•	

(*continued on next page*)

Table A.1 (*continued*)

Reference	Authors	Title	Study objective	Key findings	Section 4.1	Section 4.2	Section 4.3
[32]	N.M. Gabinet, B.A. Portnov	Investigating the combined effect of ALAN and noise on sleep by simultaneous real-time monitoring using low-cost smartphone devices	To examine the impact of artificial light and noise on sleep quality and duration	Artificial light at night and noise exposure affected sleep quality, with separate effects noted before and during sleep	•		•
[33]	E. van Lieshout-van Dal, L. Snaphaan, S. Bouwmeester, Y. de Kort, I. Bongers	Testing a Single-Case Experimental Design to Study Dynamic Light Exposure in People with Dementia Living at Home	To analyze the effects of a dynamic lighting system on individuals with dementia	The system's effectiveness depends on daylight availability and time spent near the lamps. Participant feedback indicated mixed experiences regarding the system's pleasantness, brightness, and health impact, with recommendations for improvements.	•		•
[34]	S.T. Peeters, K.C.H.J. Smolders, I.M.L.C. Vogels, Y. A.W. de Kort	Less is more? Effects of more vs. less electric light on alertness, mood, sleep and appraisals of light in an operational office	To measure the effect of illuminance levels during office hours on sleep and vitality	Exposure to electric light had acute and delayed negative effects on sleepiness and vitality, especially in spring	•	•	•
[35]	M.S. Khanie, T. Illum, N. Hosseinpour, K. Matsuo, X. Fan, P. Wargocki	Exploring the effects of spectral light exposure on University students' sleep quality: a cross-sectional study	Investigating the effects of spectral light exposure on sleep quality of university students	Variability in daylight exposure was noted, with increased exposure from winter to spring. The study highlights the influence of spectral composition on sleep quality and cognitive performance.	•	•	•
[36]	M.G. Figueiro, R. Hamner, A. Bierman, M.S. Rea	Comparisons of three practical field devices used to measure personal light exposures and activity levels	Comparative study of Daysimeter and Actiwatch Spectrum for evaluating data quality	Daysimeter was more accurate than Actiwatch Spectrum in measuring photometric data, particularly under varied light sources	•		•
[37]	J. Itzhacki, B.H.W.T. Lindert, W.P. Van Der Meijden, M.L. Kringelbach, J. Mendoza, E.J. W. Van Someren	Environmental Light and Time of Day Modulate Subjective Liking and Wanting	To investigate how the brightness of ambient light affects subjective wanting and liking	Brightness of ambient light and its relationship with subjective experiences were studied; periods of inactivity were excluded from the analysis to ensure data integrity	•	•	•
[38]	S.W. Cain, E.M. McGlashan, P. Vidafar, J. Mustafovska, S. P.N. Curran, X. Wang, A. Mohamed, V. Kalavally, A.J. K. Phillips	Evening home lighting adversely impacts the circadian system and sleep	To examine the impact of home lighting on sleep and circadian rhythms	Energy-efficient lighting and reduced incandescent use increased residential lighting's influence on circadian rhythms	•	•	•
[39]	E.L. Krüger, C. Tamura, T.W. Trento	Identifying relationships between daylight variables and human preferences in a climate chamber	To examine the effects of daylight attributes on people's preferences	Light supports the circadian rhythm. Seasonal and office orientation impact stress, anxiety, thermal perception, and susceptibility to SAD.	•		•
[56]	S. L. Hartmeyer, A. Davies, M. Andersen	Post-Occupancy Evaluation of Office Lighting What Can We Learn from Light-Dosimetry?	To evaluate the effects of office lighting on visual comfort, well-being, and cognitive performance, combining environmental measurements, physiological data, and subjective questionnaires.	Biodynamic lighting improves alertness, mood, and cognitive performance; vertical (melanopic) illuminance at eye level is a useful indicator. Significant variations were found in physiological parameters and subjective perception depending on the lighting type.	•	•	•
[57]	P. Sloane, M. Figueiro, S. Garg, L. Cohen, D. Reed, C. Williams, J. Preisser, S. Zimmerman	Effect of home-based light treatment on persons with dementia and their caregivers	Assessing home light therapy's impact on dementia patients and their caregivers	Blue-white light improved caregivers' sleep quality. No significant improvement for dementia patients	•	•	•
[58]	D. A. Wallacea, K. R. Evenson, C. R. Isasi, S. R. Patel, D. Sotres-Alvarez, P. C. Zee, S. Redline, F. A.J.L. Scheer, T. Sofer	Characteristics of objectively-measured naturalistic light exposure patterns in U.S. adults: A cross-sectional analysis of two cohorts	To quantitatively describe light exposure in two large US cohorts and its relationships with demographic, seasonal, and behavioral variables.	Light exposure varies by sex, season, latitude, age, and sleep habits. Men and summer participants are exposed to more bright light. The study supports the feasibility of light biomonitoring in the general population.	•	•	

Appendix B

Table B.1
Hardware and software used for monitoring environmental parameters as described in the text of references (the main monitored parameters are marked with the symbol "•").

Ref	hardware used (validation status)	Hardware position (form factor; size; weight)	Software used for data acquisition	Photon flux [photons/ cm^2/*sec*]	Irradiance [μW/ cm^2]	Photopic Illuminance [lx]	Melanopic Equivalent Daylight Illuminance (mEDI) [lx]	Circadian Stimulus (CS)/ Circadian Light (CLa)	Visible light spectrum	CCT [K]	Accuracy on the measured parameters
[8]	Spectrace dosimeter (prototype)	chest-level (USB-stick style; 80 × 20 × 12 mm; 50 g)	ND			•			spectral irradiance across 14 channels in the range (410–760 nm)		ND
[9]	Light Dosimeter (LiDo) (available for rental)	Vicinity of a person's face (Pendant or glasses-mounted near the eyes; 58 × 20.6 × 16 mm; 27 g)	Custom LiDo package			•	•				ND
	STS-Vis Ocean Insight spectroradiometer (market-ready device)	Forehead, 15° below horizonta	ND						•		ND
[17]	Actiwatch RGB (market-ready device)	Non dominant wrist (wristwatch; 48 × 37 × 15 mm; 30 g)	Postprocessing in SAS						RGB		
	Actiwatch-L (market-ready device)	Non dominant wrist (wristwatch; 37 × 35 × 12 mm; 25 g)	Postprocessing in SAS			•			broadband white light		
[18]	Daysimeter (prototype)	Close proximity to cornea Chest-level (Retro-ear device with fiber-optic link to optical sensor; ND; ND)	ND					•			ND
[24]	Actiwatch 2 (market-ready device)	ND (wristwatch; 43 × 23 × 10 mm; 16 g)	ND	•	•	•					±10 % at 3000 lx [105]
[29]	Wireless illuminance meters (market-ready device)	horizontally at head position vertically at 0.20 m from the bed (compact cylindrical devices; diameter 50 mm; 300 g)	ND			•					ND
[30]	Actiwatch 2 (market-ready device)	Nondominant wrist (wristwatch; 43 × 23 × 10 mm; 16 g)	ND	•	•	•					±10 % at 3000 lx [105]
[31]	Actiwatch-L (market-ready device)	Wrist (wristwatch; 37 × 35 × 12 mm; 25 g)	Postprocessing in Matlab			•					
	Actiwatch Spectrum (market-ready device)	Wrist (wristwatch; 48 × 37 × 15 mm; 31 g)	Postprocessing in Matlab	•	•	•					±10 % at 1500 lx [106]
[32]	Smartwatches (SW) and Smartphones (SP) (market-ready devices)	Wrists (ND)	Andro-sensor app for SW and SP (for ALAN)			•					ND
[33]	LYS button 1.0 (market-ready device)	Collar (clip-on button; diameter 18 mm and thickness 29.4 mm; 15 g)	LYS			•	•[1]		RGB	•[1]	ND
	Sekonic C-700 spectrometer (market-ready device)	Vertically at eye level (slim handheld rectangle; 183 mm × 73 mm × 27 mm; 230 g)	ND			•	•[1]		•	•	ND
[34]	TAOS TCS34725 (market-ready device)	close to the eyes in a vertical position (daytime) bedside table (during sleep) (Bare sensor package;	ND			•					ND

(*continued on next page*)

Table B.1 (*continued*)

Ref	hardware used (validation status)	Hardware position (form factor; size; weight)	Software used for data acquisition	Photon flux [photons/cm^2/*sec*]	Irradiance [μW/cm^2]	Photopic Illuminance [lx]	Melanopic Equivalent Daylight Illuminance (mEDI) [lx]	Circadian Stimulus (CS)/ Circadian Light (CLa)	Visible light spectrum	CCT [K]	Accuracy on the measured parameters
		2.4 × 2.0 × 0.65 mm; 12 g)									
	Eltek photometers (market-ready device)	Horizontally at desk level (i.e., 0.7 m) and vertically at eye height (i.e., 1.20 m) (ND; ND; ND)	ND			•					ND
	Specbos 1201 spectrometer (market-ready device)	Vertical plane (Handheld spectroradiometer; 140 × 58 × 34 mm; 350 g)	ND						•		±0.5 nm [107]
[35]	LYS button (market-ready device)	ND (clip-on button; diameter 18 mm and thickness 29.4 mm; 15 g)	LYS			•	•[1]		RGB	•[1]	ND
[36]	Activewatch Spectrum (market-ready device)	Wrist (wristwatch; 48 × 37 × 15 mm; 31 g)	ND	•	•	•					±10 % at 1500 lx [106]
	Daysimeter (prototype)	Eye level, wrist, torso and chest Chest-level (Retro-ear device with fiber-optic link to optical sensor; ND; ND)	ND			•[2]		•[1]	RGB		ND
[37]	Daysimeter (prototype)	Chest Chest-level (Retro-ear device with fiber-optic link to optical sensor; ND; ND)	ND			•[1]			RGB		ND
[38]	C12666MA mini-spectrometer (market-ready device)	Chest (module; 20.1 × 12.5 × 10.1 mm; 5 g)	ND			•[2]	•[2]		•		ND
[39]	Actiwatch Spectrum (market-ready device)	Forehead (wristwatch; 48 × 37 × 15 mm; 31 g)	ND	•	•	•					±10 % at 1500 lx [106]
	JETI Specbos 1201 (market-ready device)	1.5 m from the glazed façade, at desk level (0.90 m from the floor) Handheld spectroradiometer; 140 × 58 × 34 mm; 350 g)	ND			•			•	•	±0.5 nm [107]
[56]	Spectrace dosimeter (prototype)	Chest-level (USB-stick style; 80 × 20 × 12 mm; 50 g)	ND			•	•		•	•	ND
[57]	Circadian light meter (prototype)	Pinned to subjects' clothes (clip-on button; diameter 18 mm; ND)	ND					•			ND
[58]	Activewatch Spectrum (market-ready device)	Wrist (wristwatch; 48 × 37 × 15 mm; 31 g)	ND			•					±10 % at 1500 lx [106]

All information regarding form factor, dimensions, weight, and accuracy that was not directly reported in the analyzed papers was derived from the respective manufacturer's website.

[1] Derived from visible spectrum.

[2] Derived from RGB.

Table B.2

Hardware and software used for monitoring physiological and human activities and the associated monitored parameters (each selected parameter is characterized by the symbol "•").

Ref	Hardware used (validation status; form factor; size; weight)	Software used	Parameters							Accuracy on the measured parameters
			sleep/wake (activity)	DLMO	Tskin	EEG	EOG	ECG	Pupil size	

(*continued on next page*)

Table B.2 (*continued*)

Ref	Hardware used (validation status; form factor; size; weight)	Software used	Parameters							Accuracy on the measured parameters
			sleep/wake (activity)	DLMO	Tskin	EEG	EOG	ECG	Pupil size	
[2]	Temec Vitaport-3 digital recorder (market-ready device; box with strap; 9 × 15 × 4.5 cm; 700 g)	ND				•	•	•		ND
[8]	Spectrace (prototype; N/A)	ND	•							ND
[9]	Pupil Core eye tracker -pupil labs (market-ready device; Eyeglass frame; W: 160 mm x H: 51 mm; 22.75 g)	ND							•	±0.60° [67]
[11]	Jawbone UP24 (market-ready device; wristband; 14.1 × 5.18 × 5 cm; 22.68 g)	UP app for smartphone	•							ND
[17]	Philips Actiwatch-L (market-ready device; wristband; 37 L x 35 W x 12 H mm; 25 g)	ND	•							ND
[18]	Daysimeter (N/A; pendant; the board is 2 cm in diameter; 25.25 g)	ND	•							ND
[24]	Philips Actiwatch 2 (market-ready device; wristband; 43 × 23 × 10 mm;16 g)	ND	•							ND
[25]	Philips Actiwatch Spectrum (market-ready device; wristband; 48 × 37 × 15 mm; 31 g), salivary melatonin detection with 30 min samples	Philips Actiware version 6.0.9	•	•						ND
[26]	SOMNOwatch (market-ready device; wristband; Diameter: 45mm Height: 16 mm; 30 g)	ND	•							±5 % [108]
[29]	Jawbone UP3 (market-ready device; wristband; 220 × 12.2 × 3 to 9.3 mm; 29 g)	ND	•							ND
[30]	Philips Actiwatch 2 (market-ready device; wristband; 43 mm x 23 mm x 10 mm;16 g)	'nparACT' R package	•							ND
[31]	Philips Actiwatch-Spectrum (market-ready device; wristband; 48 × 37 × 15 mm; 31 g), salivary melatonin detection with 30 min samples	ND	•	•						ND
[34]	Philips Actiwatch Spectrum (market-ready device; wristband; 48 × 37 × 15 mm; 31 g)	ND	•							ND
[35]	Fitbit Charge 2 (market-ready device; wristband; width: 22 mm, thickness: 12.7 mm; 35 g), and Alta HR sleep tracker, iButton DS1922L	ND	•		•					ND
[37]	Daysimeter-D (N/A; pendant; the board is 2 cm in diameter; 25.25 g)	ND	•							ND
[38]	Philips Actiwatch Spectrum (market-ready device; wristband; 48 × 37 × 15 mm; 31 g), salivary melatonin detection with hourly samples	ND	•	•						ND
[57]	Philips Actiwatch-L (market-ready device; wristband; 37 L x 35 W x 12 H mm; 25 g)	ND	•							ND

All information regarding form factor, dimensions, weight, and accuracy that was not directly reported in the analyzed papers was derived from the respective manufacturer's website.

Table B.3
Scale used for acquiring users' feedback and the associated subjective parameters (each selected parameter is characterized by the symbol "•").

Ref	Effect size	Questionnaire/Test (Scale used)	Subjective parameters considered										
			Sleep related issues	Mood	Physical activity level	Physical health satisfaction	Mental health satisfaction	Ability to perform daily task	Depressive symptoms	Cognitive performance	Quality of life	Health	Emotional state
[2]	ND	Karolinska Sleepiness Scale (KSS) (9-point scale)	•										
		Psychomotor Vigilance Task (PVT-10A) (ND)								•			
[11]	ND	Pittsburgh Sleep Quality Index (PSQI) (from 0 to 3; 0 = best)	•										

(*continued on next page*)

Table B.3 (*continued*)

Ref	Effect size	Questionnaire/Test (Scale used)	Subjective parameters considered										
			Sleep related issues	Mood	Physical activity level	Physical health satisfaction	Mental health satisfaction	Ability to perform daily task	Depressive symptoms	Cognitive performance	Quality of life	Health	Emotional state
		Horne-Östberg Questionnaire (various)									•		
		Karolinska Sleepiness Scale (KSS) (9-point scale)	•										
		Mood (1 to 10 visual analogue scale)		•									
[17]	ND	Pittsburgh Sleep Quality Index (PSQI) (various)*	•										
		Horne-Östberg Questionnaire (various)*									•		
[25]	ND	Yale Global Tic Severity Scale (YGTSS) (various)*										•	
		Epworth Sleepiness Scale (ESS) (4-point scale)*	•										
		Morningness-Eveningness Questionnaire-Revised (various)*	•										
		Depression Anxiety Stress Scale (various)*							•				
		Sheehan Disability Scale (various)*										•	
		Pittsburgh Sleep Quality Index (PSQI) (various)*	•										
[26]	ND	Short Form Health Survey (SF-36) (various)									•		
		Horne-Östberg Questionnaire (various)									•		
		Pittsburgh Sleep Quality Index (PSQI) (0 – 3 point)	•										
[29]	ND	Karolinska Sleepiness Scale (KSS) (9-point scale)	•										
		Mood (5-point Likert positive and negative semantic scale)		•									
[30]	Generally small	Physical Activity Scale for the Elderly (PASE) (various)*			•								
		Physical Component Summary (PCS) (various)*				•							
		Mental Component Summary (MCS) (various)*					•						
		Instrumental Activities Daily Living (IADL) (various)*						•					
		Geriatric Depression Scale (GDS) (various)*							•				
		Modified Mini-Mental State (3MS) (various)*								•			

(*continued on next page*)

Table B.3 (*continued*)

Ref	Effect size	Questionnaire/Test (Scale used)	Subjective parameters considered										
			Sleep related issues	Mood	Physical activity level	Physical health satisfaction	Mental health satisfaction	Ability to perform daily task	Depressive symptoms	Cognitive performance	Quality of life	Health	Emotional state
[32]	ND	Pittsburgh Sleep Quality Index - Hebrew version (PSQI-H), (various)*	•										
[33]	Generally small	Mini Mental State Examination (MMSE) (various)*								•			
		Evaluation questionnaire about the test experience (3-point semantic scale)											•
[34]	ND	Karolinska Sleepiness Scale (KSS) (9-point Likert scale)*	•										
		Vitality, valence and tension (7-point bipolar scale)											•
		Sleep, mental and physical fatigue (7-point bipolar scale)					•						
		Light appraisals (7-point bipolar scale)		•									
[35]	ND	Baddeley resasoning test (various)								•			
[36]	ND	Mini-Mental State Examination (MMSE) (various)*								•			
[37]	Small	Liking and wanting (Visual analogue scales;0, not – 100, very much)		•							•		•
		Positive and negative mood from Daytime Insomnia Symptom Scale (Visual analogue scales)*		•									
[38]	ND	Insomnia Severity Index (ISI) (ND)	•										
		Pittsburgh Sleep Quality Index (PSQI) (ND)	•										
		Morningness-Eveningness Questionnaire (MEQ) (ND)	•										
		Epworth Sleepiness Scale (ESS) (ND)	•										
[39]	ND	Evaluation of lighting situation (7-point Likert scale)		•							•		•
[56]	ND	Consensus Sleep Diary (various)*	•										
[57]	ND	Pittsburgh Sleep Quality Index (PSQI) (various)*	•										
		Medical Outcomes Study (MOS) (various)*		•									
		Epworth Sleepiness Scale (ESS) (4-points categorical scale)*	•										

(*continued on next page*)

Table B.3 (*continued*)

Ref	Effect size	Questionnaire/Test (Scale used)	Subjective parameters considered										
			Sleep related issues	Mood	Physical activity level	Physical health satisfaction	Mental health satisfaction	Ability to perform daily task	Depressive symptoms	Cognitive performance	Quality of life	Health	Emotional state
		Cornell Scale for Depression in Dementia (CSDD) (4-point scale)*							•				
		Quality of Life in Alzheimer's Disease – modified (QoL-AD) (various)*									•		
		Caregiver Hassles Scale (CHS) (various)*									•		
		Zarit Burden Interview (ZBI) (various)*									•		

* indicates that the paper does not explicitly specify the questionnaire/test scale employed; therefore, it has been inferred from the referenced materials provided.

References

[1] S.W. Lockley, E.E. Evans, F.A.J.L. Scheer, G.C. Brainard, C.A. Czeisler, D. Aeschbach, Short-wavelength sensitivity for the direct effects of light on alertness, vigilance, and the waking electroencephalogram in humans, Sleep 29 (2006) 161–168, https://doi.org/10.1093/sleep/29.2.161.

[2] S.A. Rahman, E.E. Flynn-Evans, D. Aeschbach, G.C. Brainard, C.A. Czeisler, S. W. Lockley, Diurnal spectral sensitivity of the acute alerting effects of light, Sleep 37 (2014) 271–281, https://doi.org/10.5665/sleep.3396.

[3] M. Spitschan, K. Smolders, B. Vandendriessche, B. Bent, J.P. Bakker, I. R. Rodriguez-Chavez, C. Vetter, Verification, analytical validation and clinical validation (V3) of wearable dosimeters and light loggers, Digit. Heal. 8 (2022), https://doi.org/10.1177/20552076221144858.

[4] S.L. Hartmeyer, M. Andersen, Towards a framework for light-dosimetry studies: quantification metrics, Light. Res. Technol. (2023) 1–29, https://doi.org/10.1177/14771535231170500.

[5] E. Balajadia, S. Garcia, J. Stampfli, B. Schrader, C. Guidolin, M. Spitschan, Usability and acceptability of a corneal-plane α-opic light logger in a 24-h field trial, Digit. Biomarkers. 7 (2023) 139–149, https://doi.org/10.1159/000531404.

[6] H.K. Dollish, M. Tsyglakova, C.A. McClung, Circadian rhythms and mood disorders: time to see the light, Neuron 112 (2024) 25–40, https://doi.org/10.1016/j.neuron.2023.09.023.

[7] C. Blume, C. Garbazza, M. Spitschan, Effects of light on human circadian rhythms, sleep and mood, Somnologie 23 (2019) 147–156, https://doi.org/10.1007/s11818-019-00215-x.

[8] B. Baldursdottir, G. Agustsson, I. Gudjonsson, M. Andersen, H. Valdimarsdottir, S. Hartmeyer, Insights into spectrally resolved light-dosimetry data, (2023) 196–206. https://doi.org/10.25039/x50.2023.op052.

[9] J.R. Stampfli, B. Schrader, C. di Battista, R. Häfliger, O. Schälli, G. Wichmann, C. Zumbühl, P. Blattner, C. Cajochen, R. Lazar, M. Spitschan, The light-dosimeter: a new device to help advance research on the non-visual responses to light, Light. Res. Technol. 55 (2023) 474–486, https://doi.org/10.1177/14771535221147140.

[10] M. Yang, N. Ma, Y. Zhu, Y.-C. Su, Q. Chen, F.-C. Hsiao, Y. Ji, C.-M. Yang, G. Zhou, The acute effects of intermittent light exposure in the evening on alertness and subsequent sleep architecture, Int. J. Environ. Res. Public Health. 15 (2018) 524, https://doi.org/10.3390/ijerph15030524.

[11] C. Formentin, S. Carraro, M. Turco, L. Zarantonello, P. Angeli, S. Montagnese, Effect of morning light glasses and night short-wavelength filter glasses on sleep-wake rhythmicity in medical inpatients, Front. Physiol. 11 (2020) 1–9, https://doi.org/10.3389/fphys.2020.00005.

[12] R.R. Grunstein, C.L. Phillips, P.Y. Liu, Sleep apnea—Past, present, future, Sleep Med. Rev. 12 (2008) 1–4, https://doi.org/10.1016/j.smrv.2007.11.001.

[13] J.J. Gooley, K. Chamberlain, K.A. Smith, S.B.S. Khalsa, S.M.W. Rajaratnam, E. Van Reen, J.M. Zeitzer, C.A. Czeisler, S.W. Lockley, Exposure to room light before bedtime suppresses melatonin onset and shortens melatonin duration in humans, J. Clin. Endocrinol. Metab. 96 (2011) E463–E472, https://doi.org/10.1210/jc.2010-2098.

[14] A. Amirazar, M. Azarbayjani, M. Molavi, M. Karami, A low-cost and portable device for measuring spectrum of light source as a stimulus for the human's circadian system, Energy Build 252 (2021) 111386, https://doi.org/10.1016/j.enbuild.2021.111386.

[15] A. Mohamed, V. Kalavally, S.W. Cain, A.J.K. Phillips, E.M. McGlashan, C.P. Tan, Wearable light spectral sensor optimized for measuring daily α-opic light exposure, Opt. Express. 29 (2021) 27612, https://doi.org/10.1364/oe.431373.

[16] L.L.A. Price, M. Khazova, J.B. O'Hagan, Performance assessment of commercial circadian personal exposure devices, Light. Res. Technol. 44 (2012) 17–26, https://doi.org/10.1177/1477153511433171.

[17] H.C. Thorne, K.H. Jones, S.P. Peters, S.N. Archer, D.J. Dijk, Daily and seasonal variation in the spectral composition of light exposure in humans, Chronobiol. Int. 26 (2009) 854–866, https://doi.org/10.1080/07420520903044315.

[18] D. Miller, A. Bierman, M.G. Figueiro, E.S. Schernhammer, M.S. Rea, Ecological measurements of light exposure, activity and circadian disruption, Light. Res. Technol. 42 (2010) 271–284, https://doi.org/10.1177/1477153510367977.

[19] S. Grace Colaco, S.G. Varghese, C. Pearl Kurian, S. Kumar TM, A state-of-the-art artificial intelligent techniques in daylighting controller: models and performance, Sci. Technol. Energy Transit. 78 (2023) 37, https://doi.org/10.2516/stet/2023035.

[20] F. Salamone, M. Masullo, S. Sibilio, Wearable devices for environmental monitoring in the built environment: a systematic review, Sensors 21 (2021) 4727, https://doi.org/10.3390/s21144727.

[21] L. Piwek, D.A. Ellis, S. Andrews, A. Joinson, The rise of consumer health wearables: promises and barriers, PLOS Med 13 (2016) e1001953, https://doi.org/10.1371/journal.pmed.1001953.

[22] J. van Duijnhoven, S. Hartmeyer, A. Didikoğlu, O. Stefani, K. Houser, V. Kalavally, M. Spitschan, Overview of wearable light loggers: state-of-the-art and outlook, TechRxiv (2024), https://doi.org/10.36227/techrxiv.171742550.06025656/v1.

[23] J. van Duijnhoven, S.L. Hartmeyer, A. Didikoglu, O. Stefani, K.W. Houser, V. Kalavally, M. Spitschan, Measuring light exposure in daily life: a review of wearable light loggers, Build. Environ. 274 (2025) 112771, https://doi.org/10.1016/j.buildenv.2025.112771.

[24] E.G. Landis, V. Yang, D.M. Brown, M.T. Pardue, S.A. Read, Dim light exposure and myopia in children, Investig. Ophthalmol. Vis. Sci. 59 (2018) 4804–4811, https://doi.org/10.1167/iovs.18-24415.

[25] E.J. Ricketts, H.J. Burgess, G.E. Montalbano, M.E. Coles, J.F. McGuire, H. Thamrin, D.L. McMakin, J.T. McCracken, M.A. Carskadon, J. Piacentini, C. S. Colwell, Morning light therapy in adults with Tourette's disorder, J. Neurol. 269 (2022) 399–410, https://doi.org/10.1007/s00415-021-10645-z.

[26] M. Turco, N. Cazzagon, I. Franceschet, C. Formentin, G. Frighetto, F. Giordani, N. Cellini, G. Mazzotta, R. Costa, B. Middleton, D.J. Skene, A. Floreani, S. Montagnese, Morning bright light treatment for sleep-wake disturbances in primary biliary cholangitis: a pilot study, Front. Physiol. 9 (2018) 1–10, https://doi.org/10.3389/fphys.2018.01530.

[27] V. Martins Gnecco, I. Pigliautile, A.L. Pisello, Long-term thermal comfort monitoring via wearable sensing techniques: correlation between environmental metrics and subjective perception, Sensors 23 (2023) 576, https://doi.org/10.3390/s23020576.

[28] B. Dong, V. Prakash, F. Feng, Z. O'Neill, A review of smart building sensing system for better indoor environment control, Energy Build 199 (2019) 29–46, https://doi.org/10.1016/j.enbuild.2019.06.025.

[29] Y. Dong, X. Zhang, Study on the effect of awakening daylight in dormitories on morning alertness, mood, fatigue and sleep quality of college students, Build. Environ. 203 (2021) 108060, https://doi.org/10.1016/j.buildenv.2021.108060.

[30] R. Lok, S. Ancoli-Israel, K.E. Ensrud, S. Redline, K.L. Stone, J.M. Zeitzer, Timing of outdoor light exposure is associated with sleep-wake consolidation in community-dwelling older men, Front. Sleep. 2 (2023), https://doi.org/10.3389/frsle.2023.1268379.

[31] Y. Huang, C. Mayer, P. Cheng, A. Siddula, H.J. Burgess, C. Drake, C. Goldstein, O. Walch, D.B. Forger, D.B. Forger, Predicting circadian phase across populations: a comparison of mathematical models and wearable devices, Sleep 44 (2021) 1–11, https://doi.org/10.1093/sleep/zsab126.

[32] N.M. Gabinet, B.A. Portnov, Investigating the combined effect of ALAN and noise on sleep by simultaneous real-time monitoring using low-cost smartphone devices, Environ. Res. 214 (2022) 113941, https://doi.org/10.1016/j.envres.2022.113941.

[33] E. van Lieshout-van Dal, L. Snaphaan, S. Bouwmeester, Y. de Kort, I. Bongers, Testing a single-case experimental design to study dynamic light exposure in people with, Dementia Living at Home, Appl. Sci. 11 (2021) 10221, https://doi.org/10.3390/app112110221.
[34] S.T. Peeters, K.C.H.J. Smolders, I.M.L.C. Vogels, Y.A.W. de Kort, Less is more? Effects of more vs. less electric light on alertness, mood, sleep and appraisals of light in an operational office, J. Environ. Psychol. 74 (2021) 101583, https://doi.org/10.1016/j.jenvp.2021.101583.
[35] M.S. Khanie, T. Illum, N. Hosseinpour, K. Matsuo, X. Fan, P. Wargocki, Exploring the effects of spectral light exposure on university students' sleep quality: a cross-sectional study, in: E3S Web Conf 396, 2023, https://doi.org/10.1051/e3sconf/202339601106.
[36] M.G. Figueiro, R. Hamner, A. Bierman, M.S. Rea, Comparisons of three practical field devices used to measure personal light exposures and activity levels, Light. Res. Technol. 45 (2013) 421–434, https://doi.org/10.1177/1477153512450453.
[37] J. Itzhacki, B.H.W.T. Lindert, W.P. Van Der Meijden, M.L. Kringelbach, J. Mendoza, E.J.W. Van Someren, Environmental light and time of day modulate subjective liking and wanting, Emotion 19 (2019) 10–20, https://doi.org/10.1037/emo0000402.
[38] S.W. Cain, E.M. McGlashan, P. Vidafar, J. Mustafovska, S.P.N. Curran, X. Wang, A. Mohamed, V. Kalavally, A.J.K. Phillips, Evening home lighting adversely impacts the circadian system and sleep, Sci. Rep. 10 (2020) 1–10, https://doi.org/10.1038/s41598-020-75622-4.
[39] E.L. Krüger, C. Tamura, T.W. Trento, Identifying relationships between daylight variables and human preferences in a climate chamber, Sci. Total Environ. 642 (2018) 1292–1302, https://doi.org/10.1016/j.scitotenv.2018.06.164.
[40] A.L. Robinson-Junker, B.F. O'Hara, B.N. Gaskill, Out like a light? The effects of a diurnal husbandry schedule on mouse sleep and behavior, J. Am. Assoc. Lab. Anim. Sci. 57 (2018) 124–133.
[41] K.W. Houser, P.R. Boyce, J.M. Zeitzer, M. Herf, Human-centric lighting: myth, magic or metaphor? Light. Res. Technol. (2020) 1–22, https://doi.org/10.1177/1477153520958448.
[42] D. Kumar, S. Jeuris, J.E. Bardram, N. Dragoni, Mobile and wearable sensing frameworks for mHealth studies and applications, ACM Trans. Comput. Healthc. 2 (2021) 1–28, https://doi.org/10.1145/3422158.
[43] M.F. Bause, H. Forbes, F. Nickpour, D. Schaefer, Towards a health 4.0 framework for the design of wearables: leveraging Human-centered and robust design, procedia CIRP. 91 (2020) 639–645. https://doi.org/10.1016/j.procir.2020.02.222.
[44] F. Salamone, S. Sibilio, M. Masullo, Integrated approach for Human wellbeing and environmental assessment based on a wearable IoT system: a pilot case study in Singapore, Sensors 24 (2024) 6126, https://doi.org/10.3390/s24186126.
[45] M.E. Falagas, E.I. Pitsouni, G.A. Malietzis, G. Pappas, Comparison of PubMed, Scopus, Web of Science, and Google Scholar: strengths and weaknesses, FASEB J 22 (2008) 338–342, https://doi.org/10.1096/fj.07-9492LSF.
[46] D.M. Berson, F.A. Dunn, M. Takao, Phototransduction by retinal ganglion cells that set the circadian clock, Science 295 (2002) 1070–1073, https://doi.org/10.1126/science.1067262 (80-.).
[47] S. Hattar, H.-W. Liao, M. Takao, D.M. Berson, K.-W. Yau, Melanopsin-containing retinal ganglion cells: architecture, projections, and intrinsic photosensitivity, Science 295 (2002) 1065–1070, https://doi.org/10.1126/science.1069609 (80-.).
[48] Scopus Search Guide, (2019) 1–11. http://schema.elsevier.com/dtds/document/bkapi/search/SCOPUSSearchTips.htm (accessed November 12, 2021).
[49] S. Uddin, A. Khan, The impact of author-selected keywords on citation counts, J. Informetr. 10 (2016) 1166–1177, https://doi.org/10.1016/j.joi.2016.10.004.
[50] G.M. Campedelli, Where are we? Using Scopus to map the literature at the intersection between artificial intelligence and crime, ArXiv (2019), https://doi.org/10.1007/s42001-020-00082-9.
[51] J. Choi, S. Yi, K.C. Lee, Analysis of keyword networks in MIS research and implications for predicting knowledge evolution, Inf. Manag. 48 (2011) 371–381, https://doi.org/10.1016/j.im.2011.09.004.
[52] S. Bidwell, S.I. Chalmers, M. Clarke, G. Crosbie, A. Eastwood, A. Fry-smith, R. Harbour, R. Lewis, Undertaking systematic reviews of research on effectiveness CRD ' s guidance for those carrying out or commissioning reviews, in: CRD Rep. Number 4, 2nd Ed., 4, 2001, p. 152. http://opensigle.inist.fr/handle/10068/534964.
[53] J. Smith, H. Noble, Bias in research, Evid. Based. Nurs. 17 (2014) 100–101, https://doi.org/10.1136/eb-2014-101946.
[54] N. Buscemi, L. Hartling, B. Vandermeer, L. Tjosvold, T.P. Klassen, Single data extraction generated more errors than double data extraction in systematic reviews, J. Clin. Epidemiol. 59 (2006) 697–703, https://doi.org/10.1016/j.jclinepi.2005.11.010.
[55] A. Bellazzi, L. Bellia, G. Chinazzo, F. Corbisiero, P. D'Agostino, A. Devitofrancesco, F. Fragliasso, M. Ghellere, V. Megale, F. Salamone, Virtual reality for assessing visual quality and lighting perception: a systematic review, Build. Environ. 209 (2022), https://doi.org/10.1016/j.buildenv.2021.108674.
[56] S.L. Hartmeyer, A. Davies, M. Andersen, Post-occupancy evaluation of office lighting – What can we learn from light-dosimetry? LEUKOS (2025) 1–24, https://doi.org/10.1080/15502724.2024.2434976.
[57] P. Sloane, M. Figueiro, S. Garg, L. Cohen, D. Reed, C. Williams, J. Preisser, S. Zimmerman, Effect of home-based light treatment on persons with dementia and their caregivers, Light. Res. Technol. 47 (2015) 161–176, https://doi.org/10.1177/1477153513517255.
[58] D.A. Wallace, K.R. Evenson, C.R. Isasi, S.R. Patel, D. Sotres-Alvarez, P.C. Zee, S. Redline, F.A.J.L. Scheer, T. Sofer, Characteristics of objectively-measured naturalistic light exposure patterns in U.S. adults: a cross-sectional analysis of two cohorts, Sci. Total Environ. 969 (2025) 178839, https://doi.org/10.1016/j.scitotenv.2025.178839.
[59] Philips Actiwatch Spectrum, (n.d.). https://www.philips.dk/healthcare/product/HC1046964/actiwatch-spectrum-activity-monitor (accessed December 30, 2024).
[60] Actiwatch comparison, (n.d.). http://www.actigraphy.respironics.com/assets/AW-Product-Comparison-a27fc80a3e875818d2322530a3c6607b9b29ca5e6a982ae8b193077e3d3e4587.pdf (accessed December 30, 2024).
[61] Actiwatch L., (n.d.). https://johnawinegarden.wordpress.com/wp-content/uploads/2015/03/actiwatchsoftware.pdf#page=108.04 (accessed December 30, 2024).
[62] C.M. Howell, S.J. McCullough, L. Doyle, M.H. Murphy, K.J. Saunders, Reliability and validity of the Actiwatch and Clouclip for measuring illumination in real-world conditions, Ophthalmic Physiol. Opt. 41 (2021) 1048–1059, https://doi.org/10.1111/opo.12860.
[63] M. Figueiro, R. Nagare, L. Price, Non-visual effects of light: how to use light to promote circadian entrainment and elicit alertness, Light. Res. Technol. 50 (2018) 38–62, https://doi.org/10.1177/1477153517721598.
[64] W. Osterhaus, G.-M. M, G. N, Wearable light sensors in case study evaluations, (n.d.). https://www.ises.org/sites/default/files/webinars/NGentile-WOsterhaus-MGkaintatziMasouti-24.9.2020.pdf (accessed June 10, 2025).
[65] J.A. Veitch, M. Knoop, CIE TN 011:2020 what to document and report in studies of ipRGC-influenced responses to light, n.d. https://files.cie.co.at/CIE_TN_011_2020.pdf.
[66] S.R. Pandi-Perumal, M. Smits, W. Spence, V. Srinivasan, D.P. Cardinali, A. D. Lowe, L. Kayumov, Dim light melatonin onset (DLMO): a tool for the analysis of circadian phase in human sleep and chronobiological disorders, Prog. Neuro-Psychopharmacology Biol. Psychiatry. 31 (2007) 1–11, https://doi.org/10.1016/j.pnpbp.2006.06.020.
[67] Pupil core eye-tracker web page, (n.d.). https://pupil-labs.com/products/core (accessed August 30, 2024).
[68] A.Å. Miley, G. Kecklund, T. Åkerstedt, Comparing two versions of the Karolinska Sleepiness Scale (KSS), Sleep Biol. Rhythms. 14 (2016) 257–260, https://doi.org/10.1007/s41105-016-0048-8.
[69] D.J. Buysse, C.F. Reynolds, T.H. Monk, S.R. Berman, D.J. Kupfer, The Pittsburgh sleep quality index: a new instrument for psychiatric practice and research, Psychiatry Res 28 (1989) 193–213, https://doi.org/10.1016/0165-1781(89)90047-4.
[70] M.W. Johns, A new method for measuring daytime sleepiness: the Epworth sleepiness scale, Sleep 14 (1991) 540–545, https://doi.org/10.1093/sleep/14.6.540.
[71] P.A. Harris, J. Swafford, E.S. Serdoz, J. Eidenmuller, G. Delacqua, V. Jagtap, R. J. Taylor, A. Gelbard, A.C. Cheng, S.N. Duda, MyCap: a flexible and configurable platform for mobilizing the participant voice, JAMIA Open 5 (2022), https://doi.org/10.1093/jamiaopen/ooac047.
[72] A. Adan, H. Almirall, Horne & Östberg morningness-eveningness questionnaire: a reduced scale, Pers. Individ. Dif. 12 (1991) 241–253, https://doi.org/10.1016/0191-8869(91)90110-W.
[73] Morningness-Eveningness Questionnaire description, (n.d.). https://www.med.upenn.edu/cbti/assets/user-content/documents/Morningness-Eveningness-Questionnaire.pdf (accessed December 30, 2024).
[74] Q. Ngo-Metzger, D.H. Sorkin, C.M. Mangione, B. Gandek, R.D. Hays, Evaluating the SF-36 health survey (Version 2) in older Vietnamese Americans, J. Aging Health. 20 (2008) 420–436, https://doi.org/10.1177/0898264308315855.
[75] S. Logan, B. Gottlieb, S. Maitland, D. Meegan, L. Spriet, The physical activity scale for the elderly (PASE) questionnaire; does it predict physical health? Int. J. Environ. Res. Public Health. 10 (2013) 3967–3986, https://doi.org/10.3390/ijerph10093967.
[76] Geriatric Depression Scale (GDS), (n.d.). https://geriatrictoolkit.missouri.edu/cog/GDS_SHORT_FORM.PDF (accessed December 30, 2024).
[77] J. Römhild, S. Fleischer, G. Meyer, A. Stephan, S. Zwakhalen, H. Leino-Kilpi, A. Zabalegui, K. Saks, M. Soto-Martin, C. Sutcliffe, I. Rahm Hallberg, A. Berg, Inter-rater agreement of the Quality of Life-Alzheimer's Disease (QoL-AD) self-rating and proxy rating scale: secondary analysis of RightTimePlaceCare data, Health Qual. Life Outcomes. 16 (2018) 131, https://doi.org/10.1186/s12955-018-0959-y.
[78] C.M. Morin, G. Belleville, L. Bélanger, H. Ivers, The Insomnia Severity Index: psychometric indicators to detect insomnia cases and evaluate treatment response, Sleep 34 (2011) 601–608, https://doi.org/10.1093/sleep/34.5.601.
[79] J.F. LECKMAN, M.A. RIDDLE, M.T. HARDIN, S.I. ORT, K.L. SWARTZ, J. STEVENSON, D.J. COHEN, The Yale Global Tic Severity scale: initial testing of a clinician-rated scale of tic severity, J. Am. Acad. Child Adolesc. Psychiatry. 28 (1989) 566–573, https://doi.org/10.1097/00004583-198907000-00015.
[80] S.L. Chellappa, R. Steiner, P. Blattner, P. Oelhafen, T. Götz, C. Cajochen, Non-visual effects of light on melatonin, alertness and cognitive performance: can blue-enriched light keep us alert? PLoS One 6 (2011) e16429 https://doi.org/10.1371/journal.pone.0016429.
[81] G. Demozzi, L. Zaniboni, G. Pernigotto, A. Gasparella, Impact of visual, thermal, and indoor air quality conditions on students' Wellbeing and learning performance in a primary school of Bolzano, Italy, Build. Simul. Appl. 2022-June (2022) 489–497.
[82] C. Cajochen, S. Chellappa, C. Schmidt, What keeps us awake?—The role of clocks and hourglasses, light, and melatonin, in: 2010: pp. 57–90. https://doi.org/10.1016/S0074-7742(10)93003-1.

[83] L. Zaniboni, J. Toftum, Indoor environment perception of people with autism spectrum condition: a scoping review, Build. Environ. 243 (2023) 110545, https://doi.org/10.1016/j.buildenv.2023.110545.
[84] S. Gilani, W. O'Brien, Review of current methods, opportunities, and challenges for in-situ monitoring to support occupant modelling in office spaces, J. Build. Perform. Simul. 10 (2017) 444–470, https://doi.org/10.1080/19401493.2016.1255258.
[85] R.J. Cureau, I. Pigliautile, A.L. Pisello, M. Bavaresco, C. Berger, G. Chinazzo, Z. Deme Belafi, A. Ghahramani, A. Heydarian, D. Kastner, M. Kong, D. Licina, A. Luna-Navarro, A. Mahdavi, A. Nocente, M. Schweiker, M. Vellei, A. Wang, Bridging the gap from test rooms to field-tests for human indoor comfort studies: a critical review of the sustainability potential of living laboratories, Energy Res. Soc. Sci. 92 (2022) 102778, https://doi.org/10.1016/j.erss.2022.102778.
[86] ISO/CIE TR 21783:2022, Light and Lighting — Integrative lighting — Non-visual effects, 2022.
[87] A.L. Shields, S. Shiffman, A. Stone, Recall bias: understanding and reducing bias in PRO data collection. EPro, 2010, p. 17. https://www.taylorfrancis.com/chapters/edit/10.4324/9781315580142-2/recall-bias-understanding-reducing-bias-pro-data-collection-alan-shields-saul-shiffman-arthur-stone.
[88] S. Shiffman, A.A. Stone, M.R. Hufford, Ecological momentary assessment, Annu. Rev. Clin. Psychol. 4 (2008) 1–32, https://doi.org/10.1146/annurev.clinpsy.3.022806.091415.
[89] P. Jayathissa, M. Quintana, T. Sood, N. Nazarian, C. Miller, Is your clock-face cozie? A smartwatch methodology for the in-situ collection of occupant comfort data, J. Phys. Conf. Ser. 1343 (2019) 012145, https://doi.org/10.1088/1742-6596/1343/1/012145.
[90] N. Kelly, S. Gilbert, The WEAR Scale, in: Proc. 2016 CHI Conf. Ext. Abstr. Hum. Factors Comput. Syst., New York, NY, USA, ACM, 2016, pp. 2864–2871, https://doi.org/10.1145/2851581.2892331.
[91] R.A. Grier, A. Bangor, P. Kortum, S.C. Peres, The system usability scale, in: Proc. Hum. Factors Ergon. Soc. Annu. Meet. 57, 2013, pp. 187–191, https://doi.org/10.1177/1541931213571042.
[92] J.A. Veitch, L. Bedocs, P.R. Boyce, C. Cuttle, J.V. Kemenade, T.K. McGowan, N.J. Miller, Y. Nakamura, A. Pellegrino, CIE 213:2014 guide to protocols for describing lighting, n.d. https://www.cie.co.at/publications/guide-protocols-describing-lighting.
[93] CIE S 026/E:2018, CIE System for Metrology of Optical Radiation For Iprgc-Influenced Responses to Light, 2018, https://doi.org/10.25039/S026.2018.
[94] D. Gubin, D. Weinert, O. Stefani, K. Otsuka, M. Borisenkov, G. Cornelissen, Wearables in chronomedicine and interpretation of circadian health, Diagnostics 15 (2025) 327, https://doi.org/10.3390/diagnostics15030327.
[95] M. Spitschan, L. Kervezee, R. Lok, E. McGlashan, R.P. Najjar, A.E. Allen, M. Andersen, S. Bará, P. Blattner, C. Blume, D.B. Boivin, M.-Á. Bonmatí-Carrión, K. Broszio, T.M. Brown, S.L. Chellappa, J.F. Duffy, T. Eto, E. Flynn-Evans, S. Fotios, V. Gabel, C. Garbazza, G. Glickman, M.C. Gordijn, J.P. Hanifin, L. Hartstein, M. Herf, S. Higuchi, C.J. Hilditch, K.W. Houser, A. Hurlbert, M. K. LeBourgeois, S. Lockley, R. Lucas, C.R.C. Moreno, M. Münch, L.S. Mure, S. Peirson, S. Rahman, V.L. Revell, R.G. Rodriguez, K. Roecklein, A.V. Rukmini, J. Sammarco, N. Santhi, L.J.M. Schlangen, I. Schöllhorn, K.M. Sharkey, D. J. Skene, T.L. Sletten, K.C.H.J. Smolders, O. Stefani, J.E. Stone, P. Teikari, M. Terman, K.T. Quoc, K. Tsubota, L. Udovicic, G. Vandewalle, J.A. Veitch, L.M. Wu CélineVetter, J. Zauner, J. Zeitzer, ENLIGHT: a consensus checklist for reporting laboratory-based studies on the non-visual effects of light in humans, EBioMedicine 98 (2023) 104889, https://doi.org/10.1016/j.ebiom.2023.104889.
[96] CIE TN 011:2020, What to Document and Report in Studies of Iprgc-Influenced Responses to Light, 2020, https://doi.org/10.25039/TN.011.2020.
[97] L. Wen, H. Liu, Z. Chen, Q. Xu, Z. Hu, W. Lan, Z. Yang, Effect of mount location on the quantification of light intensity in myopia study, BMJ Open Ophthalmol 8 (2023) e001409, https://doi.org/10.1136/bmjophth-2023-001409.
[98] J. Zauner, A.M. Biller, M. Spitschan, Impact of light logger and dosimeter placement on wearability and appeal in real-life settings, (2025). https://doi.org/10.1101/2025.06.13.25329548.
[99] J.D. Cook, M.L. Prairie, D.T. Plante, Ability of the multisensory jawbone UP3 to quantify and classify sleep in patients with suspected Central disorders of hypersomnolence: a comparison against polysomnography and actigraphy, J. Clin. Sleep Med. 14 (2018) 841–848, https://doi.org/10.5664/jcsm.7120.
[100] M. Spitschan, J. Zauner, M. Nilsson Tengelin, C.A. Bouroussis, P. Caspar, F. Eloi, Illuminating the future of wearable light metrology: overview of the MeLiDos Project, Measurement 235 (2024) 114909, https://doi.org/10.1016/j.measurement.2024.114909.
[101] MeLiDos- Metrology For Wearable Light loggers and Optical Radiation Dosimeters webpage, (n.d.). https://www.melidos.eu/ (accessed October 13, 2024).
[102] C. Guidolin, S. Aerts, G.K. Agbeshie, K.O. Akuffo, S.N. Aydin, D. Baeza Moyano, J. Bolte, K. Broszio, G. Cantarero-García, A. Didikoglu, R.A. González-Lezcano, H. Joosten-Ma, S. Melero-Tur, M. Nilsson Tengelin, M.C. Pérez Gutiérrez, O. Stefani, I. Svensson, L. Udovicic, J. Zauner, M. Spitschan, Protocol for a prospective, multicentre, cross-sectional cohort study to assess personal light exposure, (2024). https://doi.org/10.1101/2024.02.11.24302663.
[103] O. Stefani, R. Marek, J. Schwarz, S. Plate, J. Zauner, B. Schrader, Wearable light loggers in field conditions: corneal light characteristics, user compliance and acceptance, (2024). https://doi.org/10.20944/preprints202409.1285.v1.
[104] E. Schreuder, J. van Erp, A. Toet, V.L. Kallen, Emotional responses to multisensory environmental stimuli: a conceptual framework and literature review, SAGE Open 6 (2016), https://doi.org/10.1177/2158244016630591.
[105] ACTIWATCH 2 webpage, (n.d.). https://shop.retailmedicalsolutions.com/productDetail.htm?productId=23255916& (accessed June 23, 2025).
[106] Actiwatch Spectrum webpage, (n.d.). https://www.philips.com.tw/healthcare/product/HC1046964/actiwatch-spectrum-activity-monitor (accessed June 23, 2025).
[107] Specbos 1201 specifications, (n.d.). https://sphereoptics.de/wp-content/uploads/2015/03/Jeti-Spectroradiometer-specbos-1201-1.pdf (accessed June 23, 2025).
[108] SOMNO watch specifications, (n.d.). https://www.hitwinhealthcare.com/products/sleep-lab/polywatch/somnowatch-plus-psg0007 (accessed June 17, 2025).