

An inventory of human light exposure related behaviour

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29 This research is supported by funding from the Wellcome Trust (204686/Z/16/Z),
30 the European Training Network LIGHTCAP (project number 860613) under the Marie
31 Skłodowska-Curie actions framework H2020-MSCA-ITN-2019, the BioClock project
32 (number 1292.19.077) of the research program Dutch Research Agenda: Onderzoek op
33 Routes door Consortia (NWA-ORC) which is (partly) financed by the Dutch Research
34 Council (NWO), and the European Union and the nationals contributing in the context of
35 the ECSEL Joint Undertaking programme (2021-2024) under the grant #101007319.

36 The authors made the following contributions. Mushfiqul Anwar Siraji: Formal
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51

Abstract

52 Light exposure is an essential driver of health and well-being, and individual behaviours
53 during rest and activity modulate physiologically-relevant aspects of light exposure.
54 Further understanding the behaviours that influence individual photic exposure patterns
55 may provide insight into volitional contributions to the physiological effects of light and
56 guide behavioral points of intervention. Here, we present a novel, self-reported and
57 psychometrically validated inventory to capture light exposure-related behaviour, the
58 Light Exposure Behaviour Assessment (LEBA).

59 An expert panel prepared the initial 48-item pool spanning different light
60 exposure-related behaviours. Responses, consisting of rating the frequency of engaging
61 in the per-item behaviour on a 5-point Likert type scale, were collected in an online
62 survey yielding responses from a geographically unconstrained sample (690 completed
63 responses, 74 countries, 28 time zones). The exploratory factor analysis (EFA) on an
64 initial subsample ($n=428$) rendered a five-factor solution with 25 items (Wearing blue
65 light filters, spending time outdoors, using a phone and smartwatch in bed, using light
66 before bedtime, using light in the morning and during daytime). In a confirmatory factor
67 analysis (CFA) performed on an independent subset of participants ($n=262$), we
68 removed two additional items to attain the best fit for the five-factor solution ($CFI=0.95$,
69 $TLI=0.95$, $RMSEA=0.06$). The internal consistency reliability coefficient for the total
70 instrument yielded McDonald's $\Omega=0.68$. Measurement model invariance analysis
71 between native and non-native English speakers showed our model attained the highest
72 level of invariance (residual invariance; $CFI=0.95$, $TLI=0.95$, $RMSEA=0.05$). Lastly, a
73 short form of the LEBA ($n=18$) was developed using Item Response Theory on the
74 complete sample ($n=690$).

75 The psychometric properties of the LEBA indicate the usability to measure light
76 exposure-related behaviours. The instrument may offer a scalable solution to

77 characterize behaviours that influence individual photic exposure patterns in remote
78 samples. The LEBA inventory will be available under the open-access CC-BY-NC-ND
79 license.

80 *Keywords:* light exposure, light-related behaviours, non-visual effects of light,
81 psychometrics

82 Word count: 6249

83 An inventory of human light exposure related behaviour

84 **Introduction**

85 Light exposure received by the eyes affects many facets of human health,
86 well-being, and performance beyond visual sensation and perception (Boyce, 2022).
87 The so-called non-image-forming (NIF) effects of light comprise light's circadian and
88 non-circadian influence on several physiological and psychological functions, such as the
89 secretion of melatonin, sleep, mood, pupil size, body temperature, alertness, and higher
90 cognitive functions (Bedrosian & Nelson, 2017; Blume, Garbazza, & Spitschan, 2019;
91 Lok, Smolders, Beersma, & de Kort, 2018; Paul & Brown, 2019; Santhi & Ball, 2020;
92 Siraji, Kalavally, Schaefer, & Haque, 2021; Zele & Gamlin, 2020). With the introduction of
93 artificial electric light, human behaviour has become somewhat independent of the
94 natural light-dark cycle – people can now frequently choose when to be exposed to light
95 or darkness. For example, they can decide whether to go outdoors and seek out
96 sunlight, switch on/off light-emitting devices, use certain types of lights at home, or avoid
97 specific light environments altogether. Additionally, when light sources can not be directly
98 manipulated, sought out, or avoided (for example, at school, work, or in public places),
99 there is still potential leeway to influence them behaviourally, for instance, by wearing
100 sunglasses, directing one's gaze away or supplementing the situation with additional light
101 sources. Although clearly yielding the potential for good, these behaviours are further
102 associated with increased electric light exposure at night and indoor time during the day,
103 compromising the natural temporal organisation of the light-dark cycle. For example, in
104 the US, an average of 87% of the time is spent in enclosed buildings (Klepeis et al.,
105 2001), and more than 80% of the population is exposed to a night sky that is brighter
106 than nights with a full moon due to electric light at night (Navara & Nelson, 2007).

107 An extensive body of scientific evidence suggests that the imbalance of light and
108 dark exposure disrupts humans' light-dependent physiological systems (Lunn et al.,

109 2017). Subsequently, this disruption gives rise to a series of adverse health
110 consequences, including the alteration of hormonal rhythms, increased cancer rates,
111 cardiovascular diseases, and metabolic disorders, such as obesity and type II diabetes
112 (Chellappa, Vujovic, Williams, & Scheer, 2019; Lunn et al., 2017; Navara & Nelson,
113 2007). These findings have sparked a significant call for assessment and guidance
114 regarding healthy light exposure as exemplified by a recently published set of
115 consensus-based experts' recommendations with specific requirements for indoor light
116 environments during the daytime, evening, and nighttime (T. M. Brown et al., 2022).
117 Furthermore, building on earlier attempts (e.g. Hubalek, Zöschg, & Schierz, 2006), there
118 was a recent push toward the development and use of portable light loggers to improve
119 ambulant light assessment and gain more insight into the NIF effects of light on human
120 health in field conditions (Aarts, Duijnhoven, Aries, & Rosemann, 2017; Duijnhoven,
121 Aarts, Aries, Böhmer, & Rosemann, 2017; Stampfli et al., 2021; Webler, Chinazzo, &
122 Andersen, 2021). Attached to different body parts (e.g., wrist; head, at eye level; chest),
123 these devices allow for the objective measurement of individual photic exposure patterns
124 under real-world conditions and thus are valuable tools for field studies. Nevertheless,
125 these devices also encompass limiting factors such as potentially being intrusive (e.g.,
126 when eye-level worn), yielding the risk of getting covered (e.g., when wrist- or
127 chest-worn) and requiring (monetary) resources and expertise for acquisition and
128 maintenance of the devices.

129 On the other hand, several attempts have been made to quantify received light
130 exposure subjectively with self-report questionnaires (**Supplementary Table 1**),
131 bypassing the cost and intrusiveness issues. However, subjective light intensity
132 assessments pose a new set of challenges: The human visual system constantly adapts
133 to brightness (Hurvich & Jameson, 1966), while the human non-visual light processing
134 works largely subconsciously (Allen, Hazelhoff, Martial, Cajochen, & Lucas, 2018),
135 making the self-report assessment of light properties potentially quite challenging.

136 Retrospectively recalling the properties of a light source can further complicate such
137 subjective evaluations. Moreover, measuring light properties alone does not yield any
138 information about how individuals might behave differently regarding diverse light
139 environments such as work, home or outdoors. These measurement limitations point to
140 a couple of research challenges we aim to take on here: How can we gain insight into
141 light exposure patterns via self-report but circumvent directly inquiring about the specific
142 properties and intensity of a light source? And how can we simultaneously assess how
143 people habitually interact with the received light? We propose that these challenges can
144 be tackled by assessing light-exposure-related behaviour. We argue that, besides
145 measuring received light exposure as intensity, it is also essential to understand people's
146 behaviours with respect to different light situations. In many cases, humans have
147 become their own agents regarding their exposure to light or darkness through daylight
148 and electric light, and as such people's light exposure-related behaviours ultimately
149 determine their light consumption and timing: People receive different light depending on
150 their daily activities, including workplace habits, bedtime hygiene, pastime and social
151 activities. Ultimately, in order to optimize lighting for human health and well being, better
152 understanding of light-related behaviours will serve to identify additional points of
153 intervention as well as to provide an added dimension to efficacy and implementation
154 studies of novel lighting strategies. We argue that assessing these activities is a
155 beneficial stepping stone for prospective behaviour change to maintain light hygiene: a
156 proper balance of exposures to light to maintain circadian rhythms.

157 To date, little effort has been made to understand and capture these activities.

158 **Supplementary Table 1** summarises the existing questionnaire literature assessing light
159 exposure-related properties. However, only a few questions of these existing tools were
160 associated with light exposure-related behaviour. For example, the "Munich Chronotype
161 Questionnaire" (Roenneberg, Wirz-Justice, & Merrow, 2003), a popular self-report tool
162 for identifying chronotypes via mid-sleep times, includes questions about the individual's

163 typical time spent outdoors on workdays and free days. The Visual Light Sensitivity
164 Questionnaire-8 (Verriotto et al., 2017) and Photosensitivity Assessment Questionnaire
165 (Bossini et al., 2006) are a couple of self-report tools measuring visual light sensitivity.
166 They contain single items which probe the preference for specific light situations such
167 as: "In the past month, how often did you need to wear dark glasses on cloudy days or
168 indoors?" (Verriotto et al., 2017); "I prefer rooms that are in semi-darkness."; (Bossini et
169 al., 2006). In addition, the "Pittsburgh Sleep Quality Index" (Buysse, Reynolds III, Monk,
170 Berman, & Kupfer, 1989), is a popular measure of sleep quality. It contains questions
171 about bedtime and wake-up times, which are relevant to light exposure around bedtime.
172 However, none of these questionnaires provides a scalable solution to capture light
173 exposure-related behaviour in various lighting situations. To fill this gap, we here present
174 the development process of a novel self-reported inventory - the "Light Exposure
175 Behaviour Assessment" (LEBA) - for characterizing diverse light exposure-related
176 behaviours.

177 Methods

178 Data Collection

179 A quantitative cross-sectional, fully anonymous, geographically unconstrained
180 online survey was conducted via REDCap (Harris et al., 2019, 2009) by way of the
181 University of Basel sciCORE. Participants were recruited via the website
182 (<https://enlightenyourclock.org/participate-in-research>) of the science-communication
183 comic book "Enlighten your clock", co-released with the survey (Weinzaepflen &
184 Spitschan, 2021), social media (i.e., LinkedIn, Twitter, Facebook), mailing lists, word of
185 mouth, the investigators' personal contacts, and supported by the distribution of the
186 survey link via f.lux (F.lux Software LLC, 2021). The initial page of the online survey
187 provided information about the study, including that participation was voluntary and that

188 respondents could withdraw from participation at any time without being penalised.
189 Subsequently, consent was recorded digitally for the adult participants (>18 years), while
190 under-aged participants (<18 years) were prompted to obtain additional assent from their
191 parents/legal guardians. Filling in all questionnaires was estimated to take less than 30
192 minutes, and participation was not compensated.

193 As a part of the demographic data, participants provided information regarding age,
194 sex, gender identity, occupational status, COVID-19-related occupational setting, time
195 zone/country of residence and native language. The demographic characteristics of our
196 sample are given in **Table 1**. Participants were further asked to confirm that they
197 participated in the survey for the first time. Additionally, five attention check items (e.g.,
198 “We want to make sure you are paying attention. What is 4+5?”) were included among
199 the questionnaires to ensure high data quality. All questions incorporating retrospective
200 recall were aligned to a “past four weeks” period.

201 We collected the survey data between 17 May 2021 and 3 September 2021 – firstly
202 from 428 participants (EFA sample) – and subsequently, another dataset from 262
203 participants (CFA sample), totalling 690.

204 **Analytic Strategy**

205 Figure 1 summarises the steps we followed while developing the LEBA. We
206 conducted all analyses with the statistical software environment R (R Core Team, 2021).
207 **Firstly**, we set an item pool of 48 items with a six-point Likert-type response format
208 (0-Does not apply/I don't know, 1-Never, 2-Rarely 3-Sometimes, 4-Often, 5-Always) for
209 our initial inventory. Our purpose was to capture light exposure-related behaviour. In that
210 context, the first two response options: “Does not apply/I don't know” and “Never”,
211 provided similar information. As such, we collapsed them into one, making it a 5-point
212 Likert-type response format (1-Never, 2-Rarely, 3-Sometimes, 4-Often, 5-Always).

213 **Secondly**, the two rounds of data collection were administered. **Thirdly**, we
214 conducted descriptive and item analyses and proceeded to the exploratory factor
215 analysis (EFA) using the “psych” package (Revelle, 2021) on the data collected in the
216 first round (EFA sample; n=428), as a part of psychometric analysis. Prior to the EFA,
217 the necessary assumptions, including sample adequacy, normality assumptions, and
218 quality of correlation matrix, were assessed. As our data violated both the univariate and
219 multivariate normality assumption and yielded ordinal response data, we used a
220 polychoric correlation matrix in the EFA and employed “principal axis” (PA) as the factor
221 extraction method (Desjardins & Bulut, 2018; Watkins, 2020). We applied a combination
222 of methods, including a Scree plot (Cattell, 1966), minimum average partials method
223 (Velicer, 1976), and Hull method (Lorenzo-Seva, Timmerman, & Kiers, 2011) to identify
224 factor numbers. To determine the latent structure, we followed the common guidelines:
225 (i) no factors with fewer than three items (ii) no factors with a factor loading <0.3 (iii) no
226 items with cross-loading > .3 across factors (Bandalos & Finney, 2018).

227 For reliability estimation, the “psych” package was applied (Revelle, 2021). Though
228 Cronbach’s internal consistency coefficient alpha is widely used for estimating internal
229 consistency, it tends to deflate the estimates for Likert-type data since the calculation is
230 based on the Pearson-correlation matrix, which requires response data to be continuous
231 in nature (Gadermann, Guhn, & Zumbo, 2012; Zumbo, Gadermann, & Zeisser, 2007).
232 Subsequently, we reported ordinal alpha for each factor obtained in the EFA which was
233 suggested as a better reliability estimates for ordinal data (Zumbo et al., 2007). We also
234 estimated the internal consistency reliability of the total inventory using McDonald’s ω_t
235 coefficient, which was suggested as a better reliability estimate for multidimensional
236 constructs (Dunn, Baguley, & Brunsden, 2014; Sijtsma, 2009). Both ordinal alpha and
237 McDonald’s ω_t coefficient values range between 0 to 1, where higher values represent
238 better reliability.

239 To validate the latent structure obtained in the EFA, we conducted a categorical

240 confirmatory factor analysis (CFA) with the weighted least squares means and variance
241 adjusted (WLSMV) estimation (Desjardins & Bulut, 2018), using the “lavaan” package
242 (Rosseel, 2012) on the data collected in the second round (CFA sample; n=262). We
243 assessed the model fit using standard model fit guidelines: (i) χ^2 test statistics: a
244 non-significant test statistics is required to accept the model (ii) comparative fit index
245 (CFI) and Tucker Lewis index (TLI): close to .95 or above/ between .90-.95 and above
246 (iii) root mean square error of approximation (RMSEA): close to .06 or below, (iv)
247 Standardized root mean square (SRMR): close to .08 or below (Hu & Bentle, 1999;
248 Schumacker & Lomax, 2004). However, the χ^2 test is sensitive to sample size (T. A.
249 Brown, 2015), and SRMR does not work well with ordinal data (Yu, 2002). Consequently,
250 we judged the model fit using CFI, TLI and RMSEA.

251 In order to evaluate whether the construct demonstrated psychometric equivalence
252 and the same meaning across native English speakers (n=129) and non-native English
253 speakers (n=133) in the CFA sample (n=262) (Kline, 2016; Putnick & Bornstein, 2016)
254 measurement invariance analysis was used. We used structural equation modelling
255 framework applying the “lavaan” package (Rosseel, 2012) to assess the measurement
256 invariance. We successively compared four nested models: configural, metric, scalar,
257 and residual models using the χ^2 difference test ($\Delta\chi^2$). Among MI models, the
258 configural model is the least restrictive, and the residual model is the most restrictive. A
259 non-significant $\Delta\chi^2$ test between two nested measurement invariance models indicates
260 mode fit does not significantly decrease for the superior model, thus allowing the
261 superior invariance model to be accepted (Dimitrov, 2010; Widaman & Reise, 1997).

262 **Fourthly**, in a secondary analysis, we identified the educational grade level (US
263 education system) required to understand the items in our inventory with the
264 Flesch-Kincaid grade level identification method (Flesch, 1948) applying the “koRpus”
265 (Michalke, 2021) package. Correspondingly, we analysed possible semantic overlap of
266 our developed inventory using the “Semantic Scale Network” (SSN) engine

267 (Rosenbusch, Wanders, & Pit, 2020). The SSN detects semantically related scales and
268 provides a cosine similarity index ranging between -.66 to 1 (Rosenbusch et al., 2020).
269 Pairs of scales with a cosine similarity index value of 1 indicate full semantical similarity,
270 suggesting redundancy.

271 **Lastly**, we derived a short form of the LEBA employing an Item Response Theory
272 (IRT) based analysis. We fitted each factor of the LEBA to the combined EFA and CFA
273 sample (n=690) using the graded response model (Samejima, Liden, & Hambleton,
274 1997) via the “mirt” package (Chalmers, 2012). IRT assesses the item quality by
275 estimating the item discrimination, item difficulty, item information curve, and test
276 information curve (Baker & Kim, 2017). Item discrimination indicates how well a
277 particular item can differentiate between participants across the given latent trait
278 continuum (θ). Item difficulty corresponds to the latent trait level at which the probability
279 of endorsing a particular response option is 50%. The item information curve (IIC)
280 indicates the amount of information an item carries along the latent trait continuum.
281 Here, we reported the item difficulty and discrimination parameter and categorized the
282 items based on their item discrimination index: (i) none = 0; (ii) very low = 0.01 to 0.34;
283 (iii) low = 0.35 to 0.64; (iv) moderate = 0.65 to 1.34 ; (v) high = 1.35 to 1.69; (vi) very high
284 >1.70 (Baker & Kim, 2017). We discarded the items with a relatively flat item information
285 curve (information <.2) to derive the short form of LEBA. We also assessed the precision
286 of the short LEBA utilizing the test information curve (TIC). TIC indicates the amount of
287 information a particular scale carries along the latent trait continuum. Additionally, the
288 item and person fit of the fitted IRT models were analysed to gather more evidence on
289 the validity and meaningfulness of our scale (Desjardins & Bulut, 2018). The item fit was
290 evaluated using the RMSEA value obtained from Signed- χ^2 index implementation,
291 where an RMSEA value $\leq .06$ was considered an adequate item fit. The person fit was
292 estimated employing the standardized fit index Zh statistics (Drasgow, Levine, &
293 Williams, 1985). Here, Zh < -2 was considered as a misfit (Drasgow et al., 1985).

294 **Ethical Approval**

295 The current research project utilizes fully anonymous online survey data and
296 therefore does not fall under the scope of the Human Research Act, making an
297 authorisation from the ethics committee redundant. Nevertheless, the cantonal ethics
298 commission (Ethikkommission Nordwest- und Zentralschweiz, EKNZ) reviewed our
299 proposition (project ID Req-2021-00488) and issued an official clarification of
300 responsibility.

301 **Data Availability**

302 The present article is a fully reproducible open access “R Markdown” document. All
303 code and data underlying this article – along with two versions of the LEBA inventory (full
304 and short) and online survey implementation templates on common survey platforms –
305 will be available under open-access licence (CC-BY-NC-ND) on a public GitHub
306 repository.

307 **Results**

308 **Development of the Initial Inventory**

309 An expert panel comprising all authors – researchers from chronobiology, light
310 research, neuroscience and psychology – developed a comprehensive item pool of 48
311 items. The 48 items were examined independently based on their relevance and
312 representativeness of the construct “Light Exposure Related Behaviour” by each panel
313 member, and modifications were suggested as required. The author team discussed the
314 suggestions and amended the items as indicated, thus creating a 48-item inventory.

315 **Anonymous Online Survey**

316 Table 1 summarises the survey participants' demographic characteristics. Only
317 participants completing the full LEBA inventory were included. Thus, there are no
318 missing values in the item analyses. (XXX??) participants were excluded from the
319 analysis due to not passing at least one of the "attention check" items. For the EFA, a
320 sample of at least 250-300 is recommended (Comrey & Lee, 2013; Schönbrodt &
321 Perugini, 2013). To assess sampling adequacy for CFA, we followed the N:q rule
322 (Bentler & Chou, 1987; Jackson, 2003; Kline, 2016; Worthington & Whittaker, 2006),
323 where at least ten participants per item are required to earn trustworthiness of the result.
324 Both our EFA and CFA sample size exceeded these requirements. Participants indicated
325 filling out the online survey from various geographic locations, including 74 countries and
326 28 time zones. For a complete list of geographic locations, see **Supplementary Table 2**.

327 Participants in our survey were aged between 11 to 84 years, with an overall mean
328 of ~ 32.95 years of age [Overall: 32.95 ± 14.57 ; EFA: 32.99 ± 15.11 ; CFA: 32.89 ± 13.66]. In
329 total, 325 (47%) of the participants indicated female sex, 351 (51%) indicated male, and
330 14 (2.0%) indicated other sex. Overall, 49 (7.2%) participants reported a gender-variant
331 identity. In a "Yes/No" question regarding native language, 320 (46%) of respondents
332 [EFA: 191 (45%); CFA: 129 (49%)] indicated to be native English speakers. For their
333 "Occupational Status", more than half of the overall sample (396 (57%)) reported that
334 they currently work, whereas 174 (25%) reported that they go to school, and 120 (17%)
335 responded that they do "Neither". With respect to the COVID-19 pandemic, we asked
336 participants to indicate their occupational setting during the last four weeks: In the overall
337 sample, 303 (44%) of the participants indicated that they were in a home office/ home
338 schooling setting, 109 (16%) reported face-to-face work/schooling, 147 (21%) reported a
339 combination of home- and face-to-face work/schooling, and 131 (19%) filled in the
340 "Neither (no work or school, or on vacation)" response option.

341 **Psychometric Analysis: Development of the Long Form**

342 **Descriptive Statistics and Item Analysis.** Figures 2 and 3 summarise the
343 response patterns of our total sample (n=690) for all 48 items. Most of the items
344 appeared skewed. The Shapiro–Wilk test of univariate normality (Shapiro & Wilk, 1965)
345 and Mardia test of multivariate normality (Mardia, 1970) indicated that our data violated
346 both univariate and multivariate normality. The multivariate skewness was 488.40 (p
347 <0.001), and the multivariate kurtosis was 2,808.17 (p <0.001).

348 **Supplementary Figure 1** summarises the univariate descriptive statistics for the
349 48 items in the EFA sample (n=428). Likewise, our data violated the univariate (Shapiro
350 & Wilk, 1965) and multivariate normality assumptions (Mardia, 1970). The multivariate
351 skew was 583.80 (p <0.001) and the multivariate kurtosis yielded a value of 2,749.15 (p
352 <0.001). The corrected item-total correlation ranged between .03 and .48. However, no
353 item was discarded based on descriptive statistics or item analysis.

354 **Exploratory Factor Analysis and Reliability Analysis.** We checked the
355 sampling adequacy by applying Kaiser-Meyer-Olkin (KMO) measures of sampling
356 adequacy on the EFA sample (n=428) (Kaiser, 1974). The overall KMO value for 48
357 items was 0.63, which exceeded the cut-off value (.50), indicating an adequate sample
358 size (Hutcheson, 1999). Additionally, Bartlett's test of sphericity (Bartlett, 1954), χ^2
359 (1128)=5042.86, p < .001 implied that the correlations between items were adequate for
360 conducting the EFA. However, only 4.96% of the inter-item correlation coefficients were
361 greater than |.30|., and the inter-item correlation coefficients ranged between -.44 to .91.
362 Figure 4-A depicts the respective correlation matrix.

363 Inspection via the Scree plot (Figure 4-B) suggested a six-factor solution, whereas
364 the minimum average partial (MAP) method (Velicer, 1976) (**Supplementary Table 3**)
365 and Hull method (Lorenzo-Seva et al., 2011) (Figure 4-C) implied a five-factor solution
366 for the LEBA inventory. As a result, we tested both five-factor and six-factor solutions.

367 Applying varimax rotation, we conducted three rounds of EFA with the initial 48
368 items and gradually discarded problematic items (cross-loading items and items with
369 factor loading <.30). Finally, a five-factor EFA solution with 25 items was accepted with
370 all factor-loading higher than .30 and no cross-loading greater than .30. Table 2 displays
371 the factor-loading (structural coefficients) and communality of the items. The absolute
372 values of the factor-loadings ranged from .32 to .99, indicating strong coefficients. The
373 commonalities ranged between .11 and .99. However, the histogram of the absolute
374 values of nonredundant residual correlations (Figure 4-D) displayed that 26% of
375 correlations were greater than the absolute value of .05, indicating a possible
376 under-factoring. (Desjardins & Bulut, 2018). Subsequently, we fitted a six-factor solution,
377 where a factor with only two salient variables emerged, thus disqualifying the six-factor
378 solution (**Supplementary Table 4**).

379 In the five-factor solution, the first factor contained three items and explained
380 10.25% of the total variance with an internal reliability coefficient ordinal $\alpha = .94$. All the
381 items in this factor encapsulated the individual's preference for using blue light filters in
382 different light environments. The second factor contained six items and explained 9.93%
383 of the total variance with an internal reliability coefficient ordinal $\alpha = .76$. Items under this
384 factor incorporated the individuals' hours spent outdoors. The third factor contained five
385 items and explained 8.83% of the total variance. Items under this factor covered the
386 specific behaviours of using a phone and smartwatch in bed. The internal consistency
387 reliability coefficient was ordinal $\alpha = .75$. The fourth factor comprised five items and
388 explained 8.44% of the total variance with an internal consistency coefficient, ordinal $\alpha =$
389 .72. These five items investigated the behaviours related to the individual's light
390 exposure before bedtime. The fifth factor encompassed six items and explained 6.14%
391 of the total variance. This factor captured the individual's morning and daytime light
392 exposure-related behaviour. The internal consistency reliability yielded ordinal $\alpha = .62$.

393 Lastly, we examined the factor's interpretability in the five-factor solution and

394 weighed it against the psychometric properties as we considered it essential to attain a
395 balance between the two. As we deemed the five derived factors interpretable and
396 relevant concerning our aim to capture light exposure-related behaviour, we retained all
397 of them with 25 items for our confirmatory factor analysis (CFA), despite the apparent
398 lower reliability of the fifth factor. Two of the items showed negative factor-loading (item
399 08: I spend 30 minutes or less per day (in total) outside. and item 37: I use a blue-filter
400 app on my computer screen within 1 hour before attempting to fall asleep.). Upon
401 re-inspection, we recognized these items to be negatively correlated to the respective
402 factor, and thus, we reverse-scored these two items in the CFA analysis. The internal
403 consistency coefficient McDonald's ω_t for the total inventory was 0.77.

404 **Confirmatory Factor Analysis.** Table 3 compares the CFA fit indices of the
405 original CFA five-factor model with 25 and the post-hoc modified model with 23 items,
406 respectively. The 25-item model attained an acceptable fit ($CFI = .92$; $TLI = .91$; $RMSEA$
407 $= .07$ [.06-.07, 90% CI]) with two imposed equity constraints on item pairs 32-33 [item 32:
408 I dim my mobile phone screen within 1 hour before attempting to fall asleep; item 33: I
409 dim my computer screen within 1 hour before attempting to fall asleep] and 16-17 [item
410 16: I wear blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day;
411 item 17: I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the
412 day]. Item pair 32-33 describes the preference for dimming the electric devices'
413 brightness before bedtime, whereas item pair 16-17 represents the use of blue filtering
414 or coloured glasses during the daytime. Given the similar nature of captured behaviours
415 within each item pair, we accepted the imposed equity constraints. Nevertheless, the
416 SRMR value exceeded the guideline recommendation ($SRMR = .12$).

417 In order to improve the model fit, we conducted a post-hoc model modification.
418 Firstly, the modification indices suggested cross-loadings between item 37 and 26 [item
419 37: I purposely leave a light on in my sleep environment while sleeping; item 26: I turn
420 on my ceiling room light when it is light outside], which were hence discarded. Secondly,

421 items 30 and 41 [item 30: I look at my smartwatch within 1 hour before attempting to fall
422 asleep; item 41: I look at my smartwatch when I wake up at night] showed a tendency to
423 co-vary in their error variance ($MI = 141.127$, $p < .001$). By allowing the latter pair of items
424 (30 & 41) to co-vary, the model's error variance attained an improved fit ($CFI = .95$; $TLI =$
425 $.95$); $RMSEA = .06$ [.05-.06, 90% CI]; $SRMR = .11$).

426 Accordingly, we accept the five-factor model with 23 items, finalizing the long Form
427 of LEBA (see **Supplementary File 1**). Internal consistency ordinal α for the five factors
428 of the LEBA were .96, .83, .70, .69, .52, respectively. The Internal consistency
429 McDonald's ω_t coefficient for the total inventory yielded .68. Figure 5 depicts the
430 obtained CFA structure, while **Supplementary Figure 2** depicts the data distribution and
431 endorsement pattern of the retained 23 items in our CFA sample.

432 **Measurement Invariance.** Our CFA sample consisted of 129 native English
433 speakers and 133 non-native English speakers, whose demographic data are contrasted
434 in **Supplementary Table 5**. As shown in Table 4, the employed five-factor model
435 generated acceptable fit indices over all of the fitted MI models. The model fit did not
436 significantly decrease across the nested models, implying the acceptability of the highest
437 measurement invariance model (residual model). This indicated the construct
438 demonstrated psychometric equivalence and the same meaning across native and
439 non-native English speaking participants

440 **Secondary Analysis: Grade Level Identification and Semantic Scale Network**

441 **Analysis**

442 A grade level identification and Semantic Scale analysis were additionally
443 administered to assess the LEBA's (23 items) language-based accessibility and its'
444 semantic relation to other questionnaires. The results of the Flesch-Kincaid grade level
445 analysis (Flesch, 1948) displayed a required educational grade level of four (US
446 education system) with age above 8.33 years. Furthermore, the Semantic Scale

447 Network (SSN) analysis (Rosenbusch et al., 2020) indicated that the LEBA appeared
448 most strongly semantically related to scales about sleep: The “Sleep Disturbance Scale
449 For Children” (Bruni et al., 1996) and the “Composite International Diagnostic Interview
450 (CIDI): Insomnia”(Robins et al., 1988). The cosine similarity yielded values between .47
451 to .51.

452 **Developing a Short Form of LEBA: IRT-Based Analysis**

453 In order to derive a short form of the LEBA inventory, we fitted each factor of the
454 LEBA with the graded response model (Samejima et al., 1997) to the combined EFA and
455 CFA sample (n=690). The resulting item discrimination parameters of the inventory fell
456 into categories of “very high” (10 items), “high” (4 items), “moderate” (4 items), and “low”
457 (5 items), indicating a good range of discrimination along the latent trait level (θ)
458 (**Supplementary Table 6**). An examination of the item information curve
459 (**Supplementary Figure 3**) revealed five items (1, 25, 30, 38, & 41) with relatively flat
460 curves ($I(\theta) < .20$). We discarded those items, culminating in a short form of LEBA with
461 five factors and 18 items (**Supplementary File 2**).

462 Subsequently, we treated each factor of the short-LEBA as a unidimensional
463 construct and obtained five test information curves (TICs). As Figure 6 illustrates, the
464 TICs of the first and fifth factors peaked on the right side of the centre of their latent
465 traits, while the TICs of the other three factors were roughly centred on the respective
466 trait continuum (θ). This points out that the LEBA short-form estimates the light
467 exposure-related behaviour most precisely near the centre of the trait continuum for the
468 second, third and fourth factors and, in contrast, to the right of the centre for the first and
469 fifth factors (Baker & Kim, 2017).

470 Finally, **Supplementary Table 7** summarises the item fit indexes of the LEBA short
471 form. All 18 items yielded RMSEA value $\leq .06$, indicating an adequate fit to the fitted IRT

472 model. Furthermore, **Supplementary Figure 4** depicts the person fit Zh statistics
473 histogram for the five IRT models. Zh statistics are larger than -2 for most participants,
474 suggesting a good person fit regarding the selected IRT models.

475 **Discussion**

476 Today, in most industrialized countries, the vast majority of time is spent in built
477 environments (Klepeis et al., 2001), where photic exposure patterns are determined not
478 only by the solar cycle but by electrical light sources as well. As a consequence, light
479 received may vary considerably, in terms of timing, intensity and spectrum, all of which
480 are subject to the further influence of individual behaviours. (reviewed in Bedrosian &
481 Nelson, 2017; Blume et al., 2019; Lok et al., 2018; Paul & Brown, 2019; Santhi & Ball,
482 2020; Siraji et al., 2021; Vetter et al., 2022; Zele & Gamlin, 2020). Thus, there is a clear
483 need for guidance (T. M. Brown et al., 2022) and assessment regarding healthy light
484 exposure and consequentially healthy light-related behaviour.

485 In reviewing the literature, we found that a handful of previously introduced
486 instruments assess aspects of light exposure by self-report (see **Supplementary Table**
487 1). Few studies to date have attempted to assess light exposure by self-report. That
488 body of research becomes even smaller when limiting it to those focusing on that
489 influence photic exposure patterns, and typically these home in only on particular
490 behaviours of interest, such as estimates of time spent outside (Roenneberg et al., 2003)
491 or preferences for specific lighting situations (Bossini et al., 2006). To our knowledge,
492 there is no questionnaire in existence that captures behaviours that modify light
493 exposure across different scenarios in a comprehensive way. We have developed two
494 versions of a self-report inventory-LEBA, that can capture light exposure-related
495 behaviours in multiple dimensions.

496 The 48 generated items were applied in a large-scale, geographically

497 unconstrained, cross-sectional study, yielding 690 completed surveys. To assure high
498 data quality, participant responses were only included when the five “attention check
499 items” throughout the survey were passed. Ultimately, data was recorded from 74
500 countries and 28 time zones, including native and non-native English speakers from a
501 sex-balanced and age-diverse sample (see Table 1). The acquired study population
502 complied with our objective to avoid bias from a selective sample, which is crucial when
503 relying on voluntary uncompensated participation.

504 Data collected in the first round was used to explore the latent structure (EFA
505 sample; n=428). The exploratory factor analysis revealed a highly interpretable
506 five-factor solution (“Wearing blue light filters”, “Spending time outdoors”, “Using phone
507 and smartwatch in bed”, “Using light before bedtime”, and “Using light in the morning and
508 during daytime”) with 25 items. Our CFA analysis (CFA sample; n=262) confirmed the
509 five-factor structure we obtained in our EFA, thus providing evidence for structural
510 validity.(CFI=.95; TLI=.95; RMSEA=.06). In this model, we discarded two more items
511 (item 26 & 37) for possible cross-loadings. As a rule of thumb, reliability coefficients
512 higher than .70 are regarded as “satisfactory”. However, at the early developmental
513 stage, a value of .50 is considered acceptable (Dall’Oglio et al., 2010; Field, 2015;
514 Nunnally, 1978). Thus, we confer, the internal consistency coefficients ordinal alpha for
515 the five factors and the total inventory were satisfactory (Ordinal alpha ranged between
516 0.52 to 0.96; McDonald’s $\omega_t = .68$).

517 The results of the measurement invariance analysis indicate that the construct
518 “Light exposure-related behaviour” is equivalent across native and non-native English
519 speakers and thus suitable for assessment in both groups. Furthermore, according to
520 the grade level identification method, the LEBA appears understandable for students at
521 least 8.33 years of age visiting grade four or higher. Interestingly, the semantic similarity
522 analysis (“Semantic Scale Network” database Rosenbusch et al. (2020)) revealed that
523 the “LEBA” is semantically related to the “Sleep Disturbance Scale For Children” (SDSC)

524 (Bruni et al., 1996) and the “Composite International Diagnostic Interview (CIDI):
525 Insomnia”(Robins et al., 1988). Upon inspecting the questionnaire contents, we found
526 that some items in the factors “Using phone and smartwatch in bed” and “Using light
527 before bedtime” have semantic overlap with the SDSC’s and CIDI’s items. However,
528 while the CIDI and the SDSC capture various clinically relevant sleep problems and
529 related activities, the LEBA aims to assess light-exposure-related behaviour. Since light
530 exposure at night has been shown to influence sleep negatively (T. M. Brown et al.,
531 2022; Santhi & Ball, 2020), this overlap confirms our aim to measure the physiologically
532 relevant aspects of light-exposure-related behaviour. Nevertheless, the general
533 objectives of the complete questionnaires and the LEBA differ evidently.

534 Often psychological measurements require application of several questionnaires
535 simultaneously. Responding to several lengthy questionnaires increases the participants
536 losing focus and becoming tried. To avoid these situations we derived a short version of
537 the LEBA (18 items) using IRT analysis. We fitted a graded response model to the
538 combined EFA and CFA sample ($n=690$) and discarded five items (1, 25, 30, 38, & 41)
539 with relatively flat item information curve [$I(\theta) < .20$]. The resulting test information curves
540 suggest that the short-LEBA is a psychometrically sound measure with adequate
541 coverage of underlying traits and can be applied to capture the frequency of different
542 light exposure related behaviours reliably.

543 Findings from the Item and person fit index analysis demonstrate that all five fitted
544 models were acceptable and provide evidence of validity for the factors. In addition, the
545 diverse item discrimination parameters indicate an appropriate range of discrimination –
546 the ability to differentiate respondents with different levels of light exposure-related
547 behaviour.

548 Known Limitations

549 We acknowledge that this work is limited concerning the following aspects:

- 550 • The fifth factor: “using light in the morning and during daytime” exhibited low
551 internal consistency both in the exploratory and confirmatory factor analysis (EFA:
552 .62; CFA:.52). Since, it was above .50, considering the developmental phase of
553 this inventory we accepted the fifth factor. This particular factor captures our
554 behaviour related to usages of light in the morning and daytime. Since, light
555 exposure during morning and daytime influences our alertness and cognition (Lok
556 et al., 2018; Siraji et al., 2021), we deemed capturing these behaviours is essential
557 for the sake of completeness of our inventory. However, the possibility of improving
558 the reliability should be investigated further by adding more appropriate and
559 relevant items to this factor.
- 560 • During the post-hoc model modification, as part of the confirmatory factor analysis,
561 we discarded two items (item 26 & 37) for possible cross-loadings, as
562 demonstrated in the data. However, two additional items covaried in their error
563 variance. By allowing the latter pair (30 & 41) to covary, the model attained an
564 improved fit (**Figure 5**). A possible explanation for the covariation is that many
565 respondents might not have used a smartwatch at all, resulting in similar response
566 patterns between these two items. Thus, though rather unconventional, we
567 decided to accept this post-hoc modification to our five-factor model.
- 568 • The habitual patterns queried in the developed inventory might not exhaustively
569 represent all relevant light-exposure-related behaviours. For instance, it is
570 conceivable that additional light-related activities not included in the LEBA depend
571 on the respondents’ profession/occupation, geographical context, and
572 socio-economic status. However, we generated the initial item pool with an

573 international team of researchers and followed a thorough psychometric analysis.

574 Therefore, we are confident that the developed LEBA inventory can serve as a
575 good starting point for exploring the light exposure related behaviours in more
576 depth and inform room for modification of light exposure-related behaviour to
577 improve light hygiene.

- 578 • As with all studies relying on retrospective self-report data, individuals filling in the
579 LEBA may have difficulties precisely recalling the inquired light-related behaviours.
580 In the interest of bypassing a substantial memory component, we limited the recall
581 period to four weeks and chose response options that do not require exact memory
582 recall. In contrast to directly assessing light properties via self-report, we assume
583 that reporting behaviours might be more manageable for inexperienced laypeople,
584 as the latter does not rely on existing knowledge about light sources. The
585 comprehensibility of the LEBA is also reflected by the Flesch-Kincaid grade level
586 identification method (Flesch, 1948) that suggested a minimum age of 8.33 years
587 and an educational grade of four or higher (US grading system). We argue that
588 measuring light-related behaviours via self-report is crucial because these
589 behaviours will hardly be as observable by anyone else or measurable with other
590 methods (like behavioural observations) with reasonable effort.

591 Future Directions

592 To our knowledge, the LEBA is the first inventory characterising light

593 exposure-related behaviour in a scalable manner. Thus, estimating convergent validity
594 with similar subjective scales was impossible. Alternatively, the validity of the LEBA
595 could be evaluated by administering it conjointly with objective field measurements of
596 light exposure (e.g. with portable light loggers, see literature review). By this route, one
597 could study how the (subjectively measured) light exposure-related behavioural patterns
598 translate into (objectively measured) received light exposure. Additionally, developing

599 daily recall scales of light-related behaviour could provide a more detailed behavioural
600 assessment to supplement the LEBA's broader (four-week) measurement approach.
601 Comparing the LEBA scores to 24-hour recall scores could provide helpful information
602 about how light exposure-related behaviour assessment is related between different time
603 perspectives. Moreover, light-exposure-related behaviour might depend on the
604 respondents' profession, geographical location, housing conditions, socio-economic
605 status, or other contextual factors. As the current data is limited to our international
606 online survey context, future research should apply the LEBA across more variable
607 populations and contexts. On the other hand, this will require the development of
608 cross-cultural adaptations and translations into other languages of the LEBA, which
609 should be targeted in prospective studies.

610 Finally, in the future, the use of the LEBA instrument need not remain restricted to
611 gathering information in cross-sectional quantitative studies. The instrument can also be
612 used for individual behavioural profiling. For instance, the LEBA could be applied in a
613 clinical context as part of Cognitive Behavioural Therapy for Insomnia (CBT-I). More
614 specifically, it could be used to supplement the sleep hygiene aspects of CBT-I, as
615 receiving light exposure at different times has implications for sleep (Santhi & Ball,
616 2020). This match was also evident in the semantic relationship between the LEBA and
617 two scales capturing sleep problems (CIDI: Insomnia; Robins et al. (1988) & SDSC;
618 Bruni et al. (1996)) found in the semantic similarity analysis. However, before applying
619 the LEBA in such contexts in the future, more work is certainly needed to understand
620 light exposure-related behaviour and its' relationship to relevant health outcomes
621 measured subjectively and objectively.

622 Conclusion

623 With the "Light exposure behaviour assessment"(LEBA), we developed a novel,
624 internally consistent and structurally valid 23-item self-report inventory for capturing light

625 exposure-related behaviour in five scalable factors. In addition, an 18-item short-form of
626 the LEBA was derived using IRT analysis, yielding adequate coverage across the
627 underlying trait continuum. Applying the LEBA inventory can provide insights into light
628 exposure-related habits on a population-based level. Furthermore, it can serve as a
629 good starting point to profile individuals based on their light exposure-related behaviour
630 and to assesses their light consumption and timing.

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Table 1

Demographic Characteristics of Participants (n=690).

Variable	Overall, N = 690	1. EFA Sample, N = 428	2. CFA Sample, N = 262
Age	32.95 (14.57)	32.99 (15.11)	32.89 (13.66)
Sex			
Female	325 (47%)	189 (44%)	136 (52%)
Male	351 (51%)	230 (54%)	121 (46%)
Other	14 (2.0%)	9 (2.1%)	5 (1.9%)
Gender-Variant Identity	49 (7.2%)	33 (7.8%)	16 (6.2%)
Native English Speaker	320 (46%)	191 (45%)	129 (49%)
Occupational Status			
Work	396 (57%)	235 (55%)	161 (61%)
School	174 (25%)	122 (29%)	52 (20%)
Neither	120 (17%)	71 (17%)	49 (19%)
Occupational setting			
Home office/Home schooling	303 (44%)	194 (45%)	109 (42%)
Face-to-face work/Face-to-face schooling	109 (16%)	68 (16%)	41 (16%)
Combination of home- and face-to-face- work/schooling	147 (21%)	94 (22%)	53 (20%)
Neither (no work or school, or in vacation)	131 (19%)	72 (17%)	59 (23%)

¹ Mean (SD); n (%)

Table 2

Factor loadings and communality of the retained items in EFA using principal axis extraction method (n=482).

item	Stem	PA1	PA2	PA3	PA4	PA5	Communality
item16	I wear blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day.	0.99					0.99
item36	I wear blue-filtering, orange-tinted, and/or red-tinted glasses within 1 hour before attempting to fall asleep.	0.94					0.90
item17	I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the day.	0.8					0.66
item11	I spend more than 3 hours per day (in total) outside.		0.79				0.64
item10	I spend between 1 and 3 hours per day (in total) outside.		0.76				0.59
item12	I spend as much time outside as possible.		0.65				0.47
item07	I go for a walk or exercise outside within 2 hours after waking up.		0.5				0.27
item08	I spend 30 minutes or less per day (in total) outside.		-0.49				0.25
item09	I spend between 30 minutes and 1 hour per day (in total) outside.		0.32				0.11
item27	I use my mobile phone within 1 hour before attempting to fall asleep.		0.8				0.66
item03	I look at my mobile phone screen immediately after waking up.		0.8				0.68
item40	I check my phone when I wake up at night.		0.65				0.46
item30	I look at my smartwatch within 1 hour before attempting to fall asleep.		0.45				0.35
item41	I look at my smartwatch when I wake up at night.		0.36				0.33

Table 2 continued

item	Stem	PA1	PA2	PA3	PA4	PA5	Communality
item33	I dim my computer screen within 1 hour before attempting to fall asleep.				0.74		0.56
item32	I dim my mobile phone screen within 1 hour before attempting to fall asleep.				0.73		0.62
item35	I use a blue-filter app on my computer screen within 1 hour before attempting to fall asleep.				0.66		0.45
item37	I purposely leave a light on in my sleep environment while sleeping.				-0.39		0.17
item38	I use as little light as possible when I get up during the night.				0.38		0.18
item46	I use tunable lights to create a healthy light environment.				0.6		0.42
item45	I use LEDs to create a healthy light environment.				0.59		0.37
item25	I use a desk lamp when I do focused work.				0.41		0.19
item04	I use an alarm with a dawn simulation light.				0.41		0.22
item01	I turn on the lights immediately after waking up.				0.4		0.17
item26	I turn on my ceiling room light when it is light outside.				0.35		0.16

Note. Only loading > .30 is reported.

Table 3

*Confirmatory Factor Analysis model fit indices of the two model: (a) Model 1: five factor model with 25 items
 (b) Model 2: five factor model with 23 items. Model 2 attained the best fit.*

Model	χ^2	df	CFI	TLI	RMSEA	RMSEA 90% Lower CI	RMSEA 90% Upper CI	SRMR
1	675.55	267.00	0.95	0.94	0.08	0.07	0.08	0.12
2	561.25	231.00	0.96	0.95	0.07	0.07	0.08	0.11

Note. df: Degrees of Freedom; CFI: Comparative Fit Index; TLI: Tucker Lewis Index; RMSEA: Root Mean Square Error of Approximation; CI: Confidence Interval; SRMR: Standardized Root Mean Square.

Table 4

Measurement Invariance analysis on CFA sample (n=262) across native and non-native English speakers.

	χ^2	df	CFI	TLI	RMSEA	RMSEA 90% Lower CI	RMSEA 90% Upper	$\Delta \chi^2$	Δdf^*	p
Configural	632.20	442.00	0.95	0.94	0.06	0.05	0.07	-	-	-
Metric	644.58	458.00	0.95	0.95	0.06	0.05	0.07	18.019a	16	0.323
Scalar	714.19	522.00	0.95	0.95	0.05	0.04	0.06	67.961b	64	0.344
Residual	714.19	522.00	0.95	0.95	0.05	0.04	0.06	0c	0	NA

Note. df: Degrees of Freedom; CFI: Comparative Fit Index; TLI: Tucker Lewis Index; RMSEA: Root Mean Square Error of Approximation; CI: Confidence Interval; SRMR: Standardized Root Mean Square; a = Metric vs Configural; b = Scalar vs Metric; c = Residual vs Scalar; * = df of model comparison.

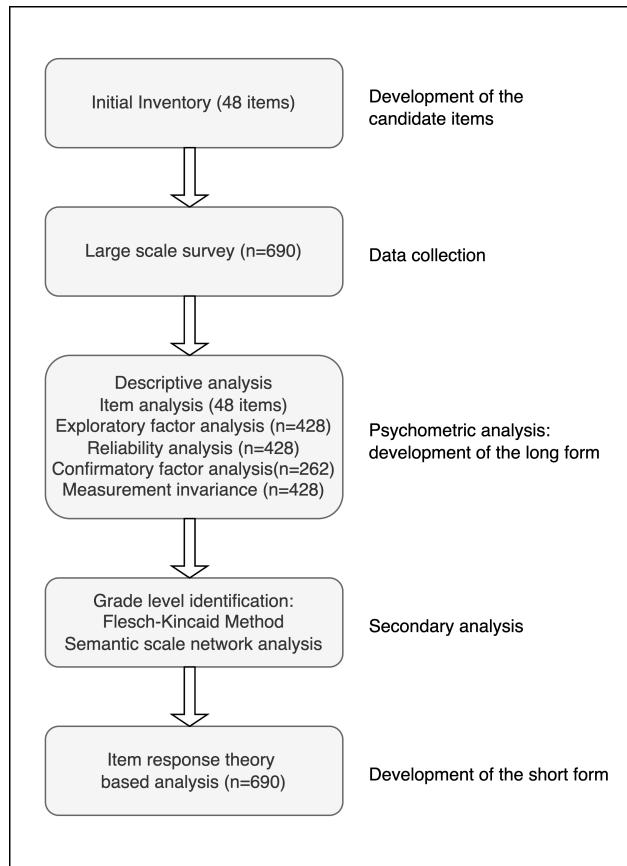


Figure 1. Flow chart of the LEBA (long and short form) development and evaluation.

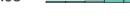
Summary Descriptives (n=690)											
Items	Item Stem	Summary Statistics			Graphics		Response Pattern				
		Mean	SD	SW ¹	Histogram	Density	Never	Rarely	Sometimes	Often	Always
●item01	I turn on the lights immediately after waking up.	2.3	1.4	0.82*			41.59% (287)	22.32% (154)	13.33% (92)	11.74% (81)	11.01% (76)
●item02	I open the curtains or blinds immediately after waking up.	2.8	1.6	0.84*			32.61% (225)	15.22% (105)	11.30% (78)	19.28% (133)	21.59% (149)
●item03	I look at my mobile phone screen immediately after waking up.	3.5	1.4	0.86*			14.35% (99)	9.86% (68)	17.39% (120)	30.00% (207)	28.41% (196)
●item04	I use an alarm with a dawn simulation light.	1.4	1.1	0.40*			86.09% (594)	3.04% (21)	2.61% (18)	2.46% (17)	5.80% (40)
●item05	I have breakfast within 3 meters from a window.	3.9	1.4	0.74*			14.35% (99)	4.78% (33)	11.01% (76)	18.26% (126)	51.59% (356)
●item06	I have breakfast in a brightly lit room (illuminated by electric light).	2.7	1.5	0.85*			33.19% (229)	15.36% (106)	16.38% (113)	16.09% (111)	18.99% (131)
●item07	I go for a walk or exercise outside within 2 hours after waking up.	2.2	1.2	0.84*			38.70% (267)	26.23% (181)	16.23% (112)	13.04% (90)	5.80% (40)
●item08	I spend 30 minutes or less per day (in total) outside.	3.0	1.2	0.91*			13.91% (96)	22.46% (155)	25.22% (174)	28.26% (195)	10.14% (70)
●item09	I spend between 30 minutes and 1 hour per day (in total) outside.	2.9	1.0	0.91*			11.30% (78)	20.58% (142)	38.99% (269)	23.91% (165)	5.22% (36)
●item10	I spend between 1 and 3 hours per day (in total) outside.	2.7	1.1	0.91*			14.06% (97)	30.58% (211)	30.43% (210)	21.74% (150)	3.19% (22)
●item11	I spend more than 3 hours per day (in total) outside.	2.2	0.9	0.86*			23.77% (164)	46.38% (320)	22.03% (152)	6.38% (44)	1.45% (10)
●item12	I spend as much time outside as possible.	2.3	1.2	0.87*			30.72% (212)	30.14% (208)	20.58% (142)	11.88% (82)	6.67% (46)
●item13	I use sunglasses when I go outside in bright daylight.	2.7	1.5	0.87*			30.14% (208)	17.54% (121)	17.83% (123)	18.70% (129)	15.80% (109)
●item14	I wear a visor or cap when I go outside in bright daylight.	2.1	1.3	0.79*			47.54% (328)	18.84% (130)	12.90% (89)	15.22% (105)	5.51% (38)
●item15	I seek shade when I am outside in bright daylight.	3.3	1.1	0.91*			7.97% (55)	13.91% (96)	35.36% (244)	27.97% (193)	14.78% (102)
●item16	I wear blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day.	1.6	1.3	0.51*			79.13% (546)	3.91% (27)	4.06% (28)	5.07% (35)	7.83% (54)
●item17	I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the day.	1.5	1.2	0.49*			80.43% (555)	3.33% (23)	5.22% (36)	3.04% (21)	7.97% (55)
●item18	I use light therapy applying a white light box.	1.1	0.5	0.27*			92.90% (641)	3.48% (24)	2.75% (19)	0.58% (4)	0.29% (2)
●item19	I use light therapy applying a blue light box.	1.0	0.3	0.12*			97.68% (674)	0.87% (6)	0.72% (5)	0.72% (5)	0.00% (0)
●item20	I use light therapy applying a light visor.	1.0	0.3	0.08*			98.70% (681)	0.14% (1)	0.58% (4)	0.43% (3)	0.14% (1)
●item21	I use light therapy applying another form of light device.	1.1	0.6	0.24*			94.06% (649)	1.45% (10)	3.04% (21)	0.58% (4)	0.87% (6)
●item22	I spend most of my daytime in a brightly lit environment.	3.5	1.1	0.88*			5.36% (37)	13.33% (92)	21.74% (150)	41.59% (287)	17.97% (124)
●item23	I close the curtains or blinds during the day if the light from outside is bright.	2.6	1.3	0.89*			26.38% (182)	24.93% (172)	23.33% (161)	17.25% (119)	8.12% (56)
●item24	I spend most of my indoor time within 3 meters from a window.	4.1	1.0	0.79*			2.90% (20)	5.65% (39)	11.45% (79)	37.83% (261)	42.17% (291)

¹ Shapiro-Wilk test

Figure 2. Summary descriptives and response pattern observed in the large-scale survey for item 01-24. All items violated normality assumption.

Summary Descriptives (n=690)

Items 25-48

LEBA Items	Item Stem	Summary Statistics			Graphics		Response Pattern				
		Mean	SD	SW ¹	Histogram	Density	Never	Rarely	Sometimes	Often	Always
●item25	I use a desk lamp when I do focused work.	2.6	1.4	0.86*			33.77% (233)	15.51% (107)	22.03% (152)	17.54% (121)	11.16% (77)
●item26	I turn on my ceiling room light when it is light outside.	3.7	1.3	0.85*			37.54% (259)	22.03% (152)	20.58% (142)	12.17% (84)	7.68% (53)
●item27	I use my mobile phone within 1 hour before attempting to fall asleep.	3.9	1.3	0.80*			7.54% (52)	9.71% (67)	10.00% (69)	31.59% (218)	41.16% (284)
●item28	I use my computer/laptop/tablet within 1 hour before attempting to fall asleep.	3.7	1.2	0.87*			5.07% (35)	13.19% (91)	17.39% (120)	35.36% (244)	28.99% (200)
●item29	I watch television within 1 hour before attempting to fall asleep.	2.5	1.3	0.87*			33.04% (228)	18.12% (125)	20.29% (140)	20.72% (143)	7.83% (54)
●item30	I look at my smartwatch within 1 hour before attempting to fall asleep.	1.5	1.1	0.47*			82.46% (569)	3.04% (21)	4.64% (32)	5.65% (39)	4.20% (29)
●item31	I dim my room light within 1 hour before attempting to fall asleep.	3.0	1.6	0.83*			31.30% (216)	10.43% (72)	12.03% (83)	20.14% (139)	26.09% (180)
●item32	I dim my mobile phone screen within 1 hour before attempting to fall asleep.	3.5	1.6	0.76*			24.20% (167)	5.94% (41)	9.42% (65)	15.65% (108)	44.78% (309)
●item33	I dim my computer screen within 1 hour before attempting to fall asleep.	3.4	1.7	0.77*			25.94% (179)	6.67% (46)	8.99% (62)	14.35% (99)	44.06% (304)
●item34	I use a blue-filter app on my mobile phone screen within 1 hour before attempting to fall asleep.	3.4	1.8	0.70*			34.06% (235)	2.90% (20)	4.20% (29)	7.83% (54)	51.01% (352)
●item35	I use a blue-filter app on my computer screen within 1 hour before attempting to fall asleep.	3.8	1.7	0.67*			24.64% (170)	2.17% (15)	5.07% (35)	8.26% (57)	59.86% (413)
●item36	I wear blue-filtering, orange-tinted, and/or red-tinted glasses within 1 hour before attempting to fall asleep.	1.6	1.3	0.47*			81.59% (563)	3.19% (22)	3.04% (21)	2.75% (19)	9.42% (65)
●item37	I purposely leave a light on in my sleep environment while sleeping.	2.3	1.3	0.44*			37.54% (259)	22.03% (152)	20.58% (142)	12.17% (84)	7.68% (53)
●item38	I use as little light as possible when I get up during the night.	4.3	1.1	0.68*			4.93% (34)	5.07% (35)	5.80% (40)	25.22% (174)	58.99% (407)
●item39	I turn on the lights when I get up during the night.	2.0	1.1	0.82*			37.97% (262)	37.10% (256)	14.78% (102)	6.52% (45)	3.62% (25)
●item40	I check my phone when I wake up at night.	2.3	1.3	0.85*			36.23% (250)	25.80% (178)	19.28% (133)	11.74% (81)	6.96% (48)
●item41	I look at my smartwatch when I wake up at night.	1.3	0.8	0.39*			86.96% (600)	4.35% (30)	4.64% (32)	2.90% (20)	1.16% (8)
●item42	I close curtains or blinds to prevent light from entering the bedroom if I want to sleep.	4.0	1.4	0.70*			13.62% (94)	5.07% (35)	8.41% (58)	15.51% (107)	57.39% (396)
●item43	I use a sleep mask that covers my eyes.	1.7	1.2	0.62*			69.86% (482)	9.28% (64)	10.00% (69)	4.20% (29)	6.67% (46)
●item44	I modify my light environment to match my current needs.	3.4	1.3	0.86*			14.49% (100)	7.68% (53)	20.29% (140)	34.93% (241)	22.61% (156)
●item45	I use LEDs to create a healthy light environment.	2.1	1.5	0.74*			57.25% (395)	6.38% (44)	13.77% (95)	11.88% (82)	10.72% (74)
●item46	I use tunable lights to create a healthy light environment.	1.7	1.2	0.63*			70.29% (485)	5.80% (40)	10.29% (71)	9.13% (63)	4.49% (31)
●item47	I discuss the effects of light on my body with other people.	2.1	1.2	0.84*			40.43% (279)	24.06% (166)	21.30% (147)	9.57% (66)	4.64% (32)
●item48	I seek out knowledge on how to improve my light exposure.	2.5	1.3	0.89*			26.81% (185)	23.33% (161)	28.12% (194)	12.46% (86)	9.28% (64)

¹ Shapiro-Wilk test

Figure 3. Summary descriptives and response pattern observed in the large-scale survey for item 25-48. All items violated normality assumption.

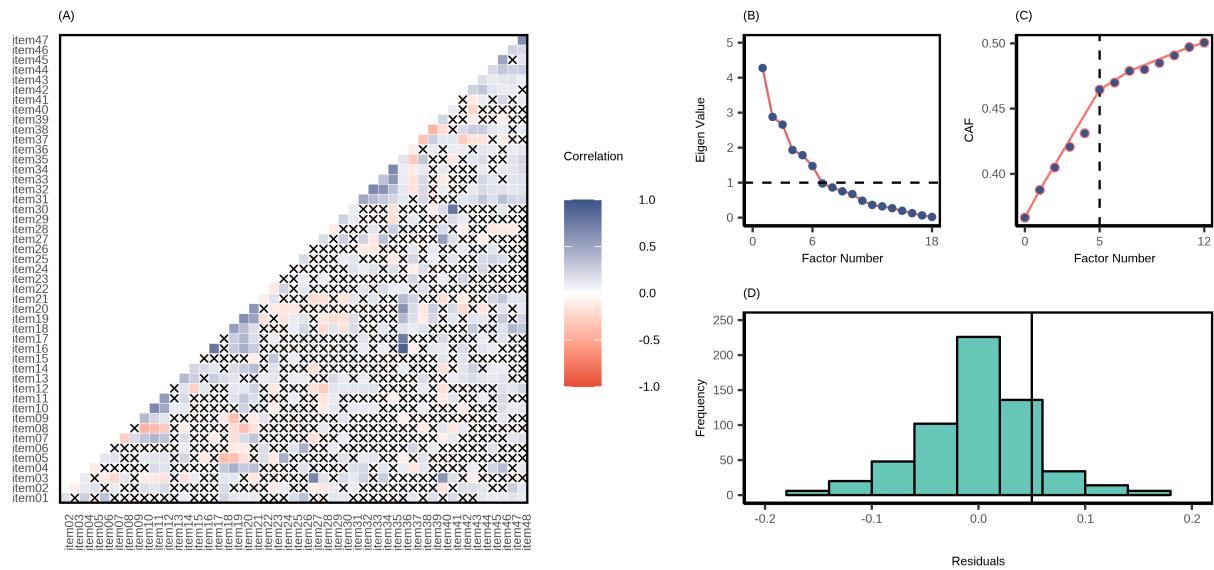


Figure 4. (A) Inter-item polychoric correlation coefficients for the 48 items. 4.9 % inter-item correlation coefficients were higher than $|.30|$. ‘x’ denotes a non-significant item-total correlation. (B) The Scree plot suggested six factors. (C) Hull method indicated that five factors were required to balance the model fit and number of parameters. (D) The histogram of nonredundant residual correlations indicated that 26% of inter-item correlations were higher than .05, hinting at a possible under-factoring.



Figure 5. Five factor model of LEBA obtained by confirmatory factor analysis. By allowing item pair 41 and 30 to co-vary their error variance our model attained the best fit.

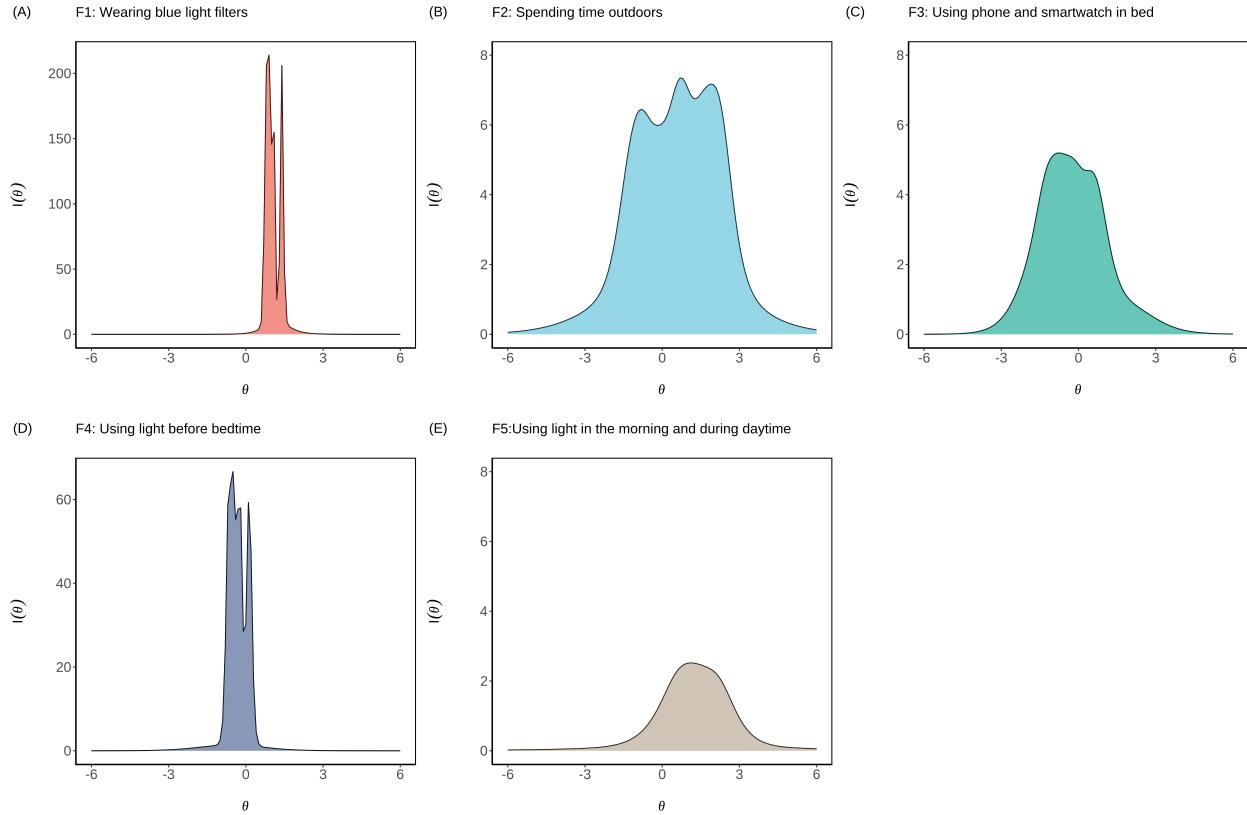


Figure 6. Test information curves for the five factors of LEBA: (A) wearing blue light filters (B) spending time outdoors (C) using a phone and smartwatch in bed (D) using light before bedtime (E) using light in the morning and during daytime. Along the x-axis, we plotted the underlying latent trait continuum for each factor. Along the y-axis, we plotted how much information a particular factor is carrying across its latent trait continuum

Supplementary File 1
Light Exposure Behaviour Assessment (LEBA): Long Form

Instructions to Participant

Please indicate how often you performed the following behaviours in the **past four weeks**

	Items	Never	Rarely	Sometimes	Often	Always
01	I wear blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day.					
02	I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the day.					
03	I wear blue-filtering, orange-tinted, and/or red-tinted glasses within 1 hour before attempting to fall asleep.					
04	I spend 30 minutes or less per day (in total) outside. <i>(Reverse-scored)</i>					
05	I spend between 30 minutes and 1 hour per day (in total) outside.					
06	I spend between 1 and 3 hours per day (in total) outside.					
07	I spend more than 3 hours per day (in total) outside.					
08	I spend as much time outside as possible.					
09	I go for a walk or exercise outside within 2 hours after waking up.					
10	I use my mobile phone within 1 hour before attempting to fall asleep.					
11	I look at my mobile phone screen immediately after waking up.					
12	I check my phone when I wake up at night.					
13	I look at my smartwatch within 1 hour before attempting to fall asleep					
14	I look at my smartwatch when I wake up at night.					
15	I dim my mobile phone screen within 1 hour before attempting to fall asleep.					
16	I use a blue-filter app on my computer screen within 1 hour before attempting to fall asleep.					
17	I use as little light as possible when I get up during the night.					
18	I dim my computer screen within 1 hour before attempting to fall asleep.					
19	I use tunable lights to create a healthy light environment.					
20	I use LEDs to create a healthy light environment.					
21	I use a desk lamp when I do focused work.					
22	I use an alarm with a dawn simulation light.					
23	I turn on the lights immediately after waking up.					

LEBA: Supplementary Materials

Scoring

(Note: R = reverse-scored item)

LEBA captures light exposure-related behaviours on a 5-point Likert-type scale ranging from 1 to 5 (1 = never; 2 = rarely; 3 = sometimes; 4 = often; 5 = always; for reversed-scored item: 1 = always; 2 = often; 3 = sometimes; 4 = rarely; 5 = never). The score of each factor is calculated by using the mean score of the corresponding items.

Factor Name	Score
F1: Wearing blue light filters	Mean score of items 01, 02, 03
F2: Spending time outdoors	Mean score of items 04(R), 05, 06, 07, 08, 09
F3: Using phone and smartwatch in bed	Mean score of items 10, 11, 12, 13, 14
F4: Using light before bedtime	Mean score of items 15, 16, 17, 18
F5: Using light in the morning and during daytime	Mean score of items 19, 20, 21, 22, 23

Supplementary File 2
Light Exposure Behaviour Assessment (LEBA): Short Form

Instructions to Participant

Please indicate how often you performed the following behaviours in the **past four weeks**.

	Items	Never	Rarely	Sometimes	Often	Always
01	I wear blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day.					
02	I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the day.					
03	I wear blue-filtering, orange-tinted, and/or red-tinted glasses within 1 hour before attempting to fall asleep.					
04	I spend 30 minutes or less per day (in total) outside. <i>(Reverse-scored)</i>					
05	I spend between 30 minutes and 1 hour per day (in total) outside.					
06	I spend between 1 and 3 hours per day (in total) outside.					
07	I spend more than 3 hours per day (in total) outside.					
08	I spend as much time outside as possible.					
09	I go for a walk or exercise outside within 2 hours after waking up.					
10	I use my mobile phone within 1 hour before attempting to fall asleep.					
11	I look at my mobile phone screen immediately after waking up.					
12	I check my phone when I wake up at night.					
15	I dim my mobile phone screen within 1 hour before attempting to fall asleep.					
16	I use a blue-filter app on my computer screen within 1 hour before attempting to fall asleep.					
18	I dim my computer screen within 1 hour before attempting to fall asleep.					
19	I use tunable lights to create a healthy light environment.					
20	I use LEDs to create a healthy light environment.					
22	I use an alarm with a dawn simulation light.					

LEBA: Supplementary Materials

Scoring

(Note: R = reverse-scored item)

LEBA captures light exposure-related behaviours on a 5-point Likert-type scale ranging from 1 to 5 (1 = never; 2 = rarely; 3 = sometimes; 4 = often; 5 = always; for reversed-scored item: 1 = always; 2 = often; 3 = sometimes; 4 = rarely; 5 = never). The score of each factor is calculated by using the mean score of the corresponding items.

Factor Name	Score
F1: Wearing blue light filters	Mean score of items 01, 02, 03
F2: Spending time outdoors	Mean score of items 04(R), 05, 06, 07, 08, 09
F3: Using phone and smartwatch in bed	Mean score of items 10, 11, 12
F4: Using light before bedtime	Mean score of items 15, 16, 18
F5: Using light in the morning and during daytime	Mean score of items 19, 20, 22

Supplementary Tables**Supplementary Table 1**

List of instruments measuring related constructs to LEBA.

Name	Number of all items	Description	Relevant items	Scale type
Visual Light Sensitivity Questionnaire-8 (Verriotto et al., 2017)	8	To assess the presence and severity of photosensitivity symptoms	None	5-point Likert scale
Office Light Survey (Eklund & Boyce, 1996)	30	To assess electrical lighting environment in office	Item 29	Mixed response format
Harvard Light Exposure Assessment Questionnaire (Bajaj et al., 2011)	1	To assess an individual's daily light exposure	None	Semi-quantitative
Hospital Lighting Survey (Dianat et al., 2013)	23	To assess light environment in a hospital	Items 16, 17	5-point Likert scale
Morningness-Eveningness Questionnaire (Horne & Ostberg, 1976)	19	To assess an individual's chronotype	items 1, 2, 8, 13, 14	Mixed response format
Munich Chronotype Questionnaire (Roenneberg et al., 2003)	17	To understand an individual's phase of entrainment	Time spent outdoors	Mixed response format
Sleep Practices and Attitudes Questionnaire (Grandner et al., 2014)	16	To assess practice, behaviour and attitude related to sleep	Activities in bed and sleep environment subscales	5-point Likert scale
The Pittsburgh Sleep Quality Index (Buysse et al., 1989)	9	To assess sleep quality and sleeping pattern	items 1-4	Mixed response format
Self-Rating of Biological Rhythm Disorder for Adolescents (Xie et al., 2022)	29	To assess four dimensions of biological rhythm disorder in adolescents	Items 3, 6, 22-25, 29	5-point Likert scale
Photosensitivity Assessment Questionnaire (PAQ) (Bossini et al., 2006)	16	To assess "photophobia" and "photophilia"	All items	Binary response option

Supplementary Table 2*Geographical location of the participants (n=690).*

	Time zone and country name	Number of Participants
1	Africa/Ceuta (UTC +01:00)	2
2	Africa/Douala (UTC +01:00)	1
3	Africa/Johannesburg (UTC +02:00)	5
4	Africa/Khartoum (UTC +02:00)	2
5	Africa/Lagos (UTC +01:00)	1
6	America/Adak (UTC -09:00)	2
7	America/Anchorage (UTC -08:00)	3
8	America/Araguaina (UTC -03:00)	2
9	America/Argentina/Buenos_Aires (UTC -03:00)	5
10	America/Argentina/Cordoba (UTC -03:00)	2
11	America/Argentina/Jujuy (UTC -03:00)	1
12	America/Bahia (UTC -03:00)	2
13	America/Blanc-Sablon (UTC -04:00)	1
14	America/Bogota (UTC -05:00)	2
15	America/Boise (UTC -06:00)	4
16	America/Cayman (UTC -05:00)	1
17	America/Chicago (UTC -05:00)	30
18	America/Costa_Rica (UTC -06:00)	2
19	America/Cuiaba (UTC -04:00)	1
20	America/Denver (UTC -06:00)	6
21	America/Detroit (UTC -04:00)	6
22	America/Edmonton (UTC -06:00)	14
23	America/Fortaleza (UTC -03:00)	1
24	America/Guatemala (UTC -06:00)	1
25	America/Guayaquil (UTC -05:00)	2
26	America/Halifax (UTC -03:00)	1
27	America/Indiana/Indianapolis (UTC -04:00)	3
28	America/Indiana/Tell_City (UTC -05:00)	1
29	America/Kentucky/Louisville (UTC -04:00)	3
30	America/Los_Angeles (UTC -07:00)	37
31	America/Martinique (UTC -04:00)	1
32	America/Mexico_City (UTC -06:00)	2
33	America/Moncton (UTC -03:00)	2
34	America/Monterrey (UTC -06:00)	1
35	America/New_York (UTC -04:00)	63
36	America/North_Dakota/Center (UTC -05:00)	1

LEBA: Supplementary Materials

37	America/North_Dakota/New_Salem (UTC -05:00)	1
38	America/Panama (UTC -05:00)	1
39	America/Phoenix (UTC -07:00)	7
40	America/Resolute (UTC -05:00)	1
41	America/Santiago (UTC -03:00)	8
42	America/Sao_Paulo (UTC -03:00)	19
43	America/Toronto (UTC -04:00)	16
44	America/Vancouver (UTC -07:00)	6
45	Antarctica/Macquarie (UTC +11:00)	1
46	Asia /Taipei City (UTC +08:00)	3
47	Asia/Amman (UTC +03:00)	2
48	Asia/Barnaul (UTC +07:00)	1
49	Asia/Dhaka (UTC +06:00)	1
50	Asia/Famagusta (UTC +02:00)	1
51	Asia/Ho_Chi_Minh (UTC +07:00),British - America/Tortola (UTC -04:00)	2
52	Asia/Hong_Kong (UTC +08:00)	2
53	Asia/Jakarta (UTC +07:00)	9
54	Asia/Jerusalem (UTC +02:00)	4
55	Asia/Karachi (UTC +05:00)	1
56	Asia/Kathmandu (UTC +05:45)	2
57	Asia/Kolkata (UTC +05:30)	38
58	Asia/Kuala_Lumpur (UTC +08:00)	7
59	Asia/Kuching (UTC +08:00)	2
60	Asia/Manila (UTC +08:00)	6
61	Asia/Novosibirsk (UTC +07:00)	1
62	Asia/Riyadh (UTC +03:00)	1
63	Asia/Seoul (UTC +09:00)	1
64	Asia/Shanghai (UTC +08:00)	7
65	Asia/Singapore (UTC +08:00)	1
66	Asia/Tokyo (UTC +09:00)	3
67	Asia/Tomsk (UTC +07:00)	1
68	Asia/Ulaanbaatar (UTC +08:00)	1
69	Asia/Vladivostok (UTC +10:00)	1
70	Asia/Yangon (UTC +06:30)	1
71	Asia/Yekaterinburg (UTC +05:00)	1
72	Atlantic/Canary (UTC)	1
73	Australia/Adelaide (UTC +10:30)	2
74	Australia/Brisbane (UTC +10:00)	4
75	Australia/Darwin (UTC +09:30)	1
76	Australia/Melbourne (UTC +11:00)	5
77	Australia/Perth (UTC +08:00)	2
78	Australia/Sydney (UTC +11:00)	2

LEBA: Supplementary Materials

79	East Africa/Dodoma (UTC +03:00)	1
80	Europe/Amsterdam (UTC +01:00)	19
81	Europe/Athens (UTC +02:00)	3
82	Europe/Belgrade (UTC +01:00)	3
83	Europe/Berlin (UTC +01:00)	53
84	Europe/Bratislava (UTC +01:00)	2
85	Europe/Brussels (UTC +01:00)	4
86	Europe/Bucharest (UTC +02:00)	3
87	Europe/Budapest (UTC +01:00)	2
88	Europe/Busingen (UTC +01:00)	3
89	Europe/Copenhagen (UTC +01:00)	3
90	Europe/Dublin (UTC)	5
91	Europe/Helsinki (UTC +02:00)	9
92	Europe/Istanbul (UTC +03:00)	6
93	Europe/Kiev (UTC +02:00)	1
94	Europe/Lisbon (UTC)	2
95	Europe/Ljubljana (UTC +01:00)	3
96	Europe/London (UTC)	57
97	Europe/Madrid (UTC +01:00)	7
98	Europe/Moscow (UTC +03:00)	8
99	Europe/Oslo (UTC +01:00)	3
100	Europe/Paris (UTC +01:00)	22
101	Europe/Prague (UTC +01:00)	3
102	Europe/Riga (UTC +02:00)	2
103	Europe/Rome (UTC +01:00)	9
104	Europe/Sofia (UTC +02:00)	1
105	Europe/Stockholm (UTC +01:00)	4
106	Europe/Tallinn (UTC +02:00)	2
107	Europe/Tirane (UTC +01:00)	1
108	Europe/Vienna (UTC +01:00)	1
109	Europe/Vilnius (UTC +02:00)	5
110	Europe/Warsaw (UTC +01:00)	15
111	Europe/Zagreb (UTC +01:00)	2
112	Europe/Zurich (UTC +01:00)	21
113	European /Skopje (UTC +01:00)	1
114	Iran /Tehran (UTC +0:30)	3
115	Pacific/Auckland (UTC +13:00)	6
116	Pacific/Chatham (UTC +13:45)	1
117	Pacific/Easter (UTC -05:00)	1
118	Pacific/Honolulu (UTC -10:00)	2

Supplementary Table 3.

Minimum average partial (MAP) method of factor number determination. MAP Statistics is the lowest in the 5th row indicating five factors are required.

MAP Statistic ¹	df	χ^2	RMSEA	BIC	SRMR
0.01125	1080	4344.31	0.08	-2199.54	0.09
0.01062	1033	3735.35	0.08	-2523.72	0.08
0.01077	987	3065.44	0.07	-2914.91	0.07
0.01042	942	2661.78	0.07	-3045.92	0.06
0.0093	898	2237.56	0.06	-3203.53	0.06
0.0094	855	2040.02	0.06	-3140.53	0.05
0.0097	813	1861.69	0.05	-3064.37	0.04
0.0100	772	1620.64	0.05	-3057.00	0.04

Note. ¹ Minimum average partial.

LEBA: Supplementary Materials

Supplementary Table 4

Factor loadings and communality of the retained in EFA with six factors. One factor emerged with only two items (n=428).

Items	PA1	PA2	PA3	PA4	PA5	PA6	Communality
Item 16	.99						.01
Item 36	.94						.10
Item 17	.80						.33
Item 11		.82					.30
Item 10		.81					.34
Item 12		.64					.53
Item 08		-.48					.75
Item 07		.47					.74
Item 09		.33					.88
Item 33			.97				.02
Item 32			.77				.31
Item 35			.54				.59
Item 31			.49				.67
Item 03				.84			.27
Item 27				.81			.33
Item 40				.69			.47
Item 46					.65		.48
Item 45					.57		.65
Item 04					.48		.67
Item 25					.40		.76
Item 01					.35		.87
Item 26					.35		.84
Item 37						-.8	.32
Item 38						.39	.76
% Of Variance	11	10	9	9	6	5	-

Note. Only loading higher than .30 is reported.

LEBA: Supplementary Materials

Supplementary Table 5

Demographics Characteristics of the native and non-native English Speakers (n=262).

Variable	Overall ¹ (n= 262)	Native English Speakers ¹ (n=129)	Non-native English Speakers ¹ (n=133)
Age	32.89 (13.66)	34.08 (15.32)	31.74 (11.77)
Sex			
Female	136 (52%)	80 (62%)	56 (42%)
Male	121 (46%)	48 (37%)	73 (55%)
Other	5 (1.9%)	1 (.08%)	4 (3.0%)
Occupational Status			
Work	161 (61%)	76 (59%)	85 (64%)
School	52 (20%)	27 (21%)	25 (19%)
Neither	49 (19%)	26 (20%)	23 (17%)
Occupational Setting			
Home Office/Home schooling	109 (42%)	50 (39%)	59 (44%)
Face-to-face work/Face-to-face schooling	41 (16%)	22 (17%)	19 (14%)
Combination of home and face-to-face work/schooling	53 (20%)	23 (18%)	30 (23%)
Neither (no work or school, or in vacation)	59 (23%)	34 (26%)	25 (19%)

¹ Mean (SD); n (%).

LEBA: Supplementary Materials

Supplementary Table 6

Items discrimination and response category difficulty thresholds of 23 items in LEBA (n=690).

Items	a	b ₁	b ₂	b ₃	b ₄	Item Discrimination Category
F1: Wearing blue light filters						
Item 16	28.13	0.78	0.90	1.06	1.40	Very High
Item 36	4.49	0.94	1.08	1.23	1.40	Very High
Item 17	2.81	0.97	1.11	1.38	1.62	Very High
F2: Spending time outdoors						
Item 11	3.27	-0.79	0.65	1.54	2.31	Very High
Item 10	3.07	-1.27	-0.09	0.82	2.00	Very High
Item 12	1.72	-0.67	0.44	1.28	2.11	Very High
Item 07	1.09	-0.50	0.73	1.63	2.97	Moderate
Item 08	1.19	-2.26	-0.48	0.64	1.91	Moderate
Item 09	0.91	-2.63	-0.96	1.11	3.49	Moderate
F3: Using phone and smartwatch in bed						
Item 27	2.21	-1.88	-1.19	-0.73	0.30	Very High
Item 03	3.03	-1.24	-0.77	-0.20	0.66	Very High
Item 40	1.55	-0.51	0.46	1.32	2.22	High
Item 30	0.49	3.27	3.74	4.64	6.52	Low
Item 41	0.51	3.87	4.78	6.39	8.91	Low
F4: Using light before bedtime						
Item 32	1.62	-1.03	-0.78	-0.42	0.16	High
Item 35	1.37	-1.09	-0.98	-0.75	-0.40	High
Item 38	0.40	-7.48	-5.56	-4.23	-0.90	Low
Item 33	12.31	-0.66	-0.48	-0.24	0.13	Very High
F5: Using light in the morning and during daytime						
Item 46	2.22	0.68	0.89	1.38	2.17	Very High
Item 45	1.51	0.30	0.55	1.17	1.91	High
Item 25	0.52	-1.37	-0.04	1.89	4.22	Low
Item 04	0.84	2.44	2.80	3.18	3.67	Moderate
Item 01	0.39	-0.91	1.52	3.25	5.53	Low

Note. a = item discrimination parameter; b(1-4) = response category difficulty parameter

LEBA: Supplementary Materials

Supplementary Table 7

Item discrimination, response category difficulty thresholds and fit statistics of the 18 items in short LEBA (n=690).

Items	a	b ₁	b ₂	b ₃	b ₄	Signed χ^2	df	RMSEA	p	Item Discrimination Category
F1: Wearing blue light filters										
Item 16	28.13	0.78	0.90	1.06	1.40	2.02	6	0.00	0.92	Very High
Item 36	4.49	0.94	1.08	1.23	1.40	39.07	13	0.05	0.00	Very High
Item 17	2.81	0.97	1.11	1.38	1.62	25.58	13	0.04	0.02	Very High
F2: Spending time outdoors										
Item 11	3.27	-0.79	0.65	1.54	2.31	55.03	27	0.04	0.00	Very High
Item 10	3.07	-1.27	-0.09	0.82	2.00	53.19	30	0.03	0.01	Very High
Item 12	1.72	-0.67	0.44	1.28	2.11	34.39	42	0.00	0.79	Very High
Item 07	1.09	-0.50	0.73	1.63	2.97	67.45	46	0.03	0.02	Moderate
Item 08	1.19	-2.26	-0.48	0.64	1.91	140.90	46	0.05	0.00	Moderate
Item 09	0.91	-2.63	-0.96	1.11	3.49	131.19	45	0.05	0.00	Moderate
F3: Using phone and smartwatch in bed										
Item 27	2.12	-1.91	-1.21	-0.74	0.31	16.41	11	0.03	0.13	Very High
Item 03	3.24	-1.22	-0.76	-0.20	0.65	15.09	11	0.02	0.18	Very High
Item 40	1.57	-0.50	0.45	1.30	2.20	9.92	9	0.01	0.36	High
F4: Using light before bedtime										
Item 32	1.60	-1.04	-0.79	-0.42	0.16	41.33	15	0.05	0.00	High
Item 35	1.34	-1.10	-0.99	-0.76	-0.41	41.71	14	0.05	0.00	High
Item 33	15.66	-0.66	-0.48	-0.24	0.13	46.89	14	0.06	0.00	Very High
F5: Using light in the morning and during daytime										
Item 46	2.34	0.66	0.88	1.36	2.12	19.00	15	0.02	0.21	Very High
Item 45	1.51	0.30	0.55	1.17	1.91	15.05	15	0.00	0.45	High
Item 25	0.49	-1.45	-0.04	1.99	4.46	31.60	15	0.04	0.01	Low

Note. a = item discrimination parameter; b₍₁₋₄₎ = response category difficulty parameter

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LEBA: Supplementary Materials

Supplementary Figures

Light Exposure Behavior Assessment
Summary Descriptives EFA Sample (n =428)

Items	Summary Statistics					Item Total Correlation	Graphics		Response Pattern				
	Mean	SD	Skew	Kurtosis	SW ^a		Histogram	Density	Never	Rarely	Sometimes	Often	Always
● item01	2.27	1.39	0.74	-0.81	0.81*	0.19			42.29% (181)	22.20% (95)	12.62% (54)	12.38% (53)	10.51% (45)
● item02	2.87	1.59	0.08	-1.60	0.83*	0.28			31.78% (136)	15.65% (67)	9.35% (40)	20.09% (86)	23.13% (99)
● item03	3.36	1.38	-0.48	-1.03	0.87*	0.23			15.89% (68)	11.45% (49)	17.29% (74)	31.07% (133)	24.30% (104)
● item04	1.47	1.18	2.38	4.00	0.43*	0.24			84.11% (360)	3.50% (15)	2.10% (9)	2.10% (9)	8.18% (35)
● item05	4.01	1.40	-1.22	0.07	0.70*	0.17			12.85% (55)	3.50% (15)	9.58% (41)	17.52% (75)	56.54% (242)
● item06	2.79	1.55	0.19	-1.48	0.85*	0.13			32.01% (137)	15.42% (66)	15.89% (68)	15.42% (66)	21.26% (91)
● item07	2.26	1.25	0.70	-0.60	0.85*	0.32			35.98% (154)	27.80% (119)	17.29% (74)	12.38% (53)	6.54% (28)
● item08	2.97	1.20	-0.06	-0.94	0.91*	0.25			13.79% (59)	22.20% (95)	27.80% (119)	25.93% (111)	10.28% (44)
● item09	2.94	1.03	-0.12	-0.40	0.91*	0.08			10.28% (44)	19.63% (84)	41.82% (179)	22.43% (96)	5.84% (25)
● item10	2.74	1.04	0.09	-0.74	0.91*	0.42			11.92% (51)	31.31% (134)	31.31% (134)	21.96% (94)	3.50% (15)
● item11	2.18	0.90	0.60	0.12	0.86*	0.41			22.43% (96)	46.26% (198)	23.13% (99)	7.01% (30)	1.17% (5)
● item12	2.36	1.22	0.59	-0.62	0.87*	0.48			29.91% (128)	29.67% (127)	21.50% (92)	12.15% (52)	6.78% (29)
● item13	2.73	1.46	0.20	-1.36	0.87*	0.25			30.14% (129)	17.52% (75)	17.76% (76)	18.69% (80)	15.89% (68)
● item14	2.14	1.31	0.77	-0.78	0.80*	0.28			47.20% (202)	18.93% (81)	12.62% (54)	15.65% (67)	5.61% (24)
● item15	3.26	1.09	-0.26	-0.45	0.91*	0.03			7.48% (32)	13.79% (59)	37.15% (159)	28.04% (120)	13.55% (58)
● item16	1.56	1.23	2.00	2.45	0.50*	0.28			79.67% (341)	4.21% (18)	3.97% (17)	4.67% (20)	7.48% (32)
● item17	1.54	1.21	2.07	2.75	0.49*	0.21			80.61% (345)	3.27% (14)	5.14% (22)	3.27% (14)	7.71% (33)
● item18	1.12	0.49	5.02	27.80	0.25*	0.18			93.22% (399)	3.50% (15)	2.10% (9)	0.70% (3)	0.47% (2)
● item19	1.05	0.36	7.23	52.98	0.13*	0.17			97.43% (417)	0.93% (4)	0.47% (2)	1.17% (5)	0.00% (0)
● item20	1.04	0.33	8.99	85.28	0.10*	0.16			98.36% (421)	0.23% (1)	0.70% (3)	0.47% (2)	0.23% (1)
● item21	1.14	0.59	4.79	24.05	0.25*	0.21			93.69% (401)	1.64% (7)	3.04% (13)	0.47% (2)	1.17% (5)
● item22	3.57	1.07	-0.65	-0.17	0.88*	0.20			4.91% (21)	11.92% (51)	21.96% (94)	43.22% (185)	17.99% (77)
● item23	2.56	1.27	0.33	-1.00	0.89*	0.08			26.40% (113)	25.23% (108)	22.66% (97)	17.76% (76)	7.94% (34)
● item24	4.14	0.99	-1.23	1.14	0.79*	0.22			2.34% (10)	5.84% (25)	10.98% (47)	37.38% (160)	43.46% (186)
● item25	2.59	1.41	0.27	-1.27	0.86*	0.15			34.35% (147)	13.79% (59)	22.20% (95)	17.99% (77)	11.68% (50)
● item26	2.25	1.27	0.69	-0.64	0.84*	0.08			38.32% (164)	23.36% (100)	20.09% (86)	10.98% (47)	7.24% (31)
● item27	3.80	1.29	-0.87	-0.42	0.82*	0.17			8.41% (36)	11.21% (48)	11.21% (48)	30.37% (130)	38.79% (166)
● item28	3.76	1.14	-0.68	-0.45	0.86*	0.18			3.97% (17)	13.08% (56)	17.06% (73)	34.81% (149)	31.07% (133)
● item29	2.44	1.31	0.38	-1.14	0.86*	0.13			34.35% (147)	20.33% (87)	19.39% (83)	19.16% (82)	6.78% (29)
● item30	1.48	1.11	2.18	3.35	0.48*	0.13			81.78% (350)	3.27% (14)	4.91% (21)	5.37% (23)	4.67% (20)
● item31	3.00	1.62	-0.08	-1.61	0.83*	0.39			31.31% (134)	10.05% (43)	11.68% (50)	20.79% (89)	26.17% (112)
● item32	3.55	1.65	-0.60	-1.34	0.76*	0.33			23.13% (99)	7.01% (30)	8.18% (35)	14.95% (64)	46.73% (200)
● item33	3.62	1.64	-0.68	-1.25	0.74*	0.37			21.96% (94)	7.01% (30)	7.24% (31)	14.49% (62)	49.30% (211)
● item34	3.42	1.83	-0.45	-1.69	0.69*	0.20			33.64% (144)	3.04% (13)	3.04% (13)	8.64% (37)	51.64% (221)
● item35	3.86	1.67	-0.99	-0.85	0.65*	0.20			22.90% (98)	1.87% (8)	3.74% (16)	9.35% (40)	62.15% (266)
● item36	1.54	1.25	2.13	2.86	0.46*	0.35			82.24% (352)	3.04% (13)	3.04% (13)	2.34% (10)	9.35% (40)
● item37	1.33	0.91	3.03	8.43	0.41*	0.09			84.58% (362)	7.01% (30)	3.04% (13)	1.64% (7)	3.74% (16)
● item38	4.30	1.08	-1.79	2.53	0.67*	0.32			5.37% (23)	3.50% (15)	5.37% (23)	27.57% (118)	58.18% (249)
● item39	1.96	0.98	1.02	0.69	0.82*	0.07			37.62% (161)	38.79% (166)	15.65% (67)	5.61% (24)	2.34% (10)
● item40	2.16	1.19	0.71	-0.54	0.84*	0.25			39.49% (169)	25.00% (107)	19.63% (84)	11.45% (49)	4.44% (19)
● item41	1.31	0.81	2.75	6.92	0.43*	0.14			85.05% (364)	4.67% (20)	6.07% (26)	3.04% (13)	1.17% (5)
● item42	3.93	1.48	-1.06	-0.44	0.71*	0.15			14.72% (63)	5.84% (25)	7.94% (34)	14.95% (64)	56.54% (242)
● item43	1.64	1.18	1.79	2.02	0.60*	0.22			71.26% (305)	9.35% (40)	10.05% (43)	2.80% (12)	6.54% (28)
● item44	3.51	1.30	-0.70	-0.59	0.85*	0.40			13.55% (58)	7.24% (31)	18.69% (80)	35.98% (154)	24.53% (105)
● item45	2.22	1.48	0.71	-1.02	0.76*	0.29			53.04% (227)	7.01% (30)	16.36% (70)	11.92% (51)	11.68% (50)
● item46	1.76	1.23	1.35	0.44	0.66*	0.39			67.06% (287)	7.71% (33)	11.68% (50)	8.88% (38)	4.67% (20)
● item47	2.11	1.17	0.77	-0.39	0.83*	0.37			41.12% (176)	24.77% (106)	20.09% (86)	9.81% (42)	4.21% (18)
● item48	2.60	1.25	0.29	-0.86	0.89*	0.36			25.00% (107)	21.50% (92)	30.84% (132)	13.79% (59)	8.88% (38)

^aShapiro-Wilk test

Sup.Fig. 1. Summary descriptive statistics and response pattern of EFA sample (n=428). All items violated normality assumptions

LEBA: Supplementary Materials

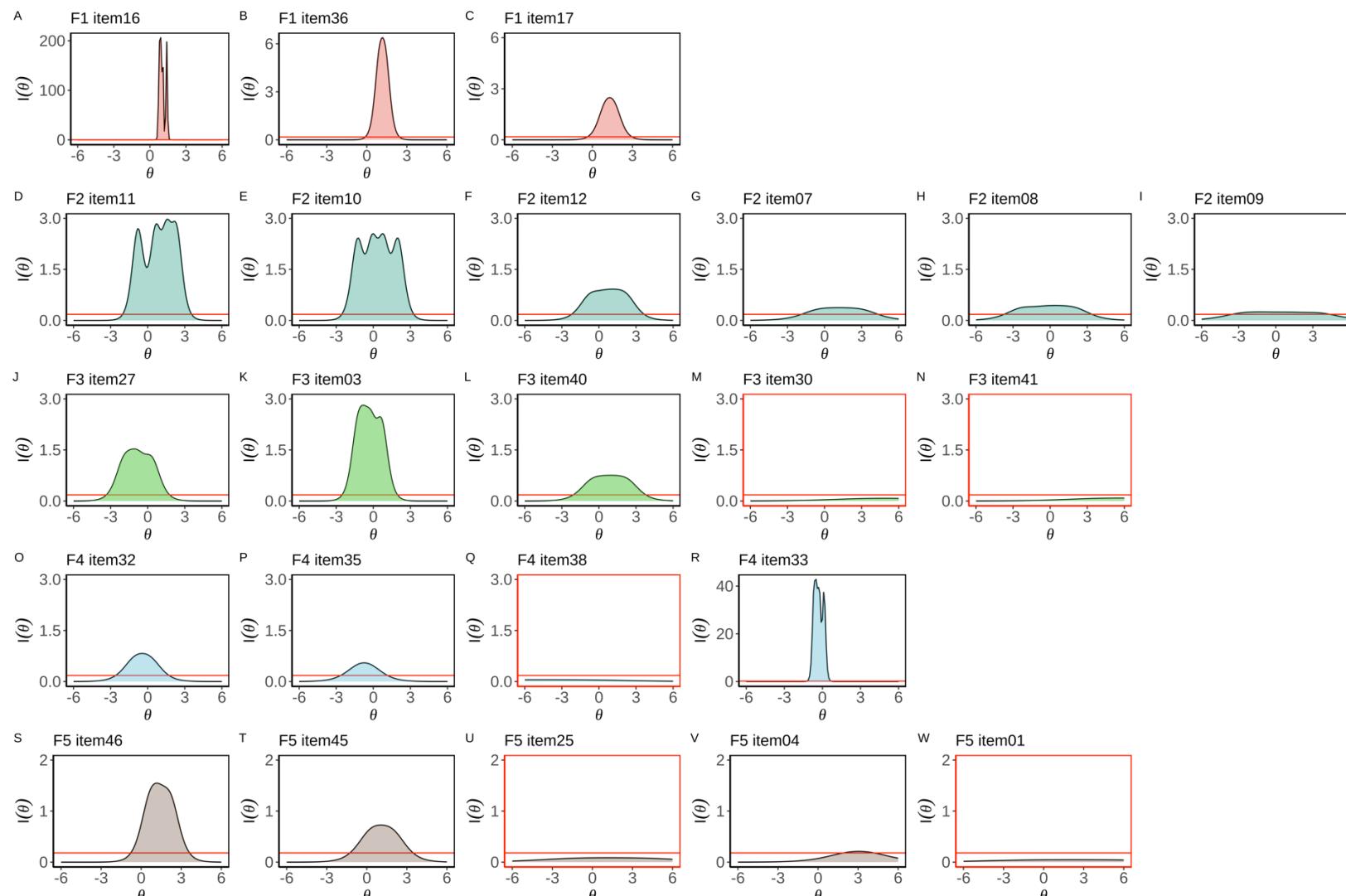
Light Exposure Behavior Assessment

Summary Descriptives CFA Sample (n=262)

Items	Summary Statistics			Graphics		Response Pattern					
	n	Mean	Median	SD	Histogram	Density	Never	Rarely	Sometimes	Often	Always
F1: Wearing blue light filters											
● item16	262	1.6	1.0	1.3			78.24% (205)	3.44% (9)	4.20% (11)	5.73% (15)	8.40% (22)
● item17	262	1.6	1.0	1.2			80.15% (210)	3.44% (9)	5.34% (14)	2.67% (7)	8.40% (22)
● item36	262	1.6	1.0	1.3			80.53% (211)	3.44% (9)	3.05% (8)	3.44% (9)	9.54% (25)
F2: Spending time outdoors											
● item07	262	2.1	2.0	1.2			43.13% (113)	23.66% (62)	14.50% (38)	14.12% (37)	4.58% (12)
● item08	262	3.0	3.0	1.2			14.12% (37)	22.90% (60)	20.99% (55)	32.06% (84)	9.92% (26)
● item09	262	2.9	3.0	1.1			12.98% (34)	22.14% (58)	34.35% (90)	26.34% (69)	4.20% (11)
● item10	262	2.6	3.0	1.1			17.56% (46)	29.39% (77)	29.01% (76)	21.37% (56)	2.67% (7)
● item11	262	2.1	2.0	0.9			25.95% (68)	46.56% (122)	20.23% (53)	5.34% (14)	1.91% (5)
● item12	262	2.3	2.0	1.2			32.06% (84)	30.92% (81)	19.08% (50)	11.45% (30)	6.49% (17)
F3: Using phone and smart-watch in bed											
● item03	262	3.7	4.0	1.3			11.83% (31)	7.25% (19)	17.56% (46)	28.24% (74)	35.11% (92)
● item27	262	4.0	4.0	1.2			6.11% (16)	7.25% (19)	8.02% (21)	33.59% (88)	45.04% (118)
● item30	262	1.4	1.0	1.1			83.59% (219)	2.67% (7)	4.20% (11)	6.11% (16)	3.44% (9)
● item40	262	2.5	2.0	1.3			30.92% (81)	27.10% (71)	18.70% (49)	12.21% (32)	11.07% (29)
● item41	262	1.2	1.0	0.7			90.08% (236)	3.82% (10)	2.29% (6)	2.67% (7)	1.15% (3)
F4: Using light before bedtime											
● item32	262	3.4	4.0	1.7			25.95% (68)	4.20% (11)	11.45% (30)	16.79% (44)	41.60% (109)
● item33	262	3.1	3.0	1.7			32.44% (85)	6.11% (16)	11.83% (31)	14.12% (37)	35.50% (93)
● item35	262	3.6	5.0	1.8			27.48% (72)	2.67% (7)	7.25% (19)	6.49% (17)	56.11% (147)
● item38	262	4.3	5.0	1.1			4.20% (11)	7.63% (20)	6.49% (17)	21.37% (56)	60.31% (158)
F5: Using light in the morning and during daytime											
● item01	262	2.3	2.0	1.4			40.46% (106)	22.52% (59)	14.50% (38)	10.69% (28)	11.83% (31)
● item04	262	1.3	1.0	0.8			89.31% (234)	2.29% (6)	3.44% (9)	3.05% (8)	1.91% (5)
● item25	262	2.5	2.0	1.4			32.82% (86)	18.32% (48)	21.76% (57)	16.79% (44)	10.31% (27)
● item45	262	2.0	1.0	1.4			64.12% (168)	5.34% (14)	9.54% (25)	11.83% (31)	9.16% (24)
● item46	262	1.6	1.0	1.2			75.57% (198)	2.67% (7)	8.02% (21)	9.54% (25)	4.20% (11)

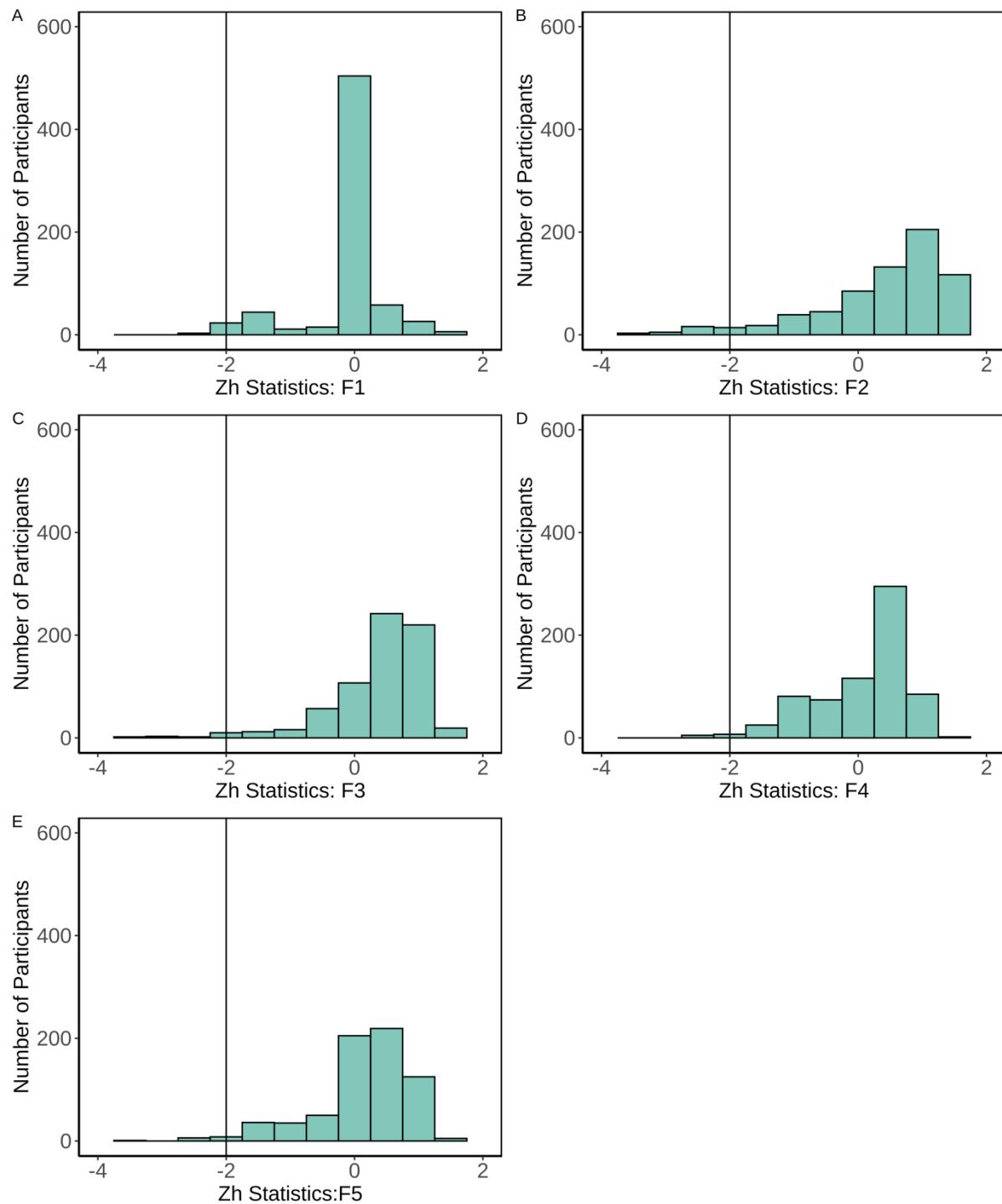
Sup.Fig.2. Summary descriptive statistics and response pattern of CFA sample (n=262).

LEBA: Supplementary Materials



Sup. Fig.3. Item information curves for all items of LEBA. The red boxed five items (1, 25, 30, 38, 41) had relatively flat information curves.

LEBA: Supplementary Materials



Sup.Fig.4. Person fit of the five fitted IRT models (a) wearing blue light filters (b) spending time outdoors (c) using phone and smart-watch in bed (d) using light before bedtime (e) using light in the morning and during daytime. Most of the Zh values are higher than -2.