

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 Our results focus on the development of the LEBA inventory and its psychometric
183 validation using a large scale online sample data (n = 690).

184 Development of the initial item pool

185 To capture the human light exposure related behaviours, 48 items were developed
186 by an expert panel (all authors – researchers from chronobiology, light research,
187 neuroscience and psychology in different geographical contexts). Face validity
188 examination by each panel member indicated all items were relevant and a few
189 modifications were suggested. The author team discussed the suggestions and
190 amended the items as indicated, thus creating a 48-item inventory.

191 Measurement of light exposure behaviour in an online sample

192 We conducted two rounds of large scale online survey between 17 May 2021 and 3
193 September 2021 to generate data from 690 participants with varied geographic locations
194 (countries = 74; time-zone = 28). For a complete list of geographic locations, see
195 **Supplementary Table 2.** Table 1 presents the survey participants' demographic
196 characteristics. Only participants completing the full LEBA inventory were included. We
197 used the data from first round for the exploratory factor analysis (EFA sample; n = 428)
198 and data from the second round was used in the confirmatory factor analysis (CFA
199 sample; n = 262). Participants in our survey were aged between 11 to 84 years, with an
200 overall mean of ~ 32.95 years of age [Overall: 32.95 ± 14.57 ; EFA: 32.99 ± 15.11 ; CFA:
201 32.89 ± 13.66]. In the entire sample, 351 (51%) were male, 325 (47%) were female, 14
202 (2.0%) reported other sex, and 49 (7.2%) reported a gender-variant identity. In a
203 "Yes/No" question regarding native language, 320 (46%) of respondents [EFA: 191
204 (45%); CFA: 129 (49%)] indicated to be native English speakers. For their "Occupational
205 Status", more than half of the overall sample (396 (57%)) reported that they currently
206 work, whereas 174 (25%) reported that they go to school, and 120 (17%) responded that
207 they do "Neither". With respect to the COVID-19 pandemic, we asked participants to
208 indicate their occupational setting during the last four weeks: In the entire sample, 303
209 (44%) of the participants indicated that they were in a home office/ home schooling
210 setting, 109 (16%) reported face-to-face work/schooling, 147 (21%) reported a
211 combination of home- and face-to-face work/schooling, and 131 (19%) filled in the
212 "Neither (no work or school, or on vacation)" response option.

213 Psychometric Analysis: Development of the Long Form

214 **Descriptive Statistics and Item Analysis.** We observed that the response
215 patterns of LEBA inventory for the entire sample (n = 690) were not normally distributed

216 (Figures 1 and 2). All items violated both univariate (Shapiro & Wilk, 1965) and
217 multivariate normality (Mardia, 1970). The multivariate skewness was 488.40 ($p < 0.001$)
218 and the multivariate kurtosis was 2,808.17 ($p < 0.001$).

219 Similar non-normal distribution of response pattern was also observed in the EFA
220 sample. **Supplementary Figure 1** depicts the univariate descriptive statistics for the
221 EFA sample ($n = 428$). Further, We observed that each item's correlation with the
222 aggregated sum of the 48-item's score varied largely (corrected item-total correlation=
223 0.03 -0.48) indicating the possibility of multi-factor structure of the LEBA inventory.

224 **Exploratory Factor Analysis and Reliability Analysis.** Exploratory analysis
225 revealed that items of LEBA inventory can be categorized into five major factors: (i)
226 wearing blue light filters; (ii) spending time out doors; (iii) using phone and smartwatch in
227 bed; (iv) using light before bedtime (v) using light in the morning and during daytime. In
228 this stage of analysis, we retained 25 items. the first factor had three items and
229 encapsulated the individual's preference for using blue light filters in different light
230 environments. The second factor contained six items that incorporated the individuals'
231 hours spent outdoors. The third factor contained five items that looked into specific
232 behaviours of using a phone and smartwatch in bed. The fourth factor comprised five
233 items investigated the other behaviours related to the individual's electric light exposure
234 before bedtime. lastly, the fifth factor encompassed six items capturing the individual's
235 morning and daytime light exposure-related behaviour.

236 Prior to conducting the EFA, we have checked the post-hoc sampling adequacy by
237 applying Kaiser-Meyer-Olkin (KMO) measures of sampling adequacy on the EFA sample
238 ($n = 428$) (Kaiser, 1974) and the quality of the correlation matrix by Bartlett's test of
239 sphericity (Bartlett, 1954). KMO>0.50 would indicate adequate sample size (Hutcheson,
240 1999) and a significant test of sphericity would indicate satisfactory quality of the
241 correlation matrix . Results indicated that we had an adequate sample size (KMO =
242 0.63) and correlation matrix ($\chi^2_{1128} = 5042.86, p < 0.001$). However, 4.96% of the

243 inter-item correlation coefficients were greater than |0.30|, and the inter-item correlation
244 coefficients ranged between -0.44 to 0.91. Figure 3-A depicts the respective correlation
245 matrix. To identify how many factors are required to optimally express human light
246 exposure related behaviors we used a combination of methods. the Scree plot (Figure
247 3-B) revealed a six-factor solution, whereas the minimum average partial (MAP) method
248 (Velicer, 1976) (**Supplementary Table 3**) and Hull method (Lorenzo-Seva, Timmerman,
249 & Kiers, 2011) implied a five-factor solution (Figure 3-C). Hence, we tested both
250 five-factor and six-factor solutions using iterative EFA where we gradually identified and
251 discarded problematic items (factor-loading <0.30 and cross-loading >0.30). In this
252 process, we found a five-factor structure for LEBA inventory with 25 items. Table 2
253 displays the factor-loading (λ) and communality of the items. Both factor loadings and
254 commonalities advocate to accept this five-factor solution ($|\lambda| = 0.32\text{--}0.99$;
255 commonalities = 0.11-0.99). These five factors explains 10.25%, 9.93%, 8.83%, 8.44%,
256 6.14% of the total variance in individual's light exposure related behaviours respectively.
257 All factors exhibited excellent to satisfactory reliability (ordinal $\alpha = 0.94, 0.76, 0.75, 0.72,$
258 0.62 respectively). The entire inventory also exhibited satisfactory reliability ($\omega_t=0.77$).

259 However, the histogram of the absolute values of nonredundant residual
260 correlations (Figure 3-D) displayed that 26% of correlations were greater $>|0.05|$,
261 indicating a possible under-factoring. (Desjardins & Bulut, 2018). Subsequently, we fitted
262 a six-factor solution, where a factor with only two salient variables emerged, thus
263 disqualifying the six-factor solution (**Supplementary Table 4**). While making the
264 judgement of accepting this five-factor solution we considered both factor's
265 interpretability and their psychometric properties. We deemed the five derived factors as
266 highly interpretable and relevant concerning our aim to capture light exposure-related
267 behaviour, we retained all of them with 25 items. Two of the items showed negative
268 factor-loading (item 08: I spend 30 minutes or less per day (in total) outside. and item
269 37: I use a blue-filter app on my computer screen within 1 hour before attempting to fall

270 asleep.). Upon re-inspection, we recognized these items to be negatively correlated to
271 the respective factor, and thus, we reverse-scored these two items.

272 **Confirmatory Factor Analysis.** To investigate the structural validity of the
273 five-factor structure obtained in EFA, we conducted a confirmatory factor analysis (CFA)
274 on the CFA sample. The five-factor structure with 25 items showed acceptable fit (Table
275 3) providing evidence of structural validity ($CFI = 0.92$; $TLI = 0.91$; $RMSEA = 0.07$
276 [0.06-0.07, 90% CI]). Two equity constraints were imposed on item pairs 32-33 (item 32:
277 I dim my mobile phone screen within 1 hour before attempting to fall asleep; item 33: I
278 dim my computer screen within 1 hour before attempting to fall asleep) and 16-17 (item
279 16: I wear blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day;
280 item 17: I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the
281 day). Item pair 32-33 describes the preference for dimming the electric devices'
282 brightness before bedtime, whereas item pair 16-17 represents the use of blue filtering
283 or coloured glasses during the daytime. Given the similar nature of captured behaviours
284 within each item pair, we accepted the imposed equity constraints. Nevertheless, the
285 SRMR value exceeded the guideline recommendation ($SRMR = 0.12$). In order to
286 improve the model fit, we conducted a post-hoc model modification. Firstly, the
287 modification indices suggested cross-loadings between item 37 and 26 (item 37: I
288 purposely leave a light on in my sleep environment while sleeping; item 26: I turn on my
289 ceiling room light when it is light outside), which were hence discarded. Secondly, items
290 30 and 41 (item 30: I look at my smartwatch within 1 hour before attempting to fall
291 asleep; item 41: I look at my smartwatch when I wake up at night) showed a tendency to
292 co-vary in their error variance ($MI = 141.127$, $p < 0.001$). By allowing the latter pair of
293 items (30 & 41) to co-vary, the model's error variance attained an improved fit ($CFI =$
294 0.95 ; $TLI = 0.95$; $RMSEA = 0.06$ [0.05-0.06, 90% CI]; $SRMR = 0.11$).

295 Accordingly, we accept the five-factor model with 23 items, finalizing the long Form
296 of LEBA inventory (see **Supplementary File 1**). Internal consistency ordinal α for the

297 five factors of the LEBA were 0.96, 0.83, 0.70, 0.69, 0.52, respectively. The reliability of
298 the total inventory was satisfactory ($\omega_t = 0.68$). Figure 4 depicts the obtained CFA
299 structure, while **Supplementary Figure 2** depicts the data distribution and endorsement
300 pattern of the retained 23 items in our CFA sample.

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

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

311 We investigated the language-based accessibility of LEBA using Flesch-Kincaid
312 grade level analysis (Flesch, 1948). Results indicated that at least a language
313 proficiency of educational grade level-four (US education system) with age above eight
314 years are required to comprehend the items used in LEBA inventory. Semantic Scale
315 analysis (Rosenbusch, Wanders, & Pit, 2020) was administered to assess the LEBA's
316 (23 items) semantic relation to other questionnaires. LEBA inventory was most strongly
317 semantically related to scales about sleep: The "Sleep Disturbance Scale For Children"
318 (Bruni et al., 1996) and the "Composite International Diagnostic Interview (CIDI):
319 Insomnia" (Robins et al., 1988). The cosine similarity index ranged between 0.47 to 0.51.

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

321 In order to derive a short form of the LEBA inventory, we fitted each factor of the
322 LEBA with the graded response model (Samejima, Liden, & Hambleton, 1997) to the
323 combined EFA and CFA sample ($n=690$). The resulting item discrimination parameters
324 of the inventory fell into categories of “very high” (10 items), “high” (4 items), “moderate”
325 (4 items), and “low” (5 items), indicating a good range of discrimination along the latent
326 trait level (θ) (**Supplementary Table 6**). An examination of the item information curve
327 (**Supplementary Figure 3**) revealed five items (1, 25, 30, 38, & 41) provided very low
328 information regarding light exposure related behaviors with relatively flat curves ($I(\theta)$
329 <0.20). We discarded those items, culminating in a short form of LEBA with five factors
330 and 18 items (**Supplementary File 2**).

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

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

345

Discussion

346 Today, in most industrialized countries, the vast majority of time is spent in built
347 environments (Klepeis et al., 2001), where photic exposure patterns are determined not
348 only by the solar cycle but by electrical light sources as well. As a consequence, light
349 received may vary considerably, in terms of timing, intensity and spectrum, all of which
350 are subject to the further influence of individual behaviours. (reviewed in Bedrosian &
351 Nelson, 2017; Blume et al., 2019; Lok et al., 2018; Paul & Brown, 2019; Santhi & Ball,
352 2020; Siraji et al., 2021; Vetter et al., 2022; Zele & Gamlin, 2020). Thus, there is a clear
353 need for guidance (T. M. Brown et al., 2022) and assessment regarding healthy light
354 exposure and consequentially healthy light-related behaviour.

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

366 The 48 generated items were applied in a large-scale, geographically
367 unconstrained, cross-sectional study, yielding 690 completed surveys. To assure high
368 data quality, participant responses were only included when the five “attention check
369 items” throughout the survey were passed. Ultimately, data was recorded from 74
370 countries and 28 time zones, including native and non-native English speakers from a

371 sex-balanced and age-diverse sample (see Table 1). The acquired study population
372 complied with our objective to avoid bias from a selective sample, which is crucial when
373 relying on voluntary uncompensated participation.

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

387 The results of the measurement invariance analysis indicate that the construct
388 “Light exposure-related behaviour” is equivalent across native and non-native English
389 speakers and thus suitable for assessment in both groups. Furthermore, according to
390 the grade level identification method, the LEBA appears understandable for students at
391 least 8.33 years of age visiting grade four or higher. Interestingly, the semantic similarity
392 analysis (“Semantic Scale Network” database Rosenbusch et al. (2020)) revealed that
393 the “LEBA” is semantically related to the “Sleep Disturbance Scale For Children” (SDSC)
394 (Bruni et al., 1996) and the “Composite International Diagnostic Interview (CIDI):
395 Insomnia”(Robins et al., 1988). Upon inspecting the questionnaire contents, we found
396 that some items in the factors “Using phone and smartwatch in bed” and “Using light
397 before bedtime” have semantic overlap with the SDSC’s and CIDI’s items. However,

398 while the CIDI and the SDSC capture various clinically relevant sleep problems and
399 related activities, the LEBA aims to assess light-exposure-related behaviour. Since light
400 exposure at night has been shown to influence sleep negatively (T. M. Brown et al.,
401 2022; Santhi & Ball, 2020), this overlap confirms our aim to measure the physiologically
402 relevant aspects of light-exposure-related behaviour. Nevertheless, the general
403 objectives of the complete questionnaires and the LEBA differ evidently.

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

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

418 Known limitations

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

420 The fifth factor, “using light in the morning and during daytime”, exhibited low
421 internal consistency both in the exploratory and confirmatory factor analysis (EFA: 0.62;
422 CFA: 0.52). Since, it was above .50, considering the developmental phase of this

423 inventory we accepted the fifth factor. This particular factor captures our behaviour
424 related to usages of light in the morning and daytime. Since, light exposure during
425 morning and daytime influences our alertness and cognition (Lok et al., 2018; Siraji et al.,
426 2021), we deemed capturing these behaviours is essential for the sake of completeness
427 of our inventory. However, the possibility of improving the reliability should be
428 investigated further by adding more appropriate and relevant items to this factor.

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

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

446 As with all studies relying on retrospective self-report data, individuals filling in the
447 LEBA may have difficulties precisely recalling the inquired light-related behaviours. In
448 the interest of bypassing a substantial memory component, we limited the recall period

449 to four weeks and chose response options that do not require exact memory recall. In
450 contrast to directly assessing light properties via self-report, we assume that reporting
451 behaviours might be more manageable for inexperienced laypeople, as the latter does
452 not rely on existing knowledge about light sources. The comprehensibility of the LEBA is
453 also reflected by the Flesch-Kincaid grade level identification method (Flesch, 1948) that
454 suggested a minimum age of 8.33 years and an educational grade of four or higher (US
455 grading system). We argue that measuring light-related behaviours via self-report is
456 crucial because these behaviours will hardly be as observable by anyone else or
457 measurable with other methods (like behavioural observations) with reasonable effort.

458 Future Directions

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

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

471 Moreover, light-exposure-related behaviour might depend on the respondents'
472 profession, geographical location, housing conditions, socio-economic status, or other
473 contextual factors. As the current data is limited to our international online survey

474 context, future research should apply the LEBA across more variable populations and
475 contexts. On the other hand, this will require the development of cross-cultural
476 adaptations and translations into other languages of the LEBA, which should be targeted
477 in prospective studies.

478 Finally, in the future, the use of the LEBA instrument need not remain restricted to
479 gathering information in cross-sectional quantitative studies. The instrument can also be
480 used for individual behavioural profiling. For instance, the LEBA could be applied in a
481 clinical context as part of Cognitive Behavioural Therapy for Insomnia (CBT-I). More
482 specifically, it could be used to supplement the sleep hygiene aspects of CBT-I, as
483 receiving light exposure at different times has implications for sleep (Santhi & Ball,
484 2020). This match was also evident in the semantic relationship between the LEBA and
485 two scales capturing sleep problems (CIDI: Insomnia; Robins et al. (1988) & SDSC;
486 Bruni et al. (1996)) found in the semantic similarity analysis. However, before applying
487 the LEBA in such contexts in the future, more work is certainly needed to understand
488 light exposure-related behaviour and its' relationship to relevant health outcomes
489 measured subjectively and objectively.

490 Conclusion

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

498

Methods

499 **Data collection**

500 A quantitative cross-sectional, fully anonymous, geographically unconstrained
501 online survey was conducted via REDCap (Harris et al., 2019, 2009) by way of the
502 University of Basel sciCORE. Participants were recruited via the website
503 (<https://enlightenyourclock.org/participate-in-research>) of the science-communication
504 comic book “Enlighten your clock”, co-released with the survey (Weinzaepflen &
505 Spitschan, 2021), social media (i.e., LinkedIn, Twitter, Facebook), mailing lists, word of
506 mouth, the investigators’ personal contacts, and supported by the distribution of the
507 survey link via f.lux (F.lux Software LLC, 2021). The initial page of the online survey
508 provided information about the study, including that participation was voluntary and that
509 respondents could withdraw from participation at any time without being penalised.
510 Subsequently, consent was recorded digitally for the adult participants (>18 years), while
511 under-aged participants (<18 years) were prompted to obtain additional assent from their
512 parents/legal guardians. Filling in all questionnaires was estimated to take less than 30
513 minutes, and participation was not compensated.

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

524 **Analytic strategy**

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

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

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

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

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

566 To validate the latent structure obtained in the EFA, we conducted a categorical
567 confirmatory factor analysis (CFA) with the weighted least squares means and variance
568 adjusted (WLSMV) estimation (Desjardins & Bulut, 2018), using the “lavaan” package
569 (Rosseel, 2012) on the CFA sample. We assessed the model fit using standard model fit
570 guidelines: (i) χ^2 test statistics: a non-significant test statistics is required to accept the
571 model (ii) comparative fit index (CFI) and Tucker Lewis index (TLI): close to 0.95 or
572 above/ between 0.90-0.95 and above (iii) root mean square error of approximation
573 (RMSEA): close to 0.06 or below, (iv) Standardized root mean square (SRMR): close to
574 0.08 or below (Hu & Bentle, 1999; Schumacker & Lomax, 2004). However, the χ^2 test is
575 sensitive to sample size (T. A. Brown, 2015), and SRMR does not work well with ordinal
576 data (Yu, 2002). Consequently, we judged the model fit using CFI, TLI and RMSEA.

577 In order to evaluate whether the construct demonstrated psychometric equivalence

578 and the same meaning across native English speakers ($n=129$) and non-native English

579 speakers ($n=133$) in the CFA sample ($n=262$) (Kline, 2016; Putnick & Bornstein, 2016)

580 measurement invariance analysis was used. We used structural equation modelling

581 framework applying the “lavaan” package (Rosseel, 2012) to assess the measurement

582 invariance. We successively compared four nested models: configural, metric, scalar,

583 and residual models using the χ^2 difference test ($\Delta\chi^2$). Among MI models, the

584 configural model is the least restrictive, and the residual model is the most restrictive. A

585 non-significant $\Delta\chi^2$ test between two nested measurement invariance models indicates

586 mode fit does not significantly decrease for the superior model, thus allowing the

587 superior invariance model to be accepted (Dimitrov, 2010; Widaman & Reise, 1997).

588 **Fourthly**, in a secondary analysis, we identified the educational grade level (US

589 education system) required to understand the items in our inventory with the

590 Flesch-Kincaid grade level identification method (Flesch, 1948) applying the “koRpus”

591 (Michalke, 2021) package. Correspondingly, we analysed possible semantic overlap of

592 our developed inventory using the “Semantic Scale Network” (SSN) engine (Rosenbusch

593 et al., 2020). The SSN detects semantically related scales and provides a cosine

594 similarity index ranging between -.66 to 1 (Rosenbusch et al., 2020). Pairs of scales with

595 a cosine similarity index value of 1 indicate full semantical similarity, suggesting

596 redundancy.

597 **Lastly**, we derived a short form of the LEBA employing an Item Response Theory

598 (IRT) based analysis. We fitted each factor of the LEBA to the combined EFA and CFA

599 sample ($n=690$) using the graded response model (Samejima et al., 1997) via the “mirt”

600 package (Chalmers, 2012). IRT assesses the item quality by estimating the item

601 discrimination, item difficulty, item information curve, and test information curve (Baker &

602 Kim, 2017). Item discrimination indicates how well a particular item can differentiate

603 between participants across the given latent trait continuum (θ). Item difficulty

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

620 Ethical approval

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

627 Data availability

628 The present article is a fully reproducible open access “R Markdown” document. All
629 code and data underlying this article – along with two versions of the LEBA inventory (full
630 and short) and online survey implementation templates on common survey platforms – is
631 available under an open-access licence (Creative Commons CC-BY-NC-ND) on a public
632 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.

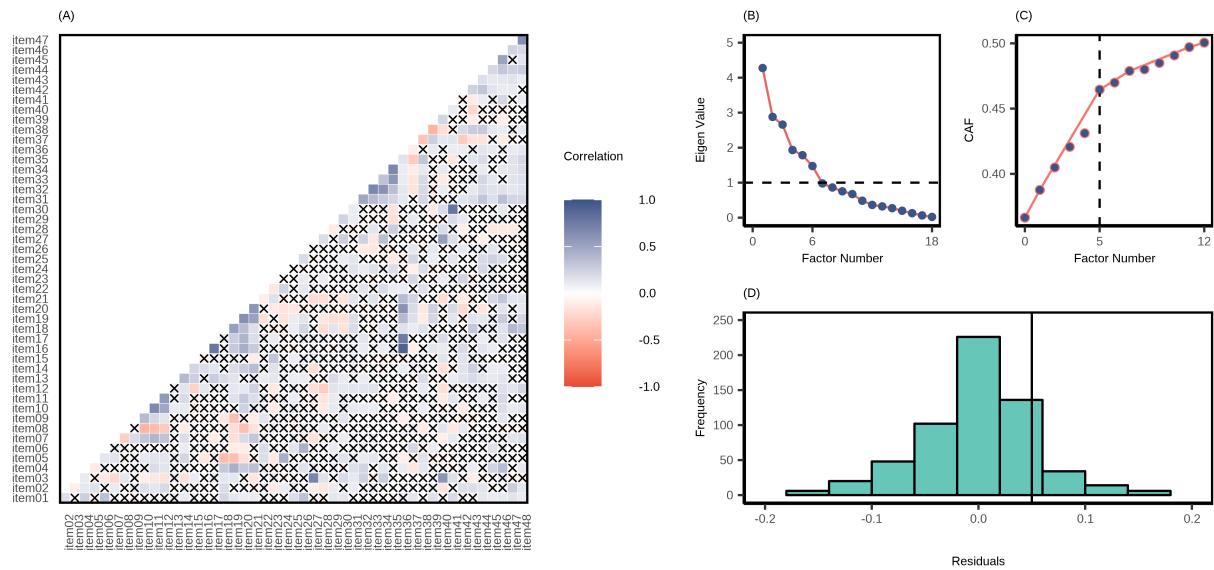


Figure 3. (A) Inter-item polychoric correlation coefficients for the 48 items. 4.9 % inter-item correlation coefficients were higher than $|.30|$. 'x' denotes non-significant correlation. (B) The Scree plot suggested six factors. (C) Hull method indicated that five factors were required to balance the 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.

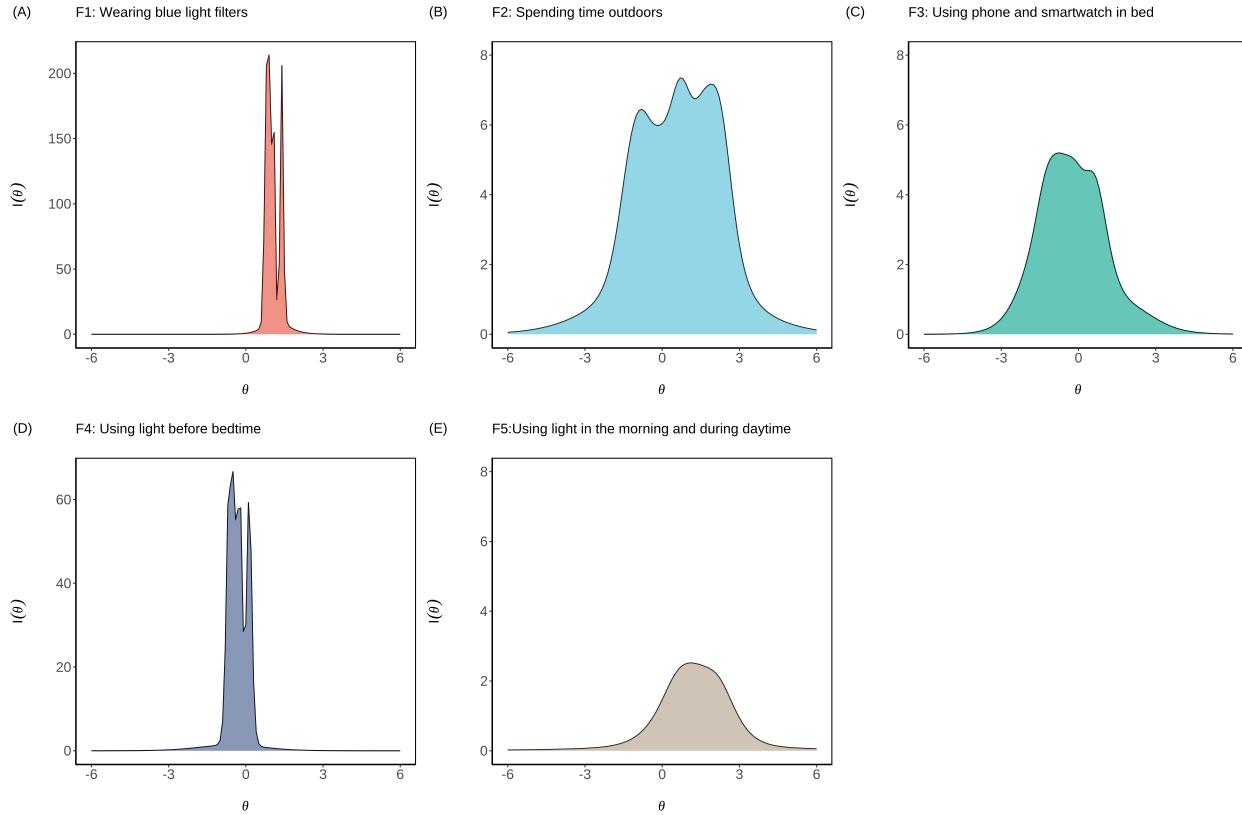


Figure 5. Test information curves for the five factors of LEBA: (A) wearing blue light filters (B) spending time outdoors (C) using a phone and smartwatch in bed (D) using light before bedtime (E) using light in the morning and during daytime. Along the x-axis, we plotted the underlying latent trait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

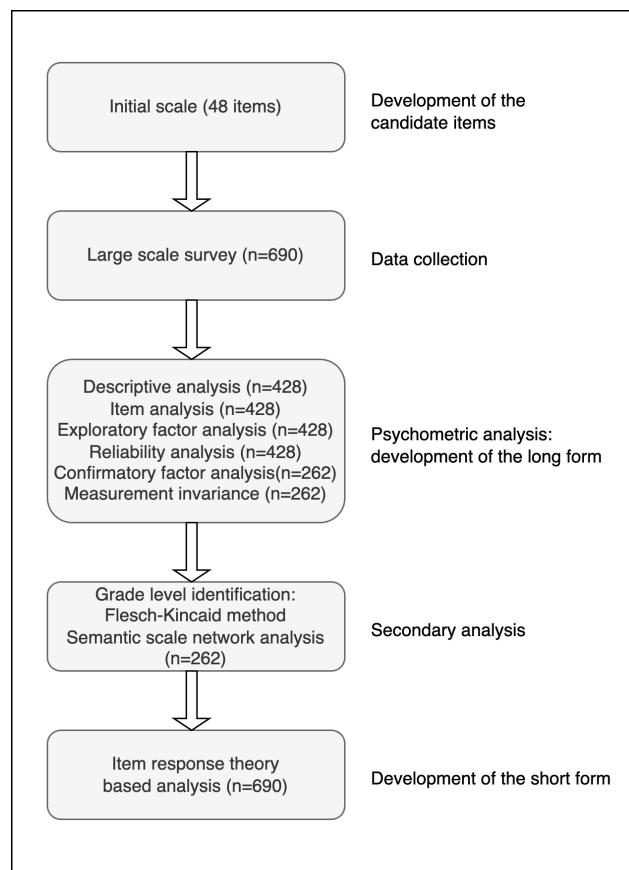


Figure 6. Flow chart of the LEBA (long and short form) development and evaluation.