

An inventory of human light exposure related behaviour

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54

Abstract

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

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

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

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

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

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89 **Introduction**

90 Light exposure received by the eyes affects many facets of human health,
91 well-being, and performance beyond visual sensation and perception¹. The
92 non-image-forming (NIF) effects of light comprise light's circadian and non-circadian
93 influence on several physiological and psychological functions, such as the secretion of
94 melatonin, sleep, mood, pupil size, body temperature, alertness, and higher cognitive
95 functions².

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, when
101 light sources cannot be directly manipulated, sought out, or avoided (for example, at
102 school, work, or in public places), there is still potential leeway to influence personal light
103 exposure behaviourally, for instance, by wearing sunglasses, directing one's gaze away
104 or supplementing the situation with additional light sources. Although clearly yielding the
105 potential for good, these behaviours are further associated with increased electric light
106 exposure at night and indoor time during the day, compromising the natural temporal
107 organisation of the light-dark cycle. For example, in the US, an average of 87% of the
108 time is spent in enclosed buildings³, and more than 80% of the population is exposed to
109 a night sky that is brighter than nights with a full moon due to electric light at night⁴.

110 An extensive body of scientific evidence suggests that improper light exposure may
111 be disruptive for health and well-being, giving rise to a series of adverse consequences,
112 including the alteration of hormonal rhythms, increased cancer rates, cardiovascular
113 diseases, and metabolic disorders, such as obesity and type II diabetes^{4–6}. These

114 findings have sparked a significant call for assessment and guidance regarding healthy
115 light exposure as exemplified by a recently published set of consensus-based experts'
116 recommendations with specific requirements for indoor light environments during the
117 daytime, evening, and nighttime⁷.

118 Furthermore, building on earlier attempts^{e.g. 8}, there was a recent push toward the
119 development and use of portable light loggers to improve ambulant light assessment and
120 gain more insight into the NIF effects of light on human health in field conditions^{9,10}.
121 Attached to different body parts (e.g., wrist; head, at eye level; chest), these light loggers
122 allow for the objective measurement of individual photic exposure patterns under
123 real-world conditions and thus are valuable tools for field studies. Nevertheless, these
124 devices also encompass limiting factors such as potentially being intrusive (e.g., when
125 eye-level worn), yielding the risk of getting covered (e.g., when wrist- or chest-worn) and
126 requiring (monetary) resources and expertise for acquisition and maintenance of the
127 devices. Moreover, it is important to note that portable light loggers alone do not collect
128 data on the specific behavioural patterns in relation to light exposure.

129 On the other hand, several attempts have been made to quantify received light
130 exposure subjectively with self-report questionnaires (Supplementary Table 1). However,
131 self-reporting light properties could be challenging for people who lack technical
132 knowledge of light sources. Moreover, it is worth considering that the human visual
133 system, unlike a photometer, continuously adapts to ambient brightness¹¹, while the
134 signals underlying the non-visual effects of light are independent from perception¹².
135 Retrospectively recalling the properties of a light source can further complicate such
136 subjective evaluations. Moreover, measuring light properties alone does not yield any
137 information about how individuals might behave differently regarding diverse light
138 environments such as work, home or outdoors.

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

140 Here, we present the development process of a novel self-reported inventory, the Light
141 Exposure Behaviour Assessment (LEBA), for characterizing diverse light
142 exposure-related behaviours. Notably, the focus of LEBA is not to estimate personal light
143 exposure. Instead, we aim to assess, in a scalable way, how people behave in relation to
144 light, focusing on habitual patterns that could guide behavioural interventions.

145 **Results**

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

148 **Development of the initial item pool**

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

155 **Measurement of light exposure behaviour in an online sample**

156 We conducted two rounds of large scale online survey between 17 May 2021 and 3
157 September 2021 to generate data from 690 participants with varied geographic locations
158 (countries=74; time-zone=28). For a complete list of geographic locations, see
159 **Supplementary Table 2**. Table 1 presents the survey participants' demographic
160 characteristics. Only participants completing the full LEBA inventory were included. We
161 used the data from first round for the exploratory factor analysis (EFA sample; n=428)
162 and data from the second round was used in the confirmatory factor analysis (CFA

sample; n=262). Participants in our survey were aged between 11 to 84 years, with an overall mean of ~ 32.95 years of age [Overall: 32.95 ± 14.57 ; EFA: 32.99 ± 15.11 ; CFA: 32.89 ± 13.66]. In the entire sample, 351 (51%) were male, 325 (47%) were female, 14 (2.0%) reported other sex, and 49 (7.2%) reported a gender-variant identity. In a “Yes/No” question regarding native language, 320 (46%) of respondents [EFA: 191 (45%); CFA: 129 (49%)] indicated to be native English speakers. For their “Occupational Status”, more than half of the overall sample (396 (57%)) reported that they currently work, whereas 174 (25%) reported that they go to school, and 120 (17%) responded that they do “Neither”. With respect to the COVID-19 pandemic, we asked participants to indicate their occupational setting during the last four weeks: In the entire sample, 303 (44%) of the participants indicated that they were in a home office/ home schooling setting, 109 (16%) reported face-to-face work/schooling, 147 (21%) reported a combination of home- and face-to-face work/schooling, and 131 (19%) filled in the “Neither (no work or school, or on vacation)” response option.

177 Psychometric analysis: Development of the long form

178 **Descriptive statistics and item analysis.** We observed that the response patterns
179 of LEBA inventory for the entire sample (n=690) were not normally distributed (Figures 1
180 and 2). All items violated both univariate¹³ and multivariate normality¹⁴. The multivariate
181 skewness was 488.40 ($p < 0.001$) and the multivariate kurtosis was 2,808.17 ($p < 0.001$).

182 Similarly, non-normal distribution of response pattern was also observed in the EFA
183 sample. **Supplementary Figure 1** depicts the univariate descriptive statistics for the EFA
184 sample (n=428). Further, We observed that each item’s correlation with the aggregated
185 sum of the 48-item’s score varied largely (corrected item-total correlation= 0.03 -0.48)
186 indicating the possibility of multi-factor structure of the LEBA inventory.

187 **Exploratory factor analysis and reliability analysis.** Exploratory analysis revealed
188 that items of LEBA inventory can be categorized into five major factors: (i) wearing blue

189 light filters; (ii) spending time out doors; (iii) using phone and smartwatch in bed; (iv)
190 using light before bedtime (v) using light in the morning and during daytime. In this stage
191 of analysis, we retained 25 items. the first factor had three items and encapsulated the
192 individual's preference for using blue light filters in different light environments. The
193 second factor contained six items that incorporated the individuals' hours spent
194 outdoors. The third factor contained five items that looked into specific behaviours of
195 using a phone and smartwatch in bed. The fourth factor comprised five items
196 investigated the other behaviours related to the individual's electric light exposure before
197 bedtime. Lastly, the fifth factor encompassed six items capturing the individual's morning
198 and daytime light exposure-related behaviour.

199 Prior to conducting the EFA, we have checked the post-hoc sampling adequacy by
200 applying Kaiser-Meyer-Olkin (KMO) measures of sampling adequacy on the EFA sample
201 ($n=428$)¹⁵ and the quality of the correlation matrix by Bartlett's test of sphericity¹⁶.
202 KMO>0.50 would indicate adequate sample size¹⁷ and a significant test of sphericity
203 would indicate satisfactory quality of the correlation matrix . Results indicated that we
204 had an adequate sample size (KMO=0.63) and correlation matrix ($\chi^2_{1128}=5042.86$, $p<$
205 0.001). However, 4.96% of the inter-item correlation coefficients were greater than
206 |0.30|, and the inter-item correlation coefficients ranged between -0.44 to 0.91. Figure
207 3-A depicts the respective correlation matrix. To identify how many factors are required
208 to optimally express human light exposure related behaviours we used a combination of
209 methods. the Scree plot (Figure 3-B) revealed a six-factor solution, whereas the
210 minimum average partial (MAP) method¹⁸ (Supplementary Table 3) and Hull method¹⁹
211 implied a five-factor solution (Figure 3-C). Hence, we tested both five-factor and
212 six-factor solutions using iterative EFA where we gradually identified and discarded
213 problematic items (factor-loading <0.30 and cross-loading >0.30). In this process, we
214 found a five-factor structure for LEBA inventory with 25 items. Table 2 displays the
215 factor-loading (λ) and communality of the items. Both factor loadings and commonalities

216 advocate to accept this five-factor solution ($|\lambda|=0.32-0.99$; commonalities=0.11-0.99).
217 These five factors explains 10.25%, 9.93%, 8.83%, 8.44%, 6.14% of the total variance in
218 individual's light exposure related behaviours respectively. All factors exhibited excellent
219 to satisfactory reliability (ordinal $\alpha=0.94, 0.76, 0.75, 0.72, 0.62$ respectively). The entire
220 inventory also exhibited satisfactory reliability ($\omega_t=0.77$).

221 However, the histogram of the absolute values of nonredundant residual
222 correlations (Figure 3-D) displayed that 26% of correlations were greater $>|0.05|$,
223 indicating a possible under-factoring.²⁰ Subsequently, we fitted a six-factor solution,
224 where a factor with only two salient variables emerged, thus disqualifying the six-factor
225 solution (Supplementary Table 4). While making the judgement of accepting this
226 five-factor solution we considered both factor's interpretability and their psychometric
227 properties. We deemed the five derived factors as highly interpretable and relevant
228 concerning our aim to capture light exposure-related behaviour, we retained all of them
229 with 25 items. Two of the items showed negative factor-loading (item 08: I spend 30
230 minutes or less per day (in total) outside. and item 37: I use a blue-filter app on my
231 computer screen within 1 hour before attempting to fall asleep.). Upon re-inspection, we
232 recognized these items to be negatively correlated to the respective factor, and thus, we
233 reverse-scored these two items.

234 **Confirmatory factor analysis.** To investigate the structural validity of the five-factor
235 structure obtained in EFA, we conducted a confirmatory factor analysis (CFA) on the
236 CFA sample. The five-factor structure with 25 items showed acceptable fit (Table 3)
237 providing evidence of structural validity (CFI=0.92; TLI=0.91; RMSEA=0.07 [0.06-0.07,
238 90% CI]). Two equity constraints were imposed on item pairs 32-33 (item 32: I dim my
239 mobile phone screen within 1 hour before attempting to fall asleep; item 33: I dim my
240 computer screen within 1 hour before attempting to fall asleep) and 16-17 (item 16: I
241 wear blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day; item
242 17: I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the

243 day). Item pair 32-33 describes the preference for dimming the electric devices'
244 brightness before bedtime, whereas item pair 16-17 represents the use of blue filtering
245 or coloured glasses during the daytime. Given the similar nature of captured behaviours
246 within each item pair, we accepted the imposed equity constraints. Nevertheless, the
247 SRMR value exceeded the guideline recommendation (SRMR=0.12). In order to
248 improve the model fit, we conducted a post-hoc model modification. Firstly, the
249 modification indices suggested cross-loadings between item 37 and 26 (item 37: I
250 purposely leave a light on in my sleep environment while sleeping; item 26: I turn on my
251 ceiling room light when it is light outside), which were hence discarded. Secondly, items
252 30 and 41 (item 30: I look at my smartwatch within 1 hour before attempting to fall
253 asleep; item 41: I look at my smartwatch when I wake up at night) showed a tendency to
254 co-vary in their error variance ($MI=141.127$, $p<0.001$). By allowing the latter pair of items
255 (30 & 41) to co-vary, the model's error variance attained an improved fit ($CFI=0.95$;
256 $TLI=0.95$); $RMSEA=0.06$ [0.05-0.06, 90% CI]; $SRMR=0.11$).

257 Accordingly, we accept the five-factor model with 23 items, finalizing the long Form
258 of LEBA inventory (see **Supplementary File 1**). Internal consistency ordinal α for the five
259 factors of the LEBA were 0.96, 0.83, 0.70, 0.69, 0.52, respectively. The reliability of the
260 total inventory was satisfactory ($\omega_t=0.68$). Figure 4 depicts the obtained CFA structure,
261 while **Supplementary Figure 2** depicts the data distribution and endorsement pattern of
262 the retained 23 items in our CFA sample.

263 **Measurement invariance.** We reported the measurement invariance (MI) analysis
264 on the CFA sample based on native ($n=129$) and non-native English speakers ($n=133$).
265 A detailed demographic description are provided in **Supplementary Table 5**. Our MI
266 results (Table 4) indicated that LEBA inventory demonstrated highest level of (residual
267 model) psychometric equivalence across native and non-native English speaking
268 participants, thus permitting group-mean based comparisons. The four fitted MI models
269 generated acceptable fit indices and the model fit did not significantly decrease across

270 the nested models ($\Delta CFI > -0.01$; $\Delta RMSEA < 0.01$).

271 **Secondary analysis: Grade level identification and semantic scale network analysis**

272 We investigated the language-based accessibility of LEBA using Flesch-Kincaid
273 grade level analysis²¹. Results indicated that at least a language proficiency of
274 educational grade level-four (US education system) with age above eight years are
275 required to comprehend the items used in LEBA inventory. Semantic Scale analysis²²
276 was administered to assess the LEBA's (23 items) semantic relation to other
277 questionnaires. LEBA inventory was most strongly semantically related to scales about
278 sleep: The "Sleep Disturbance Scale For Children"²³ and the "Composite International
279 Diagnostic Interview (CIDI): Insomnia"²⁴. The cosine similarity index ranged between
280 0.47 to 0.51.

281 **Developing a short form of LEBA: IRT-based analysis**

282 Our aim was to provide a data-driven approach to reducing the number of items for
283 cases where a small reduction of items is necessary. In order to derive a short form of
284 the LEBA inventory, we fitted each factor of the LEBA with the graded response model²⁵
285 to the combined EFA and CFA sample (n=690). The resulting item discrimination
286 parameters of the inventory fell into categories of "very high" (10 items), "high" (4 items),
287 "moderate" (4 items), and "low" (5 items), indicating a good range of discrimination along
288 the latent trait level (θ) (Supplementary Table 6). An examination of the item information
289 curve (Supplementary Figure 3) revealed five items (1, 25, 30, 38, & 41) provided very
290 low information regarding light exposure related behaviours with relatively flat curves
291 ($I(\theta) < 0.20$). We discarded those items, culminating in a short form of LEBA with five
292 factors and 18 items (Supplementary File 2).

293 Subsequently, we obtained five test information curves (TICs). As Figure 5

294 illustrates, the TICs of the first and fifth factors peaked on the right side of the centre of
295 their latent traits, while the TICs of the other three factors were roughly centred on the
296 respective trait continuum (θ). This points out that the LEBA short-form estimates the
297 light exposure-related behaviour most precisely near the centre of the trait continuum for
298 the second, third and fourth factors. In contrast, for the first and fifth factors the TICs
299 were left skewed indicating their increased sensitivity in identifying people who are
300 engaging more in those particular light exposure related behaviour dimensions²⁶.

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

306 Discussion

307 We have developed two versions of a self-report inventory, LEBA, that can capture
308 light exposure-related behaviours in multiple dimensions. The 48 generated items were
309 applied in a large-scale, geographically unconstrained, cross-sectional study, yielding
310 690 completed surveys. To assure high data quality, participant responses were only
311 included when the five “attention check items” throughout the survey were passed.
312 Ultimately, data was recorded from 74 countries and 28 time zones, including native and
313 non-native English speakers from a sex-balanced and age-diverse sample (see Table 1).
314 The acquired study population complied with our objective to avoid bias from a selective
315 sample, which is crucial when relying on voluntary uncompensated participation.

316 Data collected in the first round was used to explore the latent structure (EFA
317 sample; n=428). The exploratory factor analysis revealed a highly interpretable
318 five-factor solution (“Wearing blue light filters”, “Spending time outdoors”, “Using phone

319 and smartwatch in bed”, “Using light before bedtime”, and “Using light in the morning and
320 during daytime”) with 25 items. Our CFA analysis (CFA sample; n=262) confirmed the
321 five-factor structure we obtained in our EFA, thus providing evidence for structural
322 validity.(CFI=0.95; TLI=0.95; RMSEA=0.06). In this model, we discarded two more items
323 (item 26 & 37) for possible cross-loadings. As a rule of thumb, reliability coefficients
324 higher than .70 are regarded as “satisfactory”. However, at the early developmental
325 stage, a value of .50 is considered acceptable²⁷⁻²⁹. Thus, we confer, the internal
326 consistency coefficients ordinal alpha for the five factors and the total inventory were
327 satisfactory (Ordinal alpha ranged between 0.52 to 0.96; McDonald’s ω_t =0.68).

328 The results of the measurement invariance analysis indicate that the construct
329 “Light exposure-related behaviour” is equivalent across native and non-native English
330 speakers and thus suitable for assessment in both groups. Furthermore, according to
331 the grade level identification method, the LEBA appears understandable for students at
332 least 8.33 years of age visiting grade four or higher. Interestingly, the semantic similarity
333 analysis (“Semantic Scale Network” database²²) revealed that the “LEBA” is
334 semantically related to the “Sleep Disturbance Scale For Children” (SDSC)²³ and the
335 “Composite International Diagnostic Interview (CIDI): Insomnia”²⁴. Upon inspecting the
336 questionnaire contents, we found that some items in the factors “Using phone and
337 smartwatch in bed” and “Using light before bedtime” have semantic overlap with the
338 SDSC’s and CIDI’s items. However, while the CIDI and the SDSC capture various
339 clinically relevant sleep problems and related activities, the LEBA aims to assess
340 light-exposure-related behaviour. Since light exposure at night has been shown to
341 influence sleep negatively^{7,30}, this overlap confirms our aim to measure the
342 physiologically relevant aspects of light-exposure-related behaviour. Nevertheless, the
343 general objectives of the complete questionnaires and the LEBA differ evidently.

344 While developing and validating LEBA, we have complemented conventional
345 approaches with an Item Response Theory (IRT) analysis. IRT provides a framework to

346 interpret respondents' obtained scores in the light of latent ability (i.e. light exposure
347 behaviour) and the characteristics of the respondents – how they interpret the items³¹.
348 The benefit of implementing IRT analysis was twofold. First, we derived a shorter form of
349 LEBA (18 items). We fitted a graded response model to the combined EFA and CFA
350 sample (n=690) and discarded five items (1, 25, 30, 38, & 41) with relatively flat item
351 information curve [$I(\theta) < .20$]. The resulting test information curves suggest that the
352 short-LEBA is a psychometrically sound measure with adequate coverage of underlying
353 traits and can be applied to capture the frequency of different light exposure related
354 behaviours reliably. Often, psychological measurements require application of several
355 questionnaires simultaneously. Responding to several lengthy questionnaires increases
356 the participants losing focus and becoming tired. Thus, in some circumstances, reducing
357 the number of items even slightly may be necessary to employ the LEBA questionnaire.
358 Our aim was to provide a data-driven approach to reducing the number of items, apart
359 from the possibility of excluding a specific factor from the 23-item questionnaire.
360 Nonetheless, where possible, we strongly recommend using the extended form of the
361 questionnaire to avoid limiting the range of gained information.

362 The IRT analysis enabled us to capture individual differences in responding to the
363 items of LEBA. Findings from the item and person fit index analysis demonstrate that all
364 five fitted models were acceptable and provide evidence of validity for the factors. In
365 addition, the diverse item discrimination parameters indicate an appropriate range of
366 discrimination – the ability to differentiate respondents with different levels of light
367 exposure-related behaviour while acknowledging the interpersonal variability in
368 understanding the item.

369 Known limitations

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

371 The fifth factor, “using light in the morning and during daytime”, exhibited low
372 internal consistency both in the exploratory and confirmatory factor analysis (EFA: 0.62;
373 CFA:0.52). Since, it was above .50, considering the developmental phase of this
374 inventory we accepted the fifth factor. This particular factor captures our behaviour
375 related to usages of light in the morning and daytime. Since, light exposure during
376 morning and daytime influences our alertness and cognition^{32,33}, we deemed capturing
377 these behaviours is essential for the sake of completeness of our inventory. However,
378 the possibility of improving the reliability should be investigated further by adding more
379 appropriate and relevant items to this factor.

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

389 As with all studies relying on retrospective self-report data, individuals filling in the
390 LEBA may have difficulties precisely recalling the inquired light-related behaviours. In
391 the interest of bypassing a substantial memory component, we limited the recall period
392 to four weeks and chose response options that do not require exact memory recall. In
393 contrast to directly assessing light properties via self-report, we assume that reporting
394 behaviours might be more manageable for inexperienced laypeople, as the latter does
395 not rely on existing knowledge about light sources. The comprehensibility of the LEBA is
396 also reflected by the Flesch-Kincaid grade level identification method²¹ that suggested a
397 minimum age of 8.33 years and an educational grade of four or higher (US grading

398 system). We argue that measuring light-related behaviours via self-report is crucial
399 because these behaviours will hardly be as observable by anyone else or measurable
400 with other methods (like behavioural observations) with reasonable effort.

401 It is important to note that LEBA utilizes a five-point Likert-type response scale
402 which may be susceptible to central tendency bias, i.e. responses are biased towards
403 the central value of the response scale. Future work should evaluate other methods of
404 obtaining responses, such as using a visual-analogue scale.

405 Finally, there is limited evidence for convergent validity. LEBA being the first of its
406 kind in characterising light exposure *behaviour* at present lacks a gold standard against
407 which its convergent validity evidence could be established. A recent study³⁴
408 demonstrated the predictive validity of LEBA by successfully relating its factors to
409 self-reported chronotype, mood, sleep quality, and cognitive function. The results of their
410 study confirmed that light-related behaviours, as captured by LEBA, could led to different
411 light exposure experiences that differentially influence health, wellness and performance.
412 Further work will need to establish convergent validity of LEBA further.

413 Future directions

414 To our knowledge, the LEBA is the first inventory characterising light
415 exposure-related behaviour in a scalable manner. Further evidence for the validity of the
416 LEBA could be obtained by administering it conjointly with objective field measurements
417 of light exposure (e.g. with portable light loggers/wearables), smartphone readouts, as
418 well as subjective data in the form of 24-hour recalls. Such a study could related the
419 relationship bewteen (subjectively measured) light exposure-related behavioural patterns
420 translate into (objectively measured) received light exposure, smartphone use, and how
421 closely the retrospective questionnaire relates to daily reports of these behaviours.

422 Conclusion

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

430 Methods

431 Data collection

432 A quantitative cross-sectional, fully anonymous, geographically unconstrained
433 online survey was conducted via REDCap^{35,36} by way of the University of Basel
434 sciCORE. Participants were recruited via the website
435 (<https://enlightenyourclock.org/participate-in-research>) of the science-communication
436 comic book “Enlighten your clock”, co-released with the survey³⁷, social media (i.e.,
437 LinkedIn, Twitter, Facebook), mailing lists, word of mouth, the investigators’ personal
438 contacts, and supported by the distribution of the survey link via f.lux³⁸. The initial page
439 of the online survey provided information about the study, including that participation was
440 voluntary and that respondents could withdraw from participation at any time without
441 being penalised. Subsequently, consent was recorded digitally for the adult participants
442 (>18 years), while under-aged participants (<18 years) were prompted to obtain
443 additional assent from their parents/legal guardians. Filling in all questionnaires was
444 estimated to take less than 30 minutes, and participation was not compensated.

445 As a part of the demographic data, participants provided information regarding age,
446 sex, gender identity, occupational status, COVID-19-related occupational setting, time

447 zone/country of residence and native language. The demographic characteristics of our
448 sample are given in Table 1. Participants were further asked to confirm that they
449 participated in the survey for the first time. All questions incorporating retrospective
450 recall were aligned to a “past four weeks” period. Additionally, four attention check items
451 were included among the questionnaires to ensure high data quality, with the following
452 phrasing: - We want to make sure you are paying attention. What is 4+5? - [...] Please
453 select “Strongly disagree” here. - [...] Please type in “nineteen” as a number. - [...]
454 Please select “Does not apply/I don’t know.” here.

455 **Analytic strategy**

456 Figure 6 summarises the steps we followed while developing the LEBA. We
457 conducted all analyses with the statistical software environment R.

458 (1) We set an item pool of 48 items with a six-point Likert-type response format
459 (0-Does not apply/I don’t know, 1-Never, 2-Rarely 3-Sometimes, 4-Often,
460 5-Always) for our initial inventory. Our purpose was to capture light
461 exposure-related behaviour. In that context, the first two response options: “Does
462 not apply/I don’t know” and “Never”, provided similar information. As such, we
463 collapsed them into one, making it a 5-point Likert-type response format (1-Never,
464 2-Rarely, 3-Sometimes, 4-Often, 5-Always).

465 (2) Two rounds of data collection were administered. In the first round (EFA sample;
466 n=428) we collected data for the exploratory factor analysis (EFA). A sample of at
467 least 250-300 is recommended for EFA^{39,40}. The EFA sample exceeded this
468 recommendation. The second round data (CFA sample; n=262) was subjected to
469 confirmatory factor analysis (CFA). To assess sampling adequacy for CFA, we
470 followed the N:q rule^{41–44}, where at least ten participants per item are required to
471 earn trustworthiness of the result. Again, our CFA sample exceeded this guidelines.

(3) We conducted descriptive and item analyses and proceeded to EFA on the EFA sample. Prior to the EFA, the necessary assumptions, including sample adequacy, normality assumptions, and quality of correlation matrix, were assessed. As our data violated both the univariate and multivariate normality assumption and yielded ordinal response data, we used a polychoric correlation matrix in the EFA and employed “principal axis” (PA) as the factor extraction method^{20,45}. We applied a combination of methods, including a Scree plot⁴⁶, minimum average partials method¹⁸, and Hull method¹⁹ to identify factor numbers. To determine the latent structure, we followed the common guidelines: (i) no factors with fewer than three items (ii) no factors with a factor loading <0.3 (iii) no items with cross-loading > .3 across factors⁴⁷.

Though Cronbach’s internal consistency coefficient alpha is widely used for estimating internal consistency, it tends to deflate the estimates for Likert-type data since the calculation is based on the Pearson-correlation matrix, which requires response data to be continuous in nature^{48,49}. Subsequently, we reported ordinal alpha for each factor obtained in the EFA which was suggested as a better reliability estimate for ordinal data⁴⁹. We also estimated the internal consistency reliability of the total inventory using McDonald’s ω_t coefficient, which was suggested as a better reliability estimate for multidimensional constructs^{50,51}. Both ordinal alpha and McDonald’s ω_t coefficient values range between 0 to 1, where higher values represent better reliability.

To validate the latent structure obtained in the EFA, we conducted a categorical confirmatory factor analysis (CFA) with the weighted least squares means and variance adjusted (WLSMV) estimation²⁰ on the CFA sample. We assessed the model fit using standard model fit guidelines: (i) χ^2 test statistics: a non-significant test statistics is required to accept the model (ii) comparative fit index (CFI) and Tucker Lewis index (TLI): close to 0.95 or above/ between 0.90-0.95 and above (iii) root mean square error

498 of approximation (RMSEA): close to 0.06 or below, (iv) Standardized root mean square
499 (SRMR): close to 0.08 or below^{52,53}. However, the χ^2 test is sensitive to sample size⁵⁴,
500 and SRMR does not work well with ordinal data⁵⁵. Consequently, we judged the model fit
501 using CFI, TLI and RMSEA.

502 In order to evaluate whether the construct demonstrated psychometric equivalence
503 and the same meaning across native English speakers (n=129) and non-native English
504 speakers (n=133) in the CFA sample (n=262)^{43,56} measurement invariance analysis was
505 used. We used structural equation modelling framework to assess the measurement
506 invariance. We successively compared four nested models: configural, metric, scalar,
507 and residual models using the χ^2 difference test ($\Delta\chi^2$). Among MI models, the
508 configural model is the least restrictive, and the residual model is the most restrictive. A
509 non-significant $\Delta\chi^2$ test between two nested measurement invariance models indicates
510 mode fit does not significantly decrease for the superior model, thus allowing the
511 superior invariance model to be accepted^{57,58}.

512 (4) In a secondary analysis, we identified the educational grade level (US education
513 system) required to understand the items in our inventory with the Flesch-Kincaid
514 grade level identification method²¹. Correspondingly, we analysed possible
515 semantic overlap of our developed inventory using the “Semantic Scale Network”
516 (SSN) engine²². The SSN detects semantically related scales and provides a
517 cosine similarity index ranging between -.66 to 1²². Pairs of scales with a cosine
518 similarity index value of 1 indicate full semantical similarity, suggesting redundancy.

519 (5) We derived a short form of the LEBA employing an Item Response Theory (IRT)
520 based analysis. We fitted each factor of the LEBA to the combined EFA and CFA
521 sample (n=690) using the graded response model²⁵. IRT assesses the item quality
522 by estimating the item discrimination, item difficulty, item information curve, and
523 test information curve²⁶. Item discrimination indicates how well a particular item

can differentiate between participants across the given latent trait continuum (θ). Item difficulty corresponds to the latent trait level at which the probability of endorsing a particular response option is 50%. The item information curve (IIC) indicates the amount of information an item carries along the latent trait continuum. Here, we reported the item difficulty and discrimination parameter and categorized the items based on their item discrimination index: (i) none=0; (ii) very low=0.01 to 0.34; (iii) low=0.35 to 0.64; (iv) moderate=0.65 to 1.34 ; (v) high=1.35 to 1.69; (vi) very high $>1.70^{26}$. We discarded the items with a relatively flat item information curve (information $<.2$) to derive the short form of LEBA. We also assessed the precision of the short LEBA utilizing the test information curve (TIC). TIC indicates the amount of information a particular scale carries along the latent trait continuum. Additionally, the item and person fit of the fitted IRT models were analysed to gather more evidence on the validity and meaningfulness of our scale²⁰. The item fit was evaluated using the RMSEA value obtained from Signed- χ^2 index implementation, where an RMSEA value $\leq .06$ was considered an adequate item fit. The person fit was estimated employing the standardized fit index Z_h statistics⁵⁹. Here, $Z_h < -2$ was considered as a misfit⁵⁹.

541 Ethical approval

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

548 **Code, materials and data availability**

549 The present article is a fully reproducible open access “R Markdown” document. All
550 code and data underlying this article is available on a public GitHub repository. The
551 English version of long and short form of LEBA inventory and online survey
552 implementation templates on common survey platforms (Qualtrics and REDCap) – is
553 available on another public GitHub repository as well as on the dedicated website of the
554 LEBA inventory under an open-access licence (Creative Commons CC-BY-NC-ND).

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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	643.06	458.00	0.95	0.95	0.06	0.04	0.07	18.254a	16	0.309
Scalar	711.87	522.00	0.95	0.95	0.05	0.04	0.06	68.221b	64	0.336
Residual	711.87	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 01-24											
Items	Stem	Summary Statistics			Graphics		Response Pattern				
		Mean	SD	SW [†]	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)

[†] 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	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.

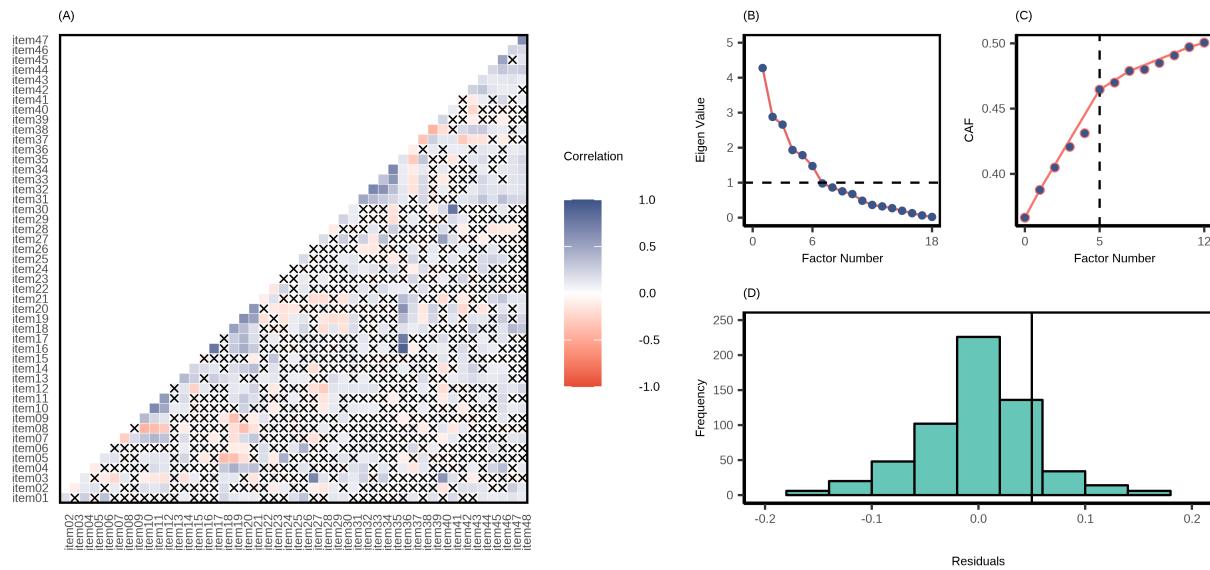


Figure 3. (A) Inter-item polychoric correlation coefficients for the 48 items. 4.9 % inter-item correlation coefficients were higher than $|.30|$. 'x' denotes non-significant correlation. (B) The Scree plot suggested six factors. (C) Hull method indicated that five factors were required to balance the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

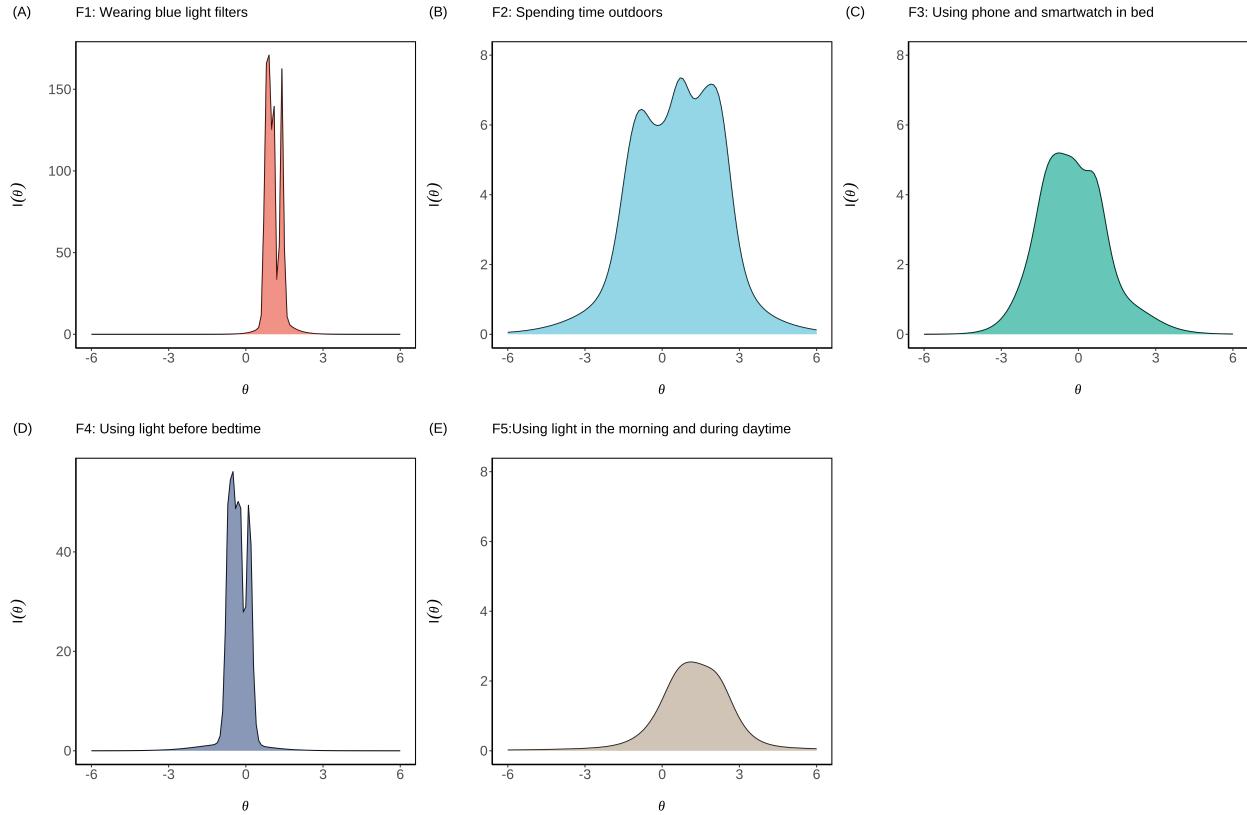


Figure 5. Test information curves for the five factors of LEBA: (A) wearing blue light filters (B) spending time outdoors (C) using a phone and smartwatch in bed (D) using light before bedtime (E) using light in the morning and during daytime. Along the x-axis, we plotted the underlying latent trait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

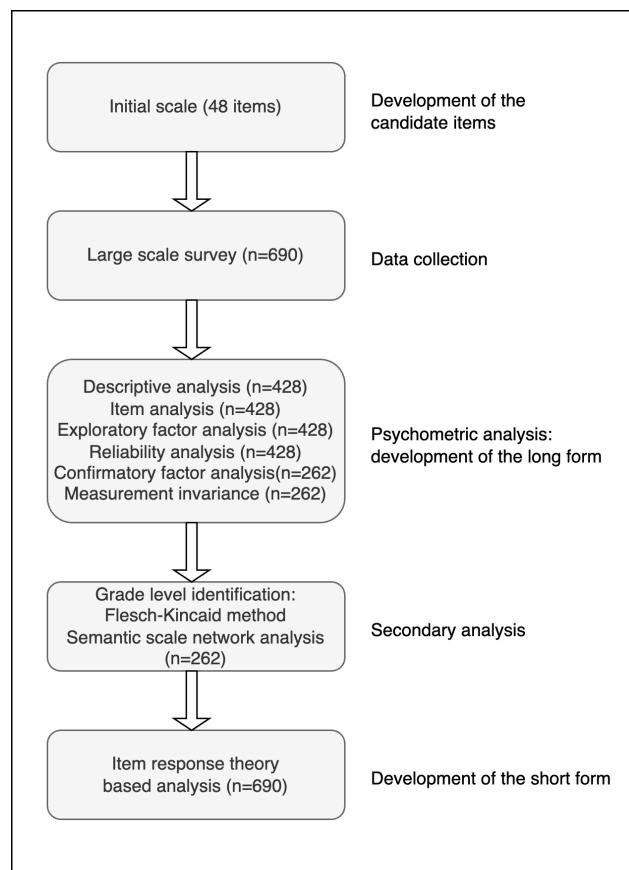


Figure 6. Flow chart of the LEBA (long and short form) development and evaluation.