

An inventory of human light exposure related behaviour

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52

Abstract

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

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

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

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

81 Instrument webpage: <https://leba-instrument.org/> GitHub repository containing this
82 manuscript: <https://github.com/leba-instrument/leba-manuscript>

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87 **Introduction**

88 Light exposure received by the eyes affects many facets of human health,
89 well-being, and performance beyond visual sensation and perception (Boyce, 2022).
90 The non-image-forming (NIF) effects of light comprise light's circadian and non-circadian
91 influence on several physiological and psychological functions, such as the secretion of
92 melatonin, sleep, mood, pupil size, body temperature, alertness, and higher cognitive
93 functions (Bedrosian & Nelson, 2017; Blume, Garbazza, & Spitschan, 2019; Lok,
94 Smolders, Beersma, & de Kort, 2018; Paul & Brown, 2019; Santhi & Ball, 2020; Siraji,
95 Kalavally, Schaefer, & Haque, 2021; Zele & Gamlin, 2020).

96 With the introduction of artificial electric light, human behaviour has become
97 dissociated from the light-dark cycle given by solar radiation. People can now frequently
98 choose when to be exposed to light or darkness. For example, they can decide whether
99 to go outdoors and seek out sunlight, switch on/off light-emitting devices, use certain
100 types of lights at home, or avoid specific light environments altogether. Additionally,
101 when light sources cannot be directly manipulated, sought out, or avoided (for example,
102 at school, work, or in public places), there is still potential leeway to influence personal
103 light exposure behaviourally, for instance, by wearing sunglasses, directing one's gaze
104 away or supplementing the situation with additional light sources. Although clearly
105 yielding the potential for good, these behaviours are further associated with increased
106 electric light exposure at night and indoor time during the day, compromising the natural
107 temporal organisation of the light-dark cycle. For example, in the US, an average of 87%
108 of the time is spent in enclosed buildings (Klepeis et al., 2001), and more than 80% of
109 the population is exposed to a night sky that is brighter than nights with a full moon due
110 to electric light at night (Navara & Nelson, 2007).

111 An extensive body of scientific evidence suggests that improper light exposure may

112 be disruptive for health and well-being, giving rise to a series of adverse consequences,
113 including the alteration of hormonal rhythms, increased cancer rates, cardiovascular
114 diseases, and metabolic disorders, such as obesity and type II diabetes (Chellappa,
115 Vujovic, Williams, & Scheer, 2019; Lunn et al., 2017; Navara & Nelson, 2007). These
116 findings have sparked a significant call for assessment and guidance regarding healthy
117 light exposure as exemplified by a recently published set of consensus-based experts'
118 recommendations with specific requirements for indoor light environments during the
119 daytime, evening, and nighttime (T. M. Brown et al., 2022).

120 Furthermore, building on earlier attempts (e.g. Hubalek, Zöschg, & Schierz, 2006),
121 there was a recent push toward the development and use of portable light loggers to
122 improve ambulant light assessment and gain more insight into the NIF effects of light on
123 human health in field conditions (Aarts, Duijnhoven, Aries, & Rosemann, 2017;
124 Duijnhoven, Aarts, Aries, Böhmer, & Rosemann, 2017; Stampfli et al., 2021; Webler,
125 Chinazzo, & Andersen, 2021). Attached to different body parts (e.g., wrist; head, at eye
126 level; chest), these light loggers allow for the objective measurement of individual photic
127 exposure patterns under real-world conditions and thus are valuable tools for field
128 studies. Nevertheless, these devices also encompass limiting factors such as potentially
129 being intrusive (e.g., when eye-level worn), yielding the risk of getting covered (e.g.,
130 when wrist- or chest-worn) and requiring (monetary) resources and expertise for
131 acquisition and maintenance of the devices.

132 On the other hand, several attempts have been made to quantify received light
133 exposure subjectively with self-report questionnaires (**Supplementary Table 1**),
134 bypassing the cost and intrusiveness issues. However, subjective light intensity
135 assessments pose a new set of challenges: The human visual system constantly adapts
136 to brightness (Hurvich & Jameson, 1966), while the signals underlying the non-visual
137 effects of light are independent from perception (Allen, Hazelhoff, Martial, Cajochen, &
138 Lucas, 2018), making the self-report assessment of light properties challenging.

139 Retrospectively recalling the properties of a light source can further complicate such
140 subjective evaluations. Moreover, measuring light properties alone does not yield any
141 information about how individuals might behave differently regarding diverse light
142 environments such as work, home or outdoors.

143 These measurement limitations point to a couple of research challenges which we
144 addressed here: How can we gain insight into light exposure patterns via self-report but
145 circumvent directly inquiring about the specific properties and intensity of a light source?
146 And how can we simultaneously assess how people habitually interact with the received
147 light? We propose that these challenges can be tackled by assessing
148 light-exposure-related behaviour. We argue that, besides measuring received light
149 exposure as intensity, it is also essential to understand people's behaviours with respect
150 to different light situations. In many cases, humans have become their own agents
151 regarding their exposure to light or darkness through daylight and electric light, and as
152 such people's light exposure-related behaviours ultimately determine their light
153 consumption and timing: People receive different light depending on their daily activities,
154 including workplace habits, bedtime hygiene, pastime and social activities. Ultimately, in
155 order to optimize lighting for human health and well being, better understanding of
156 light-related behaviours will serve to identify additional points of intervention as well as to
157 provide an added dimension to efficacy and implementation studies of novel lighting
158 strategies. We argue that assessing these activities is a beneficial stepping stone for
159 prospective behaviour change to maintain light hygiene: a proper balance of exposures
160 to light to maintain circadian rhythms.

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

162 **Supplementary Table 1** summarises the existing questionnaire literature assessing light
163 exposure-related properties. However, only a few questions of these existing tools were
164 associated with light exposure-related behaviour. For example, the "Munich Chronotype
165 Questionnaire" (Roenneberg, Wirz-Justice, & Merrow, 2003), a popular self-report tool

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

181

Results

182 **Development of the initial item pool**

183 An expert panel comprising all authors – researchers from chronobiology, light
184 research, neuroscience and psychology in different geographical contexts – developed a
185 comprehensive item pool of 48 items. Face validity examination by each panel member
186 indicated all items were relevant and a few modifications were suggested. The author
187 team discussed the suggestions and amended the items as indicated, thus creating a
188 48-item inventory.

189 Measurement of light exposure behaviour in an online sample

190 We conducted two rounds of large scale online survey to generate data from
191 various geographic locations (countries=74; time-zone=28). For a complete list of
192 geographic locations, see **Supplementary Table 2**. Table 1 presents the survey
193 participants' demographic characteristics. Only participants completing the full LEBA
194 inventory were included. We used the data from first round for the exploratory factor
195 analysis (EFA sample; n=428) and data from the second round was used in the
196 confirmatory factor analysis (CFA sample; n=262). Participants in our survey were aged
197 between 11 to 84 years, with an overall mean of ~ 32.95 years of age [Overall:
198 32.95 ± 14.57 ; EFA: 32.99 ± 15.11 ; CFA: 32.89 ± 13.66]. In total, 325 (47%) of the
199 participants indicated female sex, 351 (51%) indicated male, and 14 (2.0%) indicated
200 other sex. Overall, 49 (7.2%) participants reported a gender-variant identity. In a
201 “Yes/No” question regarding native language, 320 (46%) of respondents [EFA: 191
202 (45%); CFA: 129 (49%)] indicated to be native English speakers. For their “Occupational
203 Status”, more than half of the overall sample (396 (57%)) reported that they currently
204 work, whereas 174 (25%) reported that they go to school, and 120 (17%) responded that
205 they do “Neither”. With respect to the COVID-19 pandemic, we asked participants to
206 indicate their occupational setting during the last four weeks: In the overall sample, 303
207 (44%) of the participants indicated that they were in a home office/ home schooling
208 setting, 109 (16%) reported face-to-face work/schooling, 147 (21%) reported a
209 combination of home- and face-to-face work/schooling, and 131 (19%) filled in the
210 “Neither (no work or school, or on vacation)” response option.

211 Psychometric Analysis: Development of the Long Form

212 **Descriptive Statistics and Item Analysis.** Response patterns for the entire
213 sample (n=690) are depicted in Figures 1 and 2. All items violated univariate (Shapiro &

214 Wilk, 1965) and multivariate normality ((Mardia, 1970). The multivariate skewness
215 was 488.40 ($p < 0.001$) and the multivariate kurtosis was 2,808.17 ($p < 0.001$).

216 **Supplementary Figure 1** depicts the univariate descriptive statistics for the EFA
217 sample ($n=428$). Likewise, our data violated the both univariate (Shapiro & Wilk, 1965)
218 and multivariate normality assumptions (Mardia, 1970). The multivariate skew was
219 583.80 ($p < 0.001$) and the multivariate kurtosis was 2,749.15 ($p < 0.001$). The corrected
220 item-total correlation ranged between 0.03 and 0.48. However, no item was discarded
221 based on descriptive statistics or item analysis.

222 **Exploratory Factor Analysis and Reliability Analysis.** We checked the
223 post-hoc sampling adequacy by applying Kaiser-Meyer-Olkin (KMO) measures of
224 sampling adequacy on the EFA sample ($n=428$) (Kaiser, 1974). $KMO > 0.50$ would
225 indicate adequate sample size (Hutcheson, 1999). Results indicated that we had an
226 adequate sample size ($KMO = 0.63$). Additionally, we investigate the quality of the
227 correlation matrix by Bartlett's test of sphericity (Bartlett, 1954). Results indicated that
228 the correlation matrix was adequate to conduct EFA ($\chi^2_{1128} = 5042.86$, $p < 0.001$).
229 However, 4.96% of the inter-item correlation coefficients were greater than $|0.30|$, and
230 the inter-item correlation coefficients ranged between -0.44 to 0.91. Figure 3-A depicts
231 the respective correlation matrix.

232 While investigating the optimum factor number for the LEBA inventory, the Scree
233 plot (Figure 3-B) revealed a six-factor solution, whereas the minimum average partial
234 (MAP) method (Velicer, 1976) (**Supplementary Table 3**) and Hull method
235 (Lorenzo-Seva, Timmerman, & Kiers, 2011) (Figure 3-C) implied a five-factor solution.
236 Hence, we tested both five-factor and six-factor solutions using iterative EFA where we
237 gradually identified and discarded problematic items (factor-loading < 0.30 and
238 cross-loading > 0.30).

239 Iterative EFA revealed a five-factor structure for LEBA inventory and retained 25

240 items. Table 2 displays the factor-loading (λ) and communality of the items. Both factor
241 loadings and commonalities advocate to accept this five-factor solution ($|\lambda|= 0.32 - 0.99$;
242 commonalities= $0.11 - 0.99$). However, the histogram of the absolute values of
243 nonredundant residual correlations (Figure 3-D) displayed that 26% of correlations were
244 greater $>|0.05|$, indicating a possible under-factoring. (Desjardins & Bulut, 2018).
245 Subsequently, we fitted a six-factor solution, where a factor with only two salient
246 variables emerged, thus disqualifying the six-factor solution (**Supplementary Table 4**).

247 In the five-factor solution, the first factor had three items and encapsulated the
248 individual's preference for using blue light filters in different light environments. The
249 second factor contained six items that incorporated the individuals' hours spent
250 outdoors. The third factor contained five items that looked into specific behaviours of
251 using a phone and smartwatch in bed. The fourth factor comprised five items
252 investigated the other behaviours related to the individual's electric light exposure before
253 bedtime. lastly, the fifth factor encompassed six items capturing the individual's morning
254 and daytime light exposure-related behaviour. These five factors explains 10.25%,
255 9.93%, 8.83%, 8.44%, 6.14% of the total variance in individual's light exposure related
256 behaviours respectively. All factors exhibited excellent to satisfactory reliability (ordinal
257 $\alpha= .94, 0.76, 0.75, 0.72, 0.62$ respectively). The entire inventory also exhibited
258 satisfactory reliability ($\omega_t=0.77$). While making the judgement of accepting this five-factor
259 solution we considered both factor;s interpretability and their psychometric properties.
260 We deemed the five derived factors as highly interpretable and relevant concerning our
261 aim to capture light exposure-related behaviour, we retained all of them with 25 items.
262 Two of the items showed negative factor-loading (item 08: I spend 30 minutes or less per
263 day (in total) outside. and item 37: I use a blue-filter app on my computer screen within 1
264 hour before attempting to fall asleep.). Upon re-inspection, we recognized these items to
265 be negatively correlated to the respective factor, and thus, we reverse-scored these two
266 items.

267 **Confirmatory Factor Analysis.** CFA results (Table 3) indicated that the
268 five-factor structure fitted to the 25-item LEBA inventory attained an acceptable fit (CFI
269 = 0.92; TLI = 0.91; RMSEA = 0.07 [0.06-0.07, 90% CI]) with two imposed equity
270 constraints on item pairs 32-33 [item 32: I dim my mobile phone screen within 1 hour
271 before attempting to fall asleep; item 33: I dim my computer screen within 1 hour before
272 attempting to fall asleep] and 16-17 [item 16: I wear blue-filtering, orange-tinted, and/or
273 red-tinted glasses indoors during the day; item 17: I wear blue-filtering, orange-tinted,
274 and/or red-tinted glasses outdoors during the day]. Item pair 32-33 describes the
275 preference for dimming the electric devices' brightness before bedtime, whereas item
276 pair 16-17 represents the use of blue filtering or coloured glasses during the daytime.
277 Given the similar nature of captured behaviours within each item pair, we accepted the
278 imposed equity constraints. Nevertheless, the SRMR value exceeded the guideline
279 recommendation (SRMR = 0.12). In order to improve the model fit, we conducted a
280 post-hoc model modification. Firstly, the modification indices suggested cross-loadings
281 between item 37 and 26 [item 37: I purposely leave a light on in my sleep environment
282 while sleeping; item 26: I turn on my ceiling room light when it is light outside], which
283 were hence discarded. Secondly, items 30 and 41 [item 30: I look at my smartwatch
284 within 1 hour before attempting to fall asleep; item 41: I look at my smartwatch when I
285 wake up at night] showed a tendency to co-vary in their error variance (MI = 141.127,
286 p < 0.001). By allowing the latter pair of items (30 & 41) to co-vary, the model's error
287 variance attained an improved fit (CFI = 0.95; TLI = 0.95); RMSEA = 0.06 [0.05-0.06,
288 90% CI]; SRMR = 0.11).

289 Accordingly, we accept the five-factor model with 23 items, finalizing the long Form
290 of LEBA inventory (see **Supplementary File 1**). Internal consistency ordinal α for the
291 five factors of the LEBA were 0.96, 0.83, 0.70, 0.69, 0.52, respectively. The reliability of
292 the total inventory was satisfactory (ω_t = 0.68). Figure 4 depicts the obtained CFA
293 structure, while **Supplementary Figure 2** depicts the data distribution and endorsement

294 pattern of the retained 23 items in our CFA sample.

295 **Measurement Invariance.** We reported the measurement invariance (MI)
296 analysis on the CFA sample based on native (n=129) and non-native English speakers
297 (n=133). A detailed demographic description are provided in **Supplementary Table 5**.
298 Our MI results (Table 4) indicated that LEBA inventory demonstrated highest level of
299 (residual model) psychometric equivalence across native and non-native English
300 speaking participants, thus permitting group-mean based comparisons. The four fitted
301 MI models generated acceptable fit indices and the model fit did not significantly
302 decrease across the nested models ($\Delta\text{CFI}>-0.01$; $\Delta\text{RMSEA}<0.01$).

303 **Secondary Analysis: Grade Level Identification and Semantic Scale Network
304 Analysis**

305 We investigated the language-based accessibility of LEBA using Flesch-Kincaid
306 grade level analysis (Flesch, 1948). Results indicated that at least a language
307 proficiency of educational grade level-four (US education system) with age above eight
308 years are requied to comprehend the items used in LEBA inventory. Semantic Scale
309 analysis (Rosenbusch, Wanders, & Pit, 2020) was administered to assess the LEBA's
310 (23 items) semantic relation to other questionnaires. LEBA inventory was most strongly
311 semantically related to scales about sleep: The "Sleep Disturbance Scale For Children"
312 (Bruni et al., 1996) and the "Composite International Diagnostic Interview (CIDI):
313 Insomnia"(Robins et al., 1988). The cosine similarity index ranged between .47 to .51.

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

315 In order to derive a short form of the LEBA inventory, we fitted each factor of the
316 LEBA with the graded response model (Samejima, Liden, & Hambleton, 1997) to the
317 combined EFA and CFA sample (n=690). The resulting item discrimination parameters

318 of the inventory fell into categories of “very high” (10 items), “high” (4 items), “moderate”
319 (4 items), and “low” (5 items), indicating a good range of discrimination along the latent
320 trait level (θ) (**Supplementary Table 6**). An examination of the item information curve
321 (**Supplementary Figure 3**) revealed five items (1, 25, 30, 38, & 41) provided very low
322 information regarding light exposure related behaviors with relatively flat curves ($I(\theta)$)
323 $<.20$). We discarded those items, culminating in a short form of LEBA with five factors
324 and 18 items (**Supplementary File 2**).

325 Subsequently, we obtained five test information curves (TICs). As Figure 5
326 illustrates, the TICs of the first and fifth factors peaked on the right side of the centre of
327 their latent traits, while the TICs of the other three factors were roughly centred on the
328 respective trait continuum (θ). This points out that the LEBA short-form estimates the
329 light exposure-related behaviour most precisely near the centre of the trait continuum for
330 the second, third and fourth factors. In contrast, for the first and fifth factors the TICs
331 were left skewed indicating their increased sensitivity in identifying people who are
332 engaging more in those particular light exposure related behavior dimensions (Baker &
333 Kim, 2017).

334 Finally, **Supplementary Table 7** summarises the item fit indexes of the LEBA short
335 form. All 18 items yielded RMSEA value ≤ 0.06 , indicating an adequate fit to the fitted
336 IRT model. Furthermore, **Supplementary Figure 4** depicts the person fit Zh statistics
337 histogram for the five IRT models. Zh statistics are larger than -2 for most participants,
338 suggesting a good person fit regarding the selected IRT models.

339 Discussion

340 Today, in most industrialized countries, the vast majority of time is spent in built
341 environments (Klepeis et al., 2001), where photic exposure patterns are determined not
342 only by the solar cycle but by electrical light sources as well. As a consequence, light

343 received may vary considerably, in terms of timing, intensity and spectrum, all of which
344 are subject to the further influence of individual behaviours. (reviewed in Bedrosian &
345 Nelson, 2017; Blume et al., 2019; Lok et al., 2018; Paul & Brown, 2019; Santhi & Ball,
346 2020; Siraji et al., 2021; Vetter et al., 2022; Zele & Gamlin, 2020). Thus, there is a clear
347 need for guidance (T. M. Brown et al., 2022) and assessment regarding healthy light
348 exposure and consequentially healthy light-related behaviour.

349 In reviewing the literature, we found that a handful of previously introduced
350 instruments assess aspects of light exposure by self-report (see **Supplementary Table**
351 **1**). Few studies to date have attempted to assess light exposure by self-report. That
352 body of research becomes even smaller when limiting it to those focusing on that
353 influence photic exposure patterns, and typically these home in only on particular
354 behaviours of interest, such as estimates of time spent outside (Roenneberg et al., 2003)
355 or preferences for specific lighting situations (Bossini et al., 2006). To our knowledge,
356 there is no questionnaire in existence that captures behaviours that modify light
357 exposure across different scenarios in a comprehensive way. We have developed two
358 versions of a self-report inventory-LEBA, that can capture light exposure-related
359 behaviours in multiple dimensions.

360 The 48 generated items were applied in a large-scale, geographically
361 unconstrained, cross-sectional study, yielding 690 completed surveys. To assure high
362 data quality, participant responses were only included when the five “attention check
363 items” throughout the survey were passed. Ultimately, data was recorded from 74
364 countries and 28 time zones, including native and non-native English speakers from a
365 sex-balanced and age-diverse sample (see Table 1). The acquired study population
366 complied with our objective to avoid bias from a selective sample, which is crucial when
367 relying on voluntary uncompensated participation.

368 Data collected in the first round was used to explore the latent structure (EFA

sample; n=428). The exploratory factor analysis revealed a highly interpretable five-factor solution (“Wearing blue light filters”, “Spending time outdoors”, “Using phone and smartwatch in bed”, “Using light before bedtime”, and “Using light in the morning and during daytime”) with 25 items. Our CFA analysis (CFA sample; n=262) confirmed the five-factor structure we obtained in our EFA, thus providing evidence for structural validity.(CFI=0.95; TLI=0.95; RMSEA=0.06). In this model, we discarded two more items (item 26 & 37) for possible cross-loadings. As a rule of thumb, reliability coefficients higher than .70 are regarded as “satisfactory”. However, at the early developmental stage, a value of .50 is considered acceptable (Dall’Oglio et al., 2010; Field, 2015; Nunnally, 1978). Thus, we confer, the internal consistency coefficients ordinal alpha for the five factors and the total inventory were satisfactory (Ordinal alpha ranged between 0.52 to 0.96; McDonald’s ω_t =0.68).

The results of the measurement invariance analysis indicate that the construct “Light exposure-related behaviour” is equivalent across native and non-native English speakers and thus suitable for assessment in both groups. Furthermore, according to the grade level identification method, the LEBA appears understandable for students at least 8.33 years of age visiting grade four or higher. Interestingly, the semantic similarity analysis (“Semantic Scale Network” database Rosenbusch et al. (2020)) revealed that the “LEBA” is semantically related to the “Sleep Disturbance Scale For Children” (SDSC) (Bruni et al., 1996) and the “Composite International Diagnostic Interview (CIDI): Insomnia”(Robins et al., 1988). Upon inspecting the questionnaire contents, we found that some items in the factors “Using phone and smartwatch in bed” and “Using light before bedtime” have semantic overlap with the SDSC’s and CIDI’s items. However, while the CIDI and the SDSC capture various clinically relevant sleep problems and related activities, the LEBA aims to assess light-exposure-related behaviour. Since light exposure at night has been shown to influence sleep negatively (T. M. Brown et al., 2022; Santhi & Ball, 2020), this overlap confirms our aim to measure the physiologically

396 relevant aspects of light-exposure-related behaviour. Nevertheless, the general
397 objectives of the complete questionnaires and the LEBA differ evidently.

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

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

412 Known limitations

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

414 The fifth factor, “using light in the morning and during daytime”, exhibited low
415 internal consistency both in the exploratory and confirmatory factor analysis (EFA: 0.62;
416 CFA: 0.52). Since, it was above .50, considering the developmental phase of this
417 inventory we accepted the fifth factor. This particular factor captures our behaviour
418 related to usages of light in the morning and daytime. Since, light exposure during
419 morning and daytime influences our alertness and cognition (Lok et al., 2018; Siraji et al.,
420 2021), we deemed capturing these behaviours is essential for the sake of completeness

421 of our inventory. However, the possibility of improving the reliability should be
422 investigated further by adding more appropriate and relevant items to this factor.

423 During the post-hoc model modification, as part of the confirmatory factor analysis,
424 we discarded two items (item 26 & 37) for possible cross-loadings, as demonstrated in
425 the data. However, two additional items covaried in their error variance. By allowing the
426 latter pair (30 & 41) to covary, the model attained an improved fit (**Figure 5**). A possible
427 explanation for the covariation is that many respondents might not have used a
428 smartwatch at all, resulting in similar response patterns between these two items. Thus,
429 though rather unconventional, we decided to accept this post-hoc modification to our
430 five-factor model.

431 The habitual patterns queried in the developed inventory might not exhaustively
432 represent all relevant light-exposure-related behaviours. For instance, it is conceivable
433 that additional light-related activities not included in the LEBA depend on the
434 respondents' profession/occupation, geographical context, and socio-economic status.
435 However, we generated the initial item pool with an international team of researchers
436 and followed a thorough psychometric analysis. Therefore, we are confident that the
437 developed LEBA inventory can serve as a good starting point for exploring the light
438 exposure related behaviours in more depth and inform room for modification of light
439 exposure-related behaviour to improve light hygiene.

440 As with all studies relying on retrospective self-report data, individuals filling in the
441 LEBA may have difficulties precisely recalling the inquired light-related behaviours. In
442 the interest of bypassing a substantial memory component, we limited the recall period
443 to four weeks and chose response options that do not require exact memory recall. In
444 contrast to directly assessing light properties via self-report, we assume that reporting
445 behaviours might be more manageable for inexperienced laypeople, as the latter does
446 not rely on existing knowledge about light sources. The comprehensibility of the LEBA is

447 also reflected by the Flesch-Kincaid grade level identification method (Flesch, 1948) that
448 suggested a minimum age of 8.33 years and an educational grade of four or higher (US
449 grading system). We argue that measuring light-related behaviours via self-report is
450 crucial because these behaviours will hardly be as observable by anyone else or
451 measurable with other methods (like behavioural observations) with reasonable effort.

452 **Future Directions**

453 To our knowledge, the LEBA is the first inventory characterising light
454 exposure-related behaviour in a scalable manner. Thus, estimating convergent validity
455 with similar subjective scales was impossible. Alternatively, the validity of the LEBA
456 could be evaluated by administering it conjointly with objective field measurements of
457 light exposure (e.g. with portable light loggers, see literature review). By this route, one
458 could study how the (subjectively measured) light exposure-related behavioural patterns
459 translate into (objectively measured) received light exposure.

460 Additionally, developing daily recall scales of light-related behaviour could provide a
461 more detailed behavioural assessment to supplement the LEBA's broader (four-week)
462 measurement approach. Comparing the LEBA scores to 24-hour recall scores could
463 provide helpful information about how light exposure-related behaviour assessment is
464 related between different time perspectives.

465 Moreover, light-exposure-related behaviour might depend on the respondents'
466 profession, geographical location, housing conditions, socio-economic status, or other
467 contextual factors. As the current data is limited to our international online survey
468 context, future research should apply the LEBA across more variable populations and
469 contexts. On the other hand, this will require the development of cross-cultural
470 adaptations and translations into other languages of the LEBA, which should be targeted
471 in prospective studies.

472 Finally, in the future, the use of the LEBA instrument need not remain restricted to
473 gathering information in cross-sectinal quantitative studies. The instrument can also be
474 used for individual behavioural profiling. For instance, the LEBA could be applied in a
475 clinical context as part of Cognitive Behavioural Therapy for Insomnia (CBT-I). More
476 specifically, it could be used to supplement the sleep hygiene aspects of CBT-I, as
477 receiving light exposure at different times has implications for sleep (Santhi & Ball,
478 2020). This match was also evident in the semantic relationship between the LEBA and
479 two scales capturing sleep problems (CIDI: Insomnia; Robins et al. (1988) & SDSC;
480 Bruni et al. (1996)) found in the semantic similarity analysis. However, before applying
481 the LEBA in such contexts in the future, more work is certainly needed to understand
482 light exposure-related behaviour and its' relationship to relevant health outcomes
483 measured subjectively and objectively.

484 Conclusion

485 Here, we developed a novel, internally consistent and structurally valid 23-item
486 self-report inventory for capturing light exposure-related behaviour in five scalable
487 factors. In addition, an 18-item short-form of the LEBA was derived using IRT analysis,
488 yielding adequate coverage across the underlying trait continuum. Applying the LEBA
489 inventory can provide insights into light exposure-related habits on a population-based
490 level. Furthermore, it can serve as a good starting point to profile individuals based on
491 their light exposure-related behaviour and to asseses their light consumption and timing.

492 Methods

493 Data collection

494 A quantitative cross-sectional, fully anonymous, geographically unconstrained
495 online survey was conducted via REDCap (Harris et al., 2019, 2009) by way of the

496 University of Basel sciCORE. Participants were recruited via the website
497 (<https://enlightenyourclock.org/participate-in-research>) of the science-communication
498 comic book “Enlighten your clock”, co-released with the survey (Weinzaepflen &
499 Spitschan, 2021), social media (i.e., LinkedIn, Twitter, Facebook), mailing lists, word of
500 mouth, the investigators’ personal contacts, and supported by the distribution of the
501 survey link via f.lux (F.lux Software LLC, 2021). The initial page of the online survey
502 provided information about the study, including that participation was voluntary and that
503 respondents could withdraw from participation at any time without being penalised.
504 Subsequently, consent was recorded digitally for the adult participants (>18 years), while
505 under-aged participants (<18 years) were prompted to obtain additional assent from their
506 parents/legal guardians. Filling in all questionnaires was estimated to take less than 30
507 minutes, and participation was not compensated.

508 As a part of the demographic data, participants provided information regarding age,
509 sex, gender identity, occupational status, COVID-19-related occupational setting, time
510 zone/country of residence and native language. The demographic characteristics of our
511 sample are given in **Table 1**. Participants were further asked to confirm that they
512 participated in the survey for the first time. All questions incorporating retrospective
513 recall were aligned to a “past four weeks” period. Additionally, four attention check items
514 were included among the questionnaires to ensure high data quality, with the following
515 phrasing: - We want to make sure you are paying attention. What is 4+5? - [...] Please
516 select “Strongly disagree” here. - [...] Please type in “nineteen” as a number. - [...]
517 Please select “Does not apply/I don’t know.” here.

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

521 **Analytic strategy**

522 Figure 6 summarises the steps we followed while developing the LEBA. We
523 conducted all analyses with the statistical software environment R (R Core Team, 2021).
524 **Firstly**, we set an item pool of 48 items with a six-point Likert-type response format
525 (0-Does not apply/I don't know, 1-Never, 2-Rarely 3-Sometimes, 4-Often, 5-Always) for
526 our initial inventory. Our purpose was to capture light exposure-related behaviour. In that
527 context, the first two response options: "Does not apply/I don't know" and "Never",
528 provided similar information. As such, we collapsed them into one, making it a 5-point
529 Likert-type response format (1-Never, 2-Rarely, 3-Sometimes, 4-Often, 5-Always).

530 **Secondly**, the two rounds of data collection were administered. In the first round
531 (EFA sample; n=428) we collected data for the exploratory factor analysis (EFA). A
532 sample of at least 250-300 is recommended for EFA (Comrey & Lee, 2013; Schönbrodt
533 & Perugini, 2013). The EFA sample exceeded this recommendation. The second round
534 data (CFA sample; n=262) was subjected to confirmatory factor analysis (CFA). To
535 assess sampling adequacy for CFA, we followed the N:q rule (Bentler & Chou, 1987;
536 Jackson, 2003; Kline, 2016; Worthington & Whittaker, 2006), where at least ten
537 participants per item are required to earn trustworthiness of the result. Again, our CFA
538 sample exceeded this guidelines.

539 **Thirdly**, we conducted descriptive and item analyses and proceeded to EFA using
540 the "psych" package (Revelle, 2021) on the EFA sample. Prior to the EFA, the necessary
541 assumptions, including sample adequacy, normality assumptions, and quality of
542 correlation matrix, were assessed. As our data violated both the univariate and
543 multivariate normality assumption and yielded ordinal response data, we used a
544 polychoric correlation matrix in the EFA and employed "principal axis" (PA) as the factor
545 extraction method (Desjardins & Bulut, 2018; Watkins, 2020). We applied a combination
546 of methods, including a Scree plot (Cattell, 1966), minimum average partials method

547 (Velicer, 1976), and Hull method (Lorenzo-Seva et al., 2011) to identify factor numbers.
548 To determine the latent structure, we followed the common guidelines: (i) no factors with
549 fewer than three items (ii) no factors with a factor loading <0.3 (iii) no items with
550 cross-loading > .3 across factors (Bandalos & Finney, 2018).

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

563 To validate the latent structure obtained in the EFA, we conducted a categorical
564 confirmatory factor analysis (CFA) with the weighted least squares means and variance
565 adjusted (WLSMV) estimation (Desjardins & Bulut, 2018), using the “lavaan” package
566 (Rosseel, 2012) on the CFA sample. We assessed the model fit using standard model fit
567 guidelines: (i) χ^2 test statistics: a non-significant test statistics is required to accept the
568 model (ii) comparative fit index (CFI) and Tucker Lewis index (TLI): close to 0.95 or
569 above/ between 0.90-0.95 and above (iii) root mean square error of approximation
570 (RMSEA): close to 0.06 or below, (iv) Standardized root mean square (SRMR): close to
571 0.08 or below (Hu & Bentle, 1999; Schumacker & Lomax, 2004). However, the χ^2 test is
572 sensitive to sample size (T. A. Brown, 2015), and SRMR does not work well with ordinal
573 data (Yu, 2002). Consequently, we judged the model fit using CFI, TLI and RMSEA.

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

585 **Fourthly**, in a secondary analysis, we identified the educational grade level (US
586 education system) required to understand the items in our inventory with the
587 Flesch-Kincaid grade level identification method (Flesch, 1948) applying the “koRpus”
588 (Michalke, 2021) package. Correspondingly, we analysed possible semantic overlap of
589 our developed inventory using the “Semantic Scale Network” (SSN) engine (Rosenbusch
590 et al., 2020). The SSN detects semantically related scales and provides a cosine
591 similarity index ranging between -.66 to 1 (Rosenbusch et al., 2020). Pairs of scales with
592 a cosine similarity index value of 1 indicate full semantical similarity, suggesting
593 redundancy.

594 **Lastly**, we derived a short form of the LEBA employing an Item Response Theory
595 (IRT) based analysis. We fitted each factor of the LEBA to the combined EFA and CFA
596 sample ($n=690$) using the graded response model (Samejima et al., 1997) via the “mirt”
597 package (Chalmers, 2012). IRT assesses the item quality by estimating the item
598 discrimination, item difficulty, item information curve, and test information curve (Baker &
599 Kim, 2017). Item discrimination indicates how well a particular item can differentiate
600 between participants across the given latent trait continuum (θ). Item difficulty

601 corresponds to the latent trait level at which the probability of endorsing a particular
602 response option is 50%. The item information curve (IIC) indicates the amount of
603 information an item carries along the latent trait continuum. Here, we reported the item
604 difficulty and discrimination parameter and categorized the items based on their item
605 discrimination index: (i) none = 0; (ii) very low = 0.01 to 0.34; (iii) low = 0.35 to 0.64; (iv)
606 moderate = 0.65 to 1.34 ; (v) high = 1.35 to 1.69; (vi) very high >1.70 (Baker & Kim,
607 2017). We discarded the items with a relatively flat item information curve (information
608 <.2) to derive the short form of LEBA. We also assessed the precision of the short LEBA
609 utilizing the test information curve (TIC). TIC indicates the amount of information a
610 particular scale carries along the latent trait continuum. Additionally, the item and person
611 fit of the fitted IRT models were analysed to gather more evidence on the validity and
612 meaningfulness of our scale (Desjardins & Bulut, 2018). The item fit was evaluated using
613 the RMSEA value obtained from Signed- χ^2 index implementation, where an RMSEA
614 value $\leq .06$ was considered an adequate item fit. The person fit was estimated
615 employing the standardized fit index Zh statistics (Drasgow, Levine, & Williams, 1985).
616 Here, $Zh < -2$ was considered as a misfit (Drasgow et al., 1985).

617 **Ethical approval**

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

624 Data availability

625 The present article is a fully reproducible open access “R Markdown” document. All
626 code and data underlying this article – along with two versions of the LEBA inventory (full
627 and short) and online survey implementation templates on common survey platforms – is
628 available under an open-access licence (Creative Commons CC-BY-NC-ND) on a public
629 GitHub repository.

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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	0.92	0.91	0.07	0.06	0.07	0.12
2	561.25	231.00	0.95	0.95	0.07	0.05	0.06	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.

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

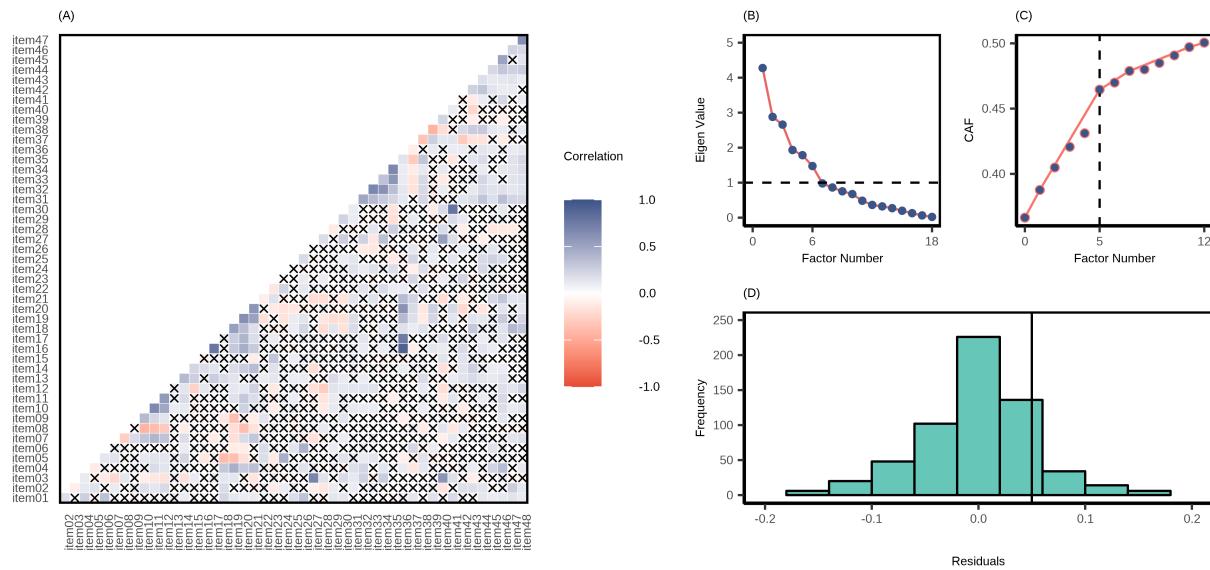


Figure 3. (A) Inter-item polychoric correlation coefficients for the 48 items. 4.9 % inter-item correlation coefficients were higher than $|.30|$. 'x' denotes non-significant correlation. (B) The Scree plot suggested six factors. (C) Hull method indicated that five factors were required to balance the model fit and number of parameters. (D) The histogram of nonredundant residual correlations in the five-factor model indicated that 26% of inter-item correlations were higher than .05, hinting at a possible under-factoring.



Figure 4. 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.

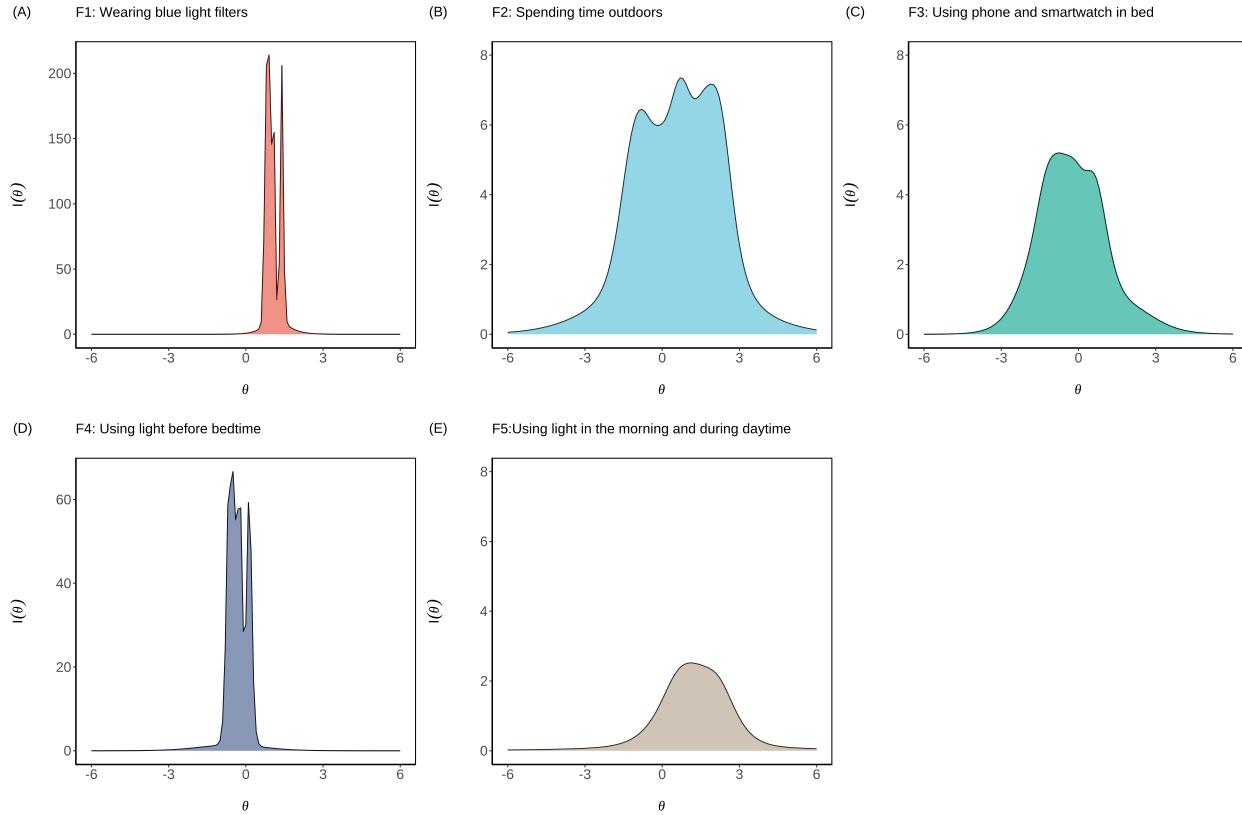


Figure 5. Test information curves for the five factors of LEBA: (A) wearing blue light filters (B) spending time outdoors (C) using a phone and smartwatch in bed (D) using light before bedtime (E) using light in the morning and during daytime. Along the x-axis, we plotted the underlying latent trait continuum for each factor. Along the y-axis, we plotted how much information a particular factor is carrying across its latent trait continuum

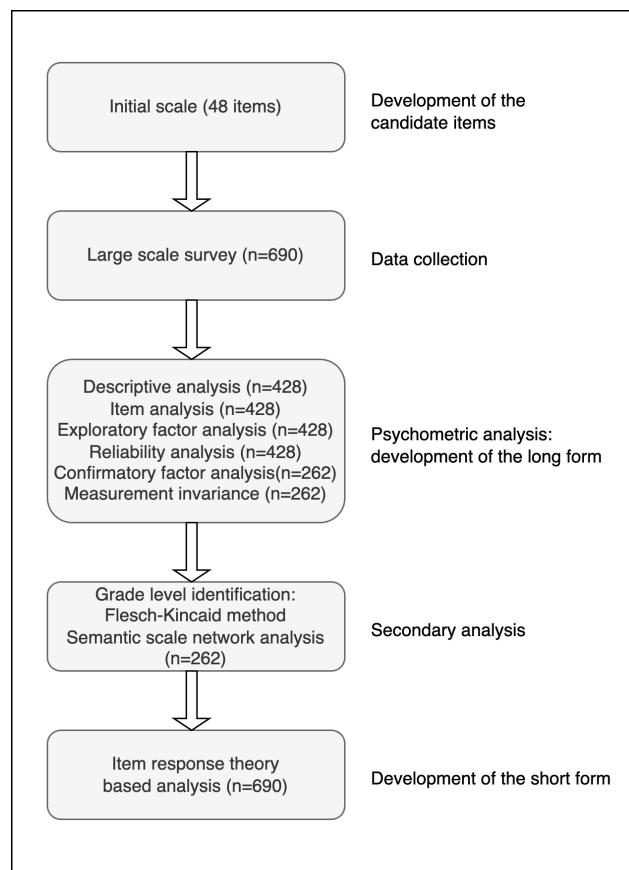


Figure 6. Flow chart of the LEBA (long and short form) development and evaluation.

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

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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

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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.

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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.

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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 (%).

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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

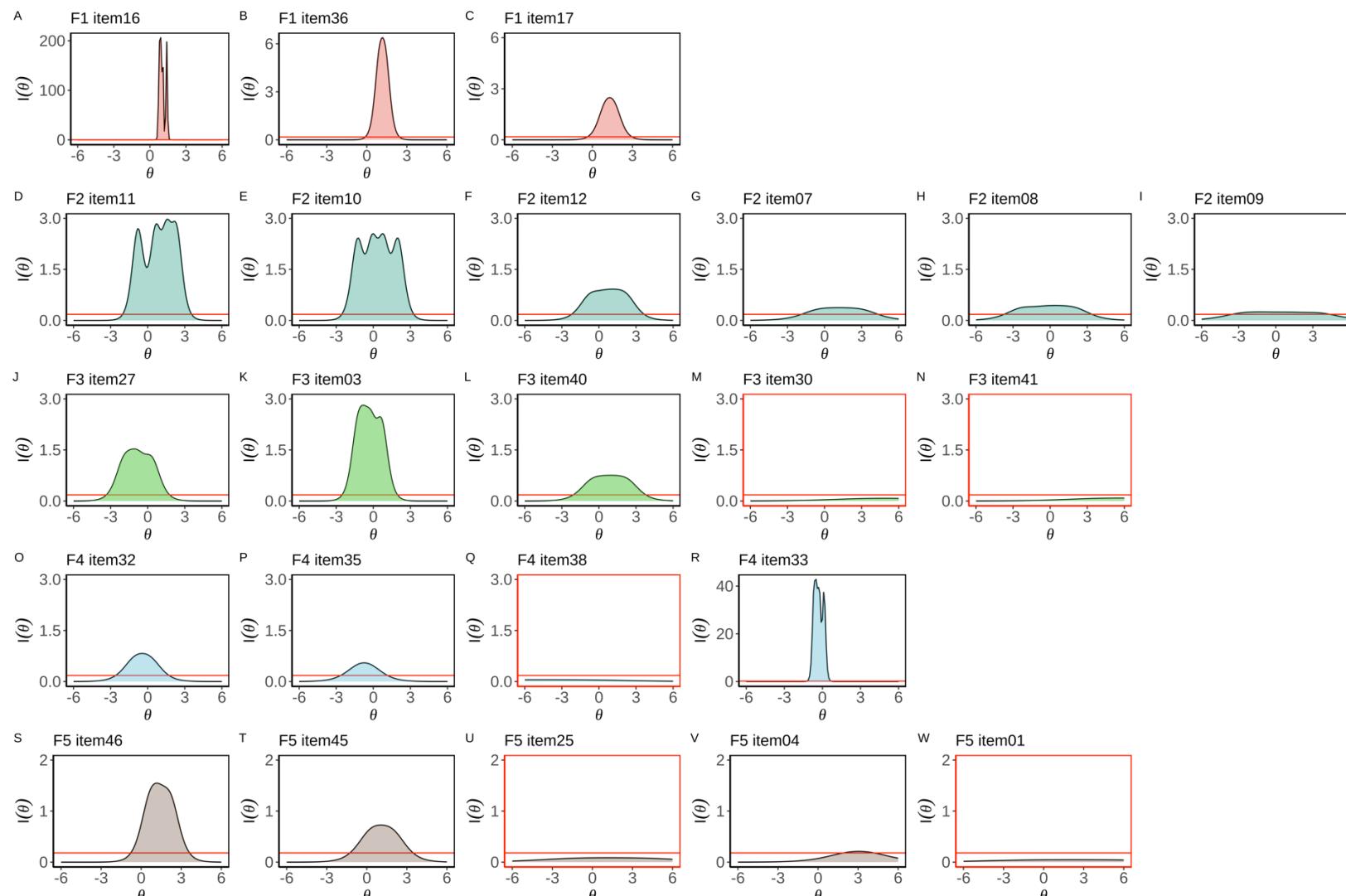
Light Exposure Behavior Assessment

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)

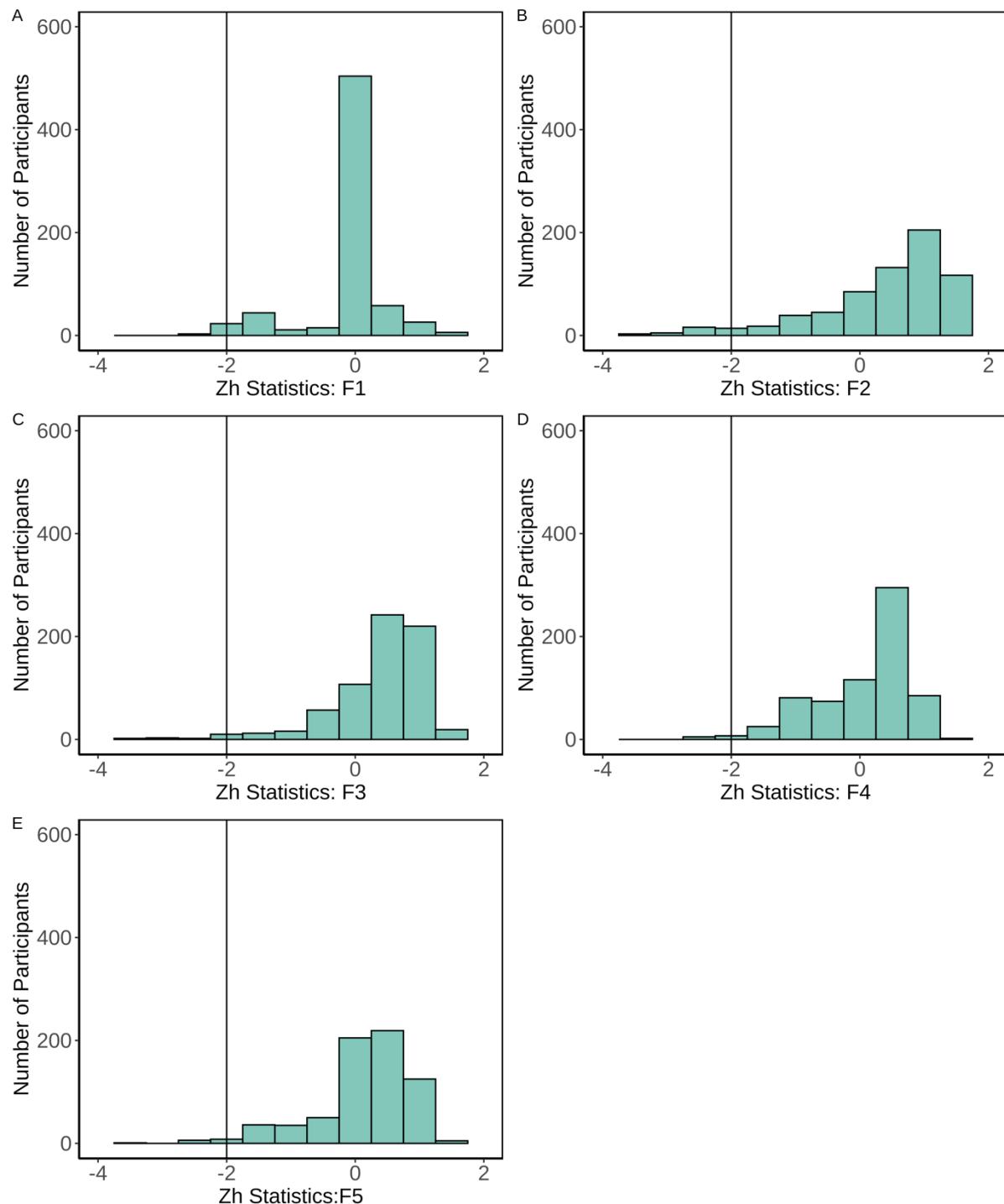
Sup.Fig.2. Summary descriptive statistics and response pattern of CFA sample (n=262).

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.