

1 An inventory of human light exposure related behaviour

2

3

4 Abstract

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

12 An expert panel prepared the initial 48-item pool spanning different light exposure-related
13 behaviours. Responses, consisting of rating the frequency of engaging in the per-item
14 behaviour on a 5-point Likert type scale, were collected in an online survey yielding
15 responses from a geographically unconstrained sample (690 completed responses, 74
16 countries, 28 time zones). The exploratory factor analysis (EFA) on an initial subsample
17 ($n=428$) rendered a five-factor solution with 25 items (Wearing blue light filters, spending
18 time outdoors, using a phone and smartwatch in bed, using light before bedtime, using
19 light in the morning and during daytime). In a confirmatory factor analysis (CFA)
20 performed on an independent subset of participants ($n=262$), we removed two additional
21 items to attain the best fit for the five-factor solution ($CFI=0.95$, $TLI=0.95$, $RMSEA=0.06$).
22 The internal consistency reliability coefficient for the total instrument yielded McDonald's
23 $\Omega=0.68$. Measurement model invariance analysis between native and non-native
24 English speakers showed our model attained the highest level of invariance (residual
25 invariance $CFI=0.95$, $TLI=0.95$, $RMSEA=0.05$). Lastly, a short form of the LEBA ($n=18$)
26 was developed using Item Response Theory on the complete sample ($n=690$).

27 The psychometric properties of the LEBA indicate the usability to measure light
28 exposure-related behaviours. The instrument may offer a scalable solution to
29 characterize behaviours that influence individual photic exposure patterns in remote

³⁰ samples. The LEBA inventory is available under the open-access CC-BY-NC-ND
³¹ license.

³² Instrument webpage: <https://leba-instrument.org/> GitHub repository containing this
³³ manuscript: <https://github.com/leba-instrument/leba-manuscript>

³⁴ *Keywords:* light exposure, light-related behaviours, non-visual effects of light,
³⁵ psychometrics

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38 **Introduction**

39 Light exposure received by the eyes affects many facets of human health,
40 well-being, and performance beyond visual sensation and perception (Boyce, 2022).
41 The non-image-forming (NIF) effects of light comprise light's circadian and non-circadian
42 influence on several physiological and psychological functions, such as the secretion of
43 melatonin, sleep, mood, pupil size, body temperature, alertness, and higher cognitive
44 functions (Blume, Garbazza, & Spitschan, 2019).

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

60 An extensive body of scientific evidence suggests that improper light exposure may
61 be disruptive for health and well-being, giving rise to a series of adverse consequences,
62 including the alteration of hormonal rhythms, increased cancer rates, cardiovascular

63 diseases, and metabolic disorders, such as obesity and type II diabetes (Chellappa,
64 Vujovic, Williams, & Scheer, 2019; Lunn et al., 2017; Navara & Nelson, 2007). These
65 findings have sparked a significant call for assessment and guidance regarding healthy
66 light exposure as exemplified by a recently published set of consensus-based experts'
67 recommendations with specific requirements for indoor light environments during the
68 daytime, evening, and nighttime (T. M. Brown et al., 2022).

69 Furthermore, building on earlier attempts (e.g. Hubalek, Zöschg, & Schierz, 2006),
70 there was a recent push toward the development and use of portable light loggers to
71 improve ambulant light assessment and gain more insight into the NIF effects of light on
72 human health in field conditions (Hartmeyer, Webler, & Andersen, 2022; Spitschan et al.,
73 2022). Attached to different body parts (e.g., wrist; head, at eye level; chest), these light
74 loggers allow for the objective measurement of individual photic exposure patterns under
75 real-world conditions and thus are valuable tools for field studies. Nevertheless, these
76 devices also encompass limiting factors such as potentially being intrusive (e.g., when
77 eye-level worn), yielding the risk of getting covered (e.g., when wrist- or chest-worn) and
78 requiring (monetary) resources and expertise for acquisition and maintenance of the
79 devices. Moreover, it is important to note that portable light loggers alone do not collect
80 data on the specific behavioural patterns in relation to light exposure.

81 On the other hand, several attempts have been made to quantify received light
82 exposure subjectively with self-report questionnaires (**Supplementary Table 1**),
83 bypassing the cost and intrusiveness issues. However, self-reporting light properties
84 could be challenging for people who lack technical knowledge of light sources.
85 Moreover, individuals may need to consider that, unlike a photometer, the human visual
86 system continuously adapts to brightness (Hurvich & Jameson, 1966), while the signals
87 underlying the non-visual effects of light are independent from perception (Allen,
88 Hazelhoff, Martial, Cajochen, & Lucas, 2018). Retrospectively recalling the properties of
89 a light source can further complicate such subjective evaluations. Moreover, measuring

90 light properties alone does not yield any information about how individuals might behave
91 differently regarding diverse light environments such as work, home or outdoors.

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

93 Here, we present the development process of a novel self-reported inventory, the Light
94 Exposure Behaviour Assessment (LEBA), for characterizing diverse light
95 exposure-related behaviours. Notably, we do not claim to be estimating the personal
96 light exposure with these questions. Instead, we aim to assess, in a scalable way, how
97 people behave in relation to light, focusing on habitual patterns that could guide
98 behavioural intervention points.

99 Results

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

102 Development of the initial item pool

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

109 Measurement of light exposure behaviour in an online sample

110 We conducted two rounds of large scale online survey between 17 May 2021 and 3
111 September 2021 to generate data from 690 participants with varied geographic locations
112 (countries=74; time-zone=28). For a complete list of geographic locations, see

113 **Supplementary Table 2.** Table 1 presents the survey participants' demographic
114 characteristics. Only participants completing the full LEBA inventory were included. We
115 used the data from first round for the exploratory factor analysis (EFA sample; n=428)
116 and data from the second round was used in the confirmatory factor analysis (CFA
117 sample; n=262). Participants in our survey were aged between 11 to 84 years, with an
118 overall mean of ~ 32.95 years of age [Overall: 32.95 ± 14.57 ; EFA: 32.99 ± 15.11 ; CFA:
119 32.89 ± 13.66]. In the entire sample, 351 (51%) were male, 325 (47%) were female, 14
120 (2.0%) reported other sex, and 49 (7.2%) reported a gender-variant identity. In a
121 "Yes/No" question regarding native language, 320 (46%) of respondents [EFA: 191
122 (45%); CFA: 129 (49%)] indicated to be native English speakers. For their "Occupational
123 Status", more than half of the overall sample (396 (57%)) reported that they currently
124 work, whereas 174 (25%) reported that they go to school, and 120 (17%) responded that
125 they do "Neither". With respect to the COVID-19 pandemic, we asked participants to
126 indicate their occupational setting during the last four weeks: In the entire sample, 303
127 (44%) of the participants indicated that they were in a home office/ home schooling
128 setting, 109 (16%) reported face-to-face work/schooling, 147 (21%) reported a
129 combination of home- and face-to-face work/schooling, and 131 (19%) filled in the
130 "Neither (no work or school, or on vacation)" response option.

131 **Psychometric analysis: Development of the long form**

132 **Descriptive statistics and item analysis.** We observed that the response patterns
133 of LEBA inventory for the entire sample (n=690) were not normally distributed (Figures 1
134 and 2). All items violated both univariate (Shapiro & Wilk, 1965) and multivariate
135 normality (Mardia, 1970). The multivariate skewness was 488.40 ($p < 0.001$) and the
136 multivariate kurtosis was 2,808.17 ($p < 0.001$).

137 Similarly, non-normal distribution of response pattern was also observed in the EFA
138 sample. **Supplementary Figure 1** depicts the univariate descriptive statistics for the EFA

139 sample (n=428). Further, We observed that each item's correlation with the aggregated
140 sum of the 48-item's score varied largely (corrected item-total correlation= 0.03 -0.48)
141 indicating the possibility of multi-factor structure of the LEBA inventory.

142 **Exploratory factor analysis and reliability analysis.** Exploratory analysis revealed
143 that items of LEBA inventory can be categorized into five major factors: (i) wearing blue
144 light filters; (ii) spending time out doors; (iii) using phone and smartwatch in bed; (iv)
145 using light before bedtime (v) using light in the morning and during daytime. In this stage
146 of analysis, we retained 25 items. the first factor had three items and encapsulated the
147 individual's preference for using blue light filters in different light environments. The
148 second factor contained six items that incorporated the individuals' hours spent
149 outdoors. The third factor contained five items that looked into specific behaviours of
150 using a phone and smartwatch in bed. The fourth factor comprised five items
151 investigated the other behaviours related to the individual's electric light exposure before
152 bedtime. lastly, the fifth factor encompassed six items capturing the individual's morning
153 and daytime light exposure-related behaviour.

154 Prior to conducting the EFA, we have checked the post-hoc sampling adequacy by
155 applying Kaiser-Meyer-Olkin (KMO) measures of sampling adequacy on the EFA sample
156 (n=428) (Kaiser, 1974) and the quality of the correlation matrix by Bartlett's test of
157 sphericity (Bartlett, 1954). KMO>0.50 would indicate adequate sample size (Hutcheson,
158 1999) and a significant test of sphericity would indicate satisfactory quality of the
159 correlation matrix . Results indicated that we had an adequate sample size (KMO=0.63)
160 and correlation matrix ($\chi^2_{1128}=5042.86$, p< 0.001). However, 4.96% of the inter-item
161 correlation coefficients were greater than |0.30|, and the inter-item correlation
162 coefficients ranged between -0.44 to 0.91. Figure 3-A depicts the respective correlation
163 matrix. To identify how many factors are required to optimally express human light
164 exposure related behaviours we used a combination of methods. the Scree plot (Figure
165 3-B) revealed a six-factor solution, whereas the minimum average partial (MAP) method

(Velicer, 1976) (Supplementary Table 3) and Hull method (Lorenzo-Seva, Timmerman, & Kiers, 2011) implied a five-factor solution (Figure 3-C). Hence, we tested both five-factor and six-factor solutions using iterative EFA where we gradually identified and discarded problematic items (factor-loading <0.30 and cross-loading >0.30). In this process, we found a five-factor structure for LEBA inventory with 25 items. Table 2 displays the factor-loading (λ) and communality of the items. Both factor loadings and commonalities advocate to accept this five-factor solution ($|\lambda|=0.32-0.99$; commonalities=0.11-0.99). These five factors explains 10.25%, 9.93%, 8.83%, 8.44%, 6.14% of the total variance in individual's light exposure related behaviours respectively. All factors exhibited excellent to satisfactory reliability (ordinal $\alpha=0.94, 0.76, 0.75, 0.72, 0.62$ respectively). The entire inventory also exhibited satisfactory reliability ($\omega_t=0.77$).

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

Confirmatory factor analysis. To investigate the structural validity of the five-factor structure obtained in EFA, we conducted a confirmatory factor analysis (CFA) on the CFA sample. The five-factor structure with 25 items showed acceptable fit (Table 3)

providing evidence of structural validity ($CFI=0.92$; $TLI=0.91$; $RMSEA=0.07$ [0.06-0.07, 90% CI]). Two equity constraints were imposed on item pairs 32-33 (item 32: I dim my mobile phone screen within 1 hour before attempting to fall asleep; item 33: I dim my computer screen within 1 hour before attempting to fall asleep) and 16-17 (item 16: I wear blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day; item 17: I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the day). Item pair 32-33 describes the preference for dimming the electric devices' brightness before bedtime, whereas item pair 16-17 represents the use of blue filtering or coloured glasses during the daytime. Given the similar nature of captured behaviours within each item pair, we accepted the imposed equity constraints. Nevertheless, the SRMR value exceeded the guideline recommendation ($SRMR=0.12$). In order to improve the model fit, we conducted a post-hoc model modification. Firstly, the modification indices suggested cross-loadings between item 37 and 26 (item 37: I purposely leave a light on in my sleep environment while sleeping; item 26: I turn on my ceiling room light when it is light outside), which were hence discarded. Secondly, items 30 and 41 (item 30: I look at my smartwatch within 1 hour before attempting to fall asleep; item 41: I look at my smartwatch when I wake up at night) showed a tendency to co-vary in their error variance ($MI=141.127$, $p<0.001$). By allowing the latter pair of items (30 & 41) to co-vary, the model's error variance attained an improved fit ($CFI=0.95$; $TLI=0.95$; $RMSEA=0.06$ [0.05-0.06, 90% CI]; $SRMR=0.11$).

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

219 **Measurement invariance.** We reported the measurement invariance (MI) analysis

220 on the CFA sample based on native (n=129) and non-native English speakers (n=133).

221 A detailed demographic description are provided in **Supplementary Table 5**. Our MI

222 results (Table 4) indicated that LEBA inventory demonstrated highest level of (residual

223 model) psychometric equivalence across native and non-native English speaking

224 participants, thus permitting group-mean based comparisons. The four fitted MI models

225 generated acceptable fit indices and the model fit did not significantly decrease across

226 the nested models ($\Delta\text{CFI}>-0.01$; $\Delta\text{RMSEA}<0.01$).

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

228 We investigated the language-based accessibility of LEBA using Flesch-Kincaid

229 grade level analysis (Flesch, 1948). Results indicated that at least a language

230 proficiency of educational grade level-four (US education system) with age above eight

231 years are required to comprehend the items used in LEBA inventory. Semantic Scale

232 analysis (Rosenbusch, Wanders, & Pit, 2020) was administered to assess the LEBA's

233 (23 items) semantic relation to other questionnaires. LEBA inventory was most strongly

234 semantically related to scales about sleep: The "Sleep Disturbance Scale For Children"

235 (Bruni et al., 1996) and the "Composite International Diagnostic Interview (CIDI):

236 Insomnia"(Robins et al., 1988). The cosine similarity index ranged between 0.47 to 0.51.

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

238 Our aim was to provide a data-driven approach to reducing the number of items for

239 cases where a small reduction of items is necessary. In order to derive a short form of

240 the LEBA inventory, we fitted each factor of the LEBA with the graded response model

241 (Samejima, Liden, & Hambleton, 1997) to the combined EFA and CFA sample (n=690).

242 The resulting item discrimination parameters of the inventory fell into categories of "very

243 high" (10 items), "high" (4 items), "moderate" (4 items), and "low" (5 items), indicating a

244 good range of discrimination along the latent trait level (θ) (Supplementary Table 6). An
245 examination of the item information curve (Supplementary Figure 3) revealed five items
246 (1, 25, 30, 38, & 41) provided very low information regarding light exposure related
247 behaviours with relatively flat curves ($I(\theta) < 0.20$). We discarded those items, culminating
248 in a short form of LEBA with five factors and 18 items (Supplementary File 2).

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

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

263 Discussion

264 We have developed two versions of a self-report inventory, LEBA, that can capture
265 light exposure-related behaviours in multiple dimensions. The 48 generated items were
266 applied in a large-scale, geographically unconstrained, cross-sectional study, yielding
267 690 completed surveys. To assure high data quality, participant responses were only
268 included when the five “attention check items” throughout the survey were passed.

269 Ultimately, data was recorded from 74 countries and 28 time zones, including native and
270 non-native English speakers from a sex-balanced and age-diverse sample (see Table 1).
271 The acquired study population complied with our objective to avoid bias from a selective
272 sample, which is crucial when relying on voluntary uncompensated participation.

273 Data collected in the first round was used to explore the latent structure (EFA
274 sample; n=428). The exploratory factor analysis revealed a highly interpretable
275 five-factor solution (“Wearing blue light filters”, “Spending time outdoors”, “Using phone
276 and smartwatch in bed”, “Using light before bedtime”, and “Using light in the morning and
277 during daytime”) with 25 items. Our CFA analysis (CFA sample; n=262) confirmed the
278 five-factor structure we obtained in our EFA, thus providing evidence for structural
279 validity.(CFI=0.95; TLI=0.95; RMSEA=0.06). In this model, we discarded two more items
280 (item 26 & 37) for possible cross-loadings. As a rule of thumb, reliability coefficients
281 higher than .70 are regarded as “satisfactory”. However, at the early developmental
282 stage, a value of .50 is considered acceptable (Dall’Oglio et al., 2010; Field, 2015;
283 Nunnally, 1978). Thus, we confer, the internal consistency coefficients ordinal alpha for
284 the five factors and the total inventory were satisfactory (Ordinal alpha ranged between
285 0.52 to 0.96; McDonald’s $\omega_t=0.68$).

286 The results of the measurement invariance analysis indicate that the construct
287 “Light exposure-related behaviour” is equivalent across native and non-native English
288 speakers and thus suitable for assessment in both groups. Furthermore, according to
289 the grade level identification method, the LEBA appears understandable for students at
290 least 8.33 years of age visiting grade four or higher. Interestingly, the semantic similarity
291 analysis (“Semantic Scale Network” database Rosenbusch et al. (2020)) revealed that
292 the “LEBA” is semantically related to the “Sleep Disturbance Scale For Children” (SDSC)
293 (Bruni et al., 1996) and the “Composite International Diagnostic Interview (CIDI):
294 Insomnia”(Robins et al., 1988). Upon inspecting the questionnaire contents, we found
295 that some items in the factors “Using phone and smartwatch in bed” and “Using light

296 before bedtime" have semantic overlap with the SDSC's and CIDI's items. However,
297 while the CIDI and the SDSC capture various clinically relevant sleep problems and
298 related activities, the LEBA aims to assess light-exposure-related behaviour. Since light
299 exposure at night has been shown to influence sleep negatively (T. M. Brown et al.,
300 2022; Santhi & Ball, 2020), this overlap confirms our aim to measure the physiologically
301 relevant aspects of light-exposure-related behaviour. Nevertheless, the general
302 objectives of the complete questionnaires and the LEBA differ evidently.

303 While developing and validating LEBA we have complemented the classical test
304 theory based analysis with based analyses (factor analysis and measurement
305 invariance) with IRT analysis. The benefit of implementing IRT analysis was twofold.
306 First, we derived a shorter form of LEBA (18 items). We fitted a graded response model
307 to the combined EFA and CFA sample ($n=690$) and discarded five items (1, 25, 30, 38, &
308 41) with relatively flat item information curve [$I(\theta) < .20$]. The resulting test information
309 curves suggest that the short-LEBA is a psychometrically sound measure with adequate
310 coverage of underlying traits and can be applied to capture the frequency of different
311 light exposure related behaviours reliably. Often, psychological measurements require
312 application of several questionnaires simultaneously. Responding to several lengthy
313 questionnaires increases the participants losing focus and becoming tired. Thus, in
314 some circumstances, reducing the number of items even slightly may be necessary to
315 employ the LEBA questionnaire. Our aim was to provide a data-driven approach to
316 reducing the number of items, apart from the possibility of excluding a specific factor from
317 the 23-item questionnaire. Nonetheless, where possible, we strongly recommend using
318 the extended form of the questionnaire to avoid limiting the range of gained information.

319 Second, IRT analysis enabled us to acknowledge the individual differences in
320 responding to the items of LEBA. IRT provides a framework to interpret respondents'
321 obtained scores in the light of latent ability (i.e. light exposure behaviour) and the
322 characteristics of the respondents—how they interpret the items (Thomas, 2019).

323 Findings from the Item and person fit index analysis demonstrate that all five fitted
324 models were acceptable and provide evidence of validity for the factors. In addition, the
325 diverse item discrimination parameters indicate an appropriate range of discrimination –
326 the ability to differentiate respondents with different levels of light exposure-related
327 behaviour while acknowledging the interpersonal variability in understanding the item.

328 **Known limitations**

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

330 The fifth factor, “using light in the morning and during daytime”, exhibited low
331 internal consistency both in the exploratory and confirmatory factor analysis (EFA: 0.62;
332 CFA:0.52). Since, it was above .50, considering the developmental phase of this
333 inventory we accepted the fifth factor. This particular factor captures our behaviour
334 related to usages of light in the morning and daytime. Since, light exposure during
335 morning and daytime influences our alertness and cognition (Lok, Smolders, Beersma, &
336 de Kort, 2018; Siraji, Kalavally, Schaefer, & Haque, 2021), we deemed capturing these
337 behaviours is essential for the sake of completeness of our inventory. However, the
338 possibility of improving the reliability should be investigated further by adding more
339 appropriate and relevant items to this factor.

340 The habitual patterns queried in the developed inventory might not exhaustively
341 represent all relevant light-exposure-related behaviours. For instance, it is conceivable
342 that additional light-related activities not included in the LEBA depend on the
343 respondents’ profession/occupation, geographical context, and socio-economic status.
344 However, we generated the initial item pool with an international team of researchers
345 and followed a thorough psychometric analysis. Therefore, we are confident that the
346 developed LEBA inventory can serve as a good starting point for exploring the light
347 exposure related behaviours in more depth and inform room for modification of light

348 exposure-related behaviour to improve light hygiene.

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

361 It is important to note that, LEBA utilizes a five-point Likert-type response scale
362 which is often susceptible to central tendency bias, where responses are biased towards
363 the central value of the response scale (Aston, Negen, Nardini, & Beierholm, 2022).
364 Without proper corrections of the response pattern, the interpretation of the scores could
365 be erroneous. We recommend using the sensory precision suggested by Aston et al.
366 (2022) method to correct the central tendency bias.

367 Lastly, this study is the lack of convergent validity evidence. LEBA being the first of
368 its kind, lacks golden standard against which its convergent validity evidence could be
369 established. However, a recent study (Siraji, Spitschan, Kalavally, & Haque, 2023)
370 demonstrates the predictive validity of LEBA by successfully relating LEBA behaviour
371 factors to chronotype, mood, sleep quality, and memory and concentration difficulties.
372 The results of their study confirmed the very essence of LEBA-behaviour could lead to
373 different light exposure experiences that differentially influence health, wellness and

374 performance.

375 **Future directions**

376 To our knowledge, the LEBA is the first inventory characterising light
377 exposure-related behaviour in a scalable manner. Further evidence for the validity of the
378 LEBA could be obtained by administering it conjointly with objective field measurements
379 of light exposure (e.g. with portable light loggers/wearables, see literature review),
380 smartphone readouts as well as subjective data in the form of 24-hour recalls. By this
381 route, one could study how the (subjectively measured) light exposure-related
382 behavioural patterns translate into (objectively measured) received light exposure,
383 (objectively measured) smartphone use, and how closely the retrospective questionnaire
384 relates to daily reports of these behaviours.

385 **Conclusion**

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

393 **Methods**

394 **Data collection**

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

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

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

419 Analytic strategy

420 Figure 6 summarises the steps we followed while developing the LEBA. We
421 conducted all analyses with the statistical software environment R. Firstly, we set an item
422 pool of 48 items with a six-point Likert-type response format (0-Does not apply/I don’t

423 know, 1-Never, 2-Rarely 3-Sometimes, 4-Often, 5-Always) for our initial inventory. Our
424 purpose was to capture light exposure-related behaviour. In that context, the first two
425 response options: “Does not apply/I don’t know” and “Never”, provided similar
426 information. As such, we collapsed them into one, making it a 5-point Likert-type
427 response format (1-Never, 2-Rarely, 3-Sometimes, 4-Often, 5-Always).

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

437 Thirdly, we conducted descriptive and item analyses and proceeded to EFA on the
438 EFA sample. Prior to the EFA, the necessary assumptions, including sample adequacy,
439 normality assumptions, and quality of correlation matrix, were assessed. As our data
440 violated both the univariate and multivariate normality assumption and yielded ordinal
441 response data, we used a polychoric correlation matrix in the EFA and employed
442 “principal axis” (PA) as the factor extraction method (Desjardins & Bulut, 2018; Watkins,
443 2020). We applied a combination of methods, including a Scree plot (Cattell, 1966),
444 minimum average partials method (Velicer, 1976), and Hull method (Lorenzo-Seva et al.,
445 2011) to identify factor numbers. To determine the latent structure, we followed the
446 common guidelines: (i) no factors with fewer than three items (ii) no factors with a factor
447 loading <0.3 (iii) no items with cross-loading > .3 across factors (Bandalos & Finney,
448 2018).

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 (Gadermann, Guhn, & Zumbo, 2012; Zumbo, Gadermann, & Zeisser, 2007). Subsequently, we reported ordinal alpha for each factor obtained in the EFA which was suggested as a better reliability estimates for ordinal data (Zumbo et al., 2007). 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 (Dunn, Baguley, & Brunsden, 2014; Sijtsma, 2009). 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) estimation (Desjardins & Bulut, 2018) 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 of approximation (RMSEA): close to 0.06 or below, (iv) Standardized root mean square (SRMR): close to 0.08 or below (Hu & Bentle, 1999; Schumacker & Lomax, 2004). However, the χ^2 test is sensitive to sample size (T. A. Brown, 2015), and SRMR does not work well with ordinal data (Yu, 2002). Consequently, we judged the model fit using CFI, TLI and RMSEA.

In order to evaluate whether the construct demonstrated psychometric equivalence and the same meaning across native English speakers ($n=129$) and non-native English speakers ($n=133$) in the CFA sample ($n=262$) (Kline, 2016; Putnick & Bornstein, 2016) measurement invariance analysis was used. We used structural equation modelling framework to assess the measurement invariance. We successively compared four

476 nested models: configural, metric, scalar, and residual models using the χ^2 difference
477 test ($\Delta\chi^2$). Among MI models, the configural model is the least restrictive, and the
478 residual model is the most restrictive. A non-significant $\Delta\chi^2$ test between two nested
479 measurement invariance models indicates mode fit does not significantly decrease for
480 the superior model, thus allowing the superior invariance model to be accepted
481 (Dimitrov, 2010; Widaman & Reise, 1997).

482 Fourthly, in a secondary analysis, we identified the educational grade level (US
483 education system) required to understand the items in our inventory with the
484 Flesch-Kincaid grade level identification method (Flesch, 1948). Correspondingly, we
485 analysed possible semantic overlap of our developed inventory using the “Semantic
486 Scale Network” (SSN) engine (Rosenbusch et al., 2020). The SSN detects semantically
487 related scales and provides a cosine similarity index ranging between -.66 to 1
488 (Rosenbusch et al., 2020). Pairs of scales with a cosine similarity index value of 1
489 indicate full semantical similarity, suggesting redundancy.

490 Lastly, we derived a short form of the LEBA employing an Item Response Theory
491 (IRT) based analysis. We fitted each factor of the LEBA to the combined EFA and CFA
492 sample (n=690) using the graded response model (Samejima et al., 1997). IRT assesses
493 the item quality by estimating the item discrimination, item difficulty, item information
494 curve, and test information curve (Baker & Kim, 2017). Item discrimination indicates how
495 well a particular item can differentiate between participants across the given latent trait
496 continuum (θ). Item difficulty corresponds to the latent trait level at which the probability
497 of endorsing a particular response option is 50%. The item information curve (IIC)
498 indicates the amount of information an item carries along the latent trait continuum.
499 Here, we reported the item difficulty and discrimination parameter and categorized the
500 items based on their item discrimination index: (i) none=0; (ii) very low=0.01 to 0.34; (iii)
501 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
502 (Baker & Kim, 2017). We discarded the items with a relatively flat item information curve

503 (information <.2) to derive the short form of LEBA. We also assessed the precision of the
504 short LEBA utilizing the test information curve (TIC). TIC indicates the amount of
505 information a particular scale carries along the latent trait continuum. Additionally, the
506 item and person fit of the fitted IRT models were analysed to gather more evidence on
507 the validity and meaningfulness of our scale (Desjardins & Bulut, 2018). The item fit was
508 evaluated using the RMSEA value obtained from Signed- χ^2 index implementation,
509 where an RMSEA value $\leq .06$ was considered an adequate item fit. The person fit was
510 estimated employing the standardized fit index Z_h statistics (Drasgow, Levine, &
511 Williams, 1985). Here, $Z_h < -2$ was considered as a misfit (Drasgow et al., 1985).

512 **Ethical approval**

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

519 **Code, materials and data availability**

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

References

- Allen, A. E., Hazelhoff, E. M., Martial, F. P., Cajochen, C., & Lucas, R. J. (2018). Exploiting metamerism to regulate the impact of a visual display on alertness and melatonin suppression independent of visual appearance. *Sleep*, 41(8), zsy100. <https://doi.org/10.1093/sleep/zsy100>
- Aston, S., Negen, J., Nardini, M., & Beierholm, U. (2022). Central tendency biases must be accounted for to consistently capture bayesian cue combination in continuous response data. *Behavior Research Methods*, 54(1), 508–521.
- Bajaj, A., Rosner, B., Lockley, S. W., & Schernhammer, E. S. (2011). Validation of a light questionnaire with real-life photopic illuminance measurements: The harvard light exposure assessment questionnaire. *Cancer Epidemiology and Prevention Biomarkers*, 20(7), 1341–1349.
- Baker, F. B., & Kim, S.-H. (2017). *The basics of item response theory using r* (1st ed.). Springer.
- Bandalos, D. L., & Finney, S. J. (2018). Factor analysis: Exploratory and confirmatory. In *The reviewer's guide to quantitative methods in the social sciences* (pp. 98–122). Routledge.
- Bartlett, M. (1954). A Note on the Multiplying Factors for Various Chi-square Approximations. *Journal of the Royal Statistical Society. Series B, Methodological*, 16(2), 296–298.
- Bentler, P. M., & Chou, C.-P. (1987). Practical Issues in Structural Modeling. *Sociological Methods & Research*, 16(1), 78–117.
<https://doi.org/10.1177/0049124187016001004>
- Blume, C., Garbazza, C., & Spitschan, M. (2019). Effects of light on human circadian rhythms, sleep and mood. *Somnologie : Schlafforschung Und Schlafmedizin = Somnology : Sleep Research and Sleep Medicine*, 23(3), 147–156. <https://doi.org/10.1007/s11818-019-00215-x>

- 553 Bossini, L., Valdagno, M., Padula, L., De Capua, A., Pacchierotti, C., &
554 Castrogiovanni, P. (2006). Sensibilità alla luce e psicopatologia: Validazione
555 del questionario per la valutazione della fotosensibilità (QVF). *Med
556 Psicosomatica*, 51, 167–176.
- 557 Boyce, P. (2022). Light, lighting and human health. *Lighting Research &
558 Technology*, 54(2), 101–144. <https://doi.org/10.1177/14771535211010267>
- 559 Brown, T. A. (2015). *Confirmatory factor analysis for applied research* (2nd ed.).
560 New York, NY, US: The Guilford Press.
- 561 Brown, T. M., Brainard, G. C., Cajochen, C., Czeisler, C. A., Hanifin, J. P., Lockley,
562 S. W., ... Wright, K. P. (2022). Recommendations for daytime, evening, and
563 nighttime indoor light exposure to best support physiology, sleep, and
564 wakefulness in healthy adults. *PLoS Biology*, 20(3), e3001571.
565 <https://doi.org/10.1371/journal.pbio.3001571>
- 566 Bruni, O., Ottaviano, S., Guidetti, V., Romoli, M., Innocenzi, M., Cortesi, F., &
567 Giannotti, F. (1996). The sleep disturbance scale for children (SDSC)
568 construction and validation of an instrument to evaluate sleep disturbances in
569 childhood and adolescence. *Journal of Sleep Research*, 5(4), 251–261.
- 570 Buysse, D. J., Reynolds III, C. F., Monk, T. H., Berman, S. R., & Kupfer, D. J.
571 (1989). The pittsburgh sleep quality index: A new instrument for psychiatric
572 practice and research. *Psychiatry Research*, 28(2), 193–213.
- 573 Cattell, R. B. (1966). The Scree Test For The Number Of Factors. *Multivariate
574 Behavioral Research*, 1(2), 245–276.
575 https://doi.org/10.1207/s15327906mbr0102_10
- 576 Chellappa, S. L., Vujoovic, N., Williams, J. S., & Scheer, F. A. J. L. (2019). Impact
577 of circadian disruption on cardiovascular function and disease. *Trends in
578 Endocrinology and Metabolism: TEM*, 30(10), 767–779.
579 <https://doi.org/10.1016/j.tem.2019.07.008>

- 580 Comrey, A. L., & Lee, H. B. (2013). *A first course in factor analysis*. Psychology
581 press.
- 582 Dall'Oglio, A. M., Rossiello, B., Coletti, M. F., Caselli, M. C., Ravà, L., Di Ciommo,
583 V., ... Pasqualetti, P. (2010). Developmental evaluation at age 4: Validity of an
584 Italian parental questionnaire. *Journal of Paediatrics and Child Health*,
585 46(7-8), 419–426.
- 586 Desjardins, C., & Bulut, O. (2018). *Handbook of Educational Measurement and*
587 *Psychometrics Using R*. London: Chapman and Hall/CRC.
588 <https://doi.org/10.1201/b20498>
- 589 Dianat, I., Sedghi, A., Bagherzade, J., Jafarabadi, M. A., & Stedmon, A. W.
590 (2013). Objective and subjective assessments of lighting in a hospital setting:
591 Implications for health, safety and performance. *Ergonomics*, 56(10),
592 1535–1545.
- 593 Dimitrov, D. M. (2010). Testing for factorial invariance in the context of construct
594 validation. *Measurement and Evaluation in Counseling and Development*,
595 43(2), 121–149.
- 596 Drasgow, F., Levine, M. V., & Williams, E. A. (1985). Appropriateness
597 measurement with polychotomous item response models and standardized
598 indices. *British Journal of Mathematical and Statistical Psychology*, 38(1),
599 67–86.
- 600 Dunn, T. J., Baguley, T., & Brunsden, V. (2014). From alpha to omega: A practical
601 solution to the pervasive problem of internal consistency estimation. *British*
602 *Journal of Psychology*, 105(3), 399–412.
- 603 Eklund, N., & Boyce, P. (1996). The development of a reliable, valid, and simple
604 office lighting survey. *Journal of the Illuminating Engineering Society*, 25(2),
605 25–40.
- 606 Field, A. (2015). *Discovering statistics using IBM SPSS statistics* (5th ed.). sage.

- 607 Flesch, R. (1948). A new readability yardstick. *Journal of Applied Psychology*,
608 32(3), 221.
- 609 Flux Software LLC. (2021). *F.lux*. Retrieved from <https://justgetflux.com/>
- 610 Gadermann, A. M., Guhn, M., & Zumbo, B. D. (2012). Estimating ordinal reliability
611 for likert-type and ordinal item response data: A conceptual, empirical, and
612 practical guide. *Practical Assessment, Research, and Evaluation*, 17(1), 3.
- 613 Grandner, M. A., Jackson, N., Gooneratne, N. S., & Patel, N. P. (2014). The
614 development of a questionnaire to assess sleep-related practices, beliefs, and
615 attitudes. *Behavioral Sleep Medicine*, 12(2), 123–142.
- 616 Harris, P. A., Taylor, R., Minor, B. L., Elliott, V., Fernandez, M., O'Neal, L., et
617 al.others. (2019). The REDCap consortium: Building an international
618 community of software platform partners. *Journal of Biomedical Informatics*,
619 95, 103208.
- 620 Harris, P. A., Taylor, R., Thielke, R., Payne, J., Gonzalez, N., & Conde, J. G.
621 (2009). Research electronic data capture (REDCap)—a metadata-driven
622 methodology and workflow process for providing translational research
623 informatics support. *Journal of Biomedical Informatics*, 42(2), 377–381.
- 624 Hartmeyer, S. L., Webler, F. S., & Andersen, M. (2022). Towards a framework for
625 light-dosimetry studies: Methodological considerations. *Lighting Research &*
626 *Technology*, 14771535221103258.
- 627 Horne, J. A., & Östberg, O. (1976). A self-assessment questionnaire to determine
628 morningness-eveningness in human circadian rhythms. *International Journal*
629 *of Chronobiology*.
- 630 Hu, L., & Bentle, P. M. (1999). Cutoff criteria for fit indexes in covariance structure
631 analysis: Conventional criteria versus new alternatives. *Structural Equation*
632 *Modeling: A Multidisciplinary Journal*, 6(1), 1–55.
- 633 <https://doi.org/10.1080/10705519909540118>

- 634 Hubalek, S., Zöschg, D., & Schierz, C. (2006). Ambulant recording of light for
635 vision and non-visual biological effects. *Lighting Research & Technology*,
636 38(4), 314–321. <https://doi.org/10.1177/1477153506070687>
- 637 Hurvich, L. M., & Jameson, D. (1966). *The perception of brightness and darkness*.
638 Hutcheson, G. D. (1999). *The multivariate social scientist : Introductory statistics
639 using generalized linear models*. London : SAGE.
- 640 Jackson, D. L. (2003). Revisiting Sample Size and Number of Parameter
641 Estimates: Some Support for the N:q Hypothesis. *Structural Equation
642 Modeling*, 10(1), 128–141. https://doi.org/10.1207/S15328007SEM1001_6
- 643 Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika*, 39(1), 31–36.
644 <https://doi.org/10.1007/bf02291575>
- 645 Klepeis, N. E., Nelson, W. C., Ott, W. R., Robinson, J. P., Tsang, A. M., Switzer,
646 P., ... Engelmann, W. H. (2001). The national human activity pattern survey
647 (NHAPS): A resource for assessing exposure to environmental pollutants.
648 *Journal of Exposure Analysis and Environmental Epidemiology*, 11(3),
649 231–252. <https://doi.org/10.1038/sj.jea.7500165>
- 650 Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th
651 ed.). New York: The Guilford Press.
- 652 Lok, R., Smolders, K. C., Beersma, D. G., & de Kort, Y. A. (2018). Light,
653 alertness, and alerting effects of white light: A literature overview. *Journal of
654 Biological Rhythms*, 33(6), 589–601.
- 655 Lorenzo-Seva, U., Timmerman, M., & Kiers, H. (2011). The Hull Method for
656 Selecting the Number of Common Factors. *Multivariate Behavioral Research*,
657 46, 340–364. <https://doi.org/10.1080/00273171.2011.564527>
- 658 Lunn, R. M., Blask, D. E., Coogan, A. N., Figueiro, M. G., Gorman, M. R., Hall, J.
659 E., ... Boyd, W. A. (2017). Health consequences of electric lighting practices in
660 the modern world: A report on the national toxicology program's workshop on

- shift work at night, artificial light at night, and circadian disruption. *The Science of the Total Environment*, 607-608, 1073–1084.
- <https://doi.org/10.1016/j.scitotenv.2017.07.056>
- Mardia, K. V. (1970). Measures of multivariate skewness and kurtosis with applications. *Biometrika*, 57(3), 519–530.
<https://doi.org/10.1093/biomet/57.3.519>
- Navara, K. J., & Nelson, R. J. (2007). The dark side of light at night: Physiological, epidemiological, and ecological consequences. *Journal of Pineal Research*, 43(3), 215–224.
- Nunnally, J. C. (1978). *Psychometric theory*. New York: McGraw-Hill.
- Putnick, D. L., & Bornstein, M. H. (2016). Measurement invariance conventions and reporting: The state of the art and future directions for psychological research. *Developmental Review*, 41, 71–90.
- Robins, L. N., Wing, J., Wittchen, H. U., Helzer, J. E., Babor, T. F., Burke, J., et al.others. (1988). The composite international diagnostic interview: An epidemiologic instrument suitable for use in conjunction with different diagnostic systems and in different cultures. *Archives of General Psychiatry*, 45(12), 1069–1077.
- Roenneberg, T., Wirz-Justice, A., & Merrow, M. (2003). Life between clocks: Daily temporal patterns of human chronotypes. *Journal of Biological Rhythms*, 18(1), 80–90.
- Rosenbusch, H., Wanders, F., & Pit, I. L. (2020). The semantic scale network: An online tool to detect semantic overlap of psychological scales and prevent scale redundancies. *Psychological Methods*, 25(3), 380.
- Samejima, F., Liden, W. van der, & Hambleton, R. (1997). *Handbook of modern item response theory*. New York, NY: Springer.
- Santhi, N., & Ball, D. M. (2020). Applications in sleep: How light affects sleep.

- 688 *Progress in Brain Research*, 253, 17–24.
- 689 <https://doi.org/10.1016/bs.pbr.2020.05.029>
- 690 Schönbrodt, F. D., & Perugini, M. (2013). At what sample size do correlations
691 stabilize? *Journal of Research in Personality*, 47(5), 609–612.
692 <https://doi.org/10.1016/j.jrp.2013.05.009>
- 693 Schumacker, R. E., & Lomax, R. G. (2004). *A beginner's guide to structural*
694 *equation modeling*. psychology press.
- 695 Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality
696 (complete samples). *Biometrika*, 52(3-4), 591–611.
697 <https://doi.org/10.1093/biomet/52.3-4.591>
- 698 Sijtsma, K. (2009). On the use, the misuse, and the very limited usefulness of
699 cronbach's alpha. *Psychometrika*, 74(1), 107.
- 700 Siraji, M. A., Kalavally, V., Schaefer, A., & Haque, S. (2021). Effects of daytime
701 electric light exposure on human alertness and higher cognitive functions: A
702 systematic review. *Frontiers in Psychology*, 12, 765750–765750.
- 703 Siraji, M. A., Spitschan, M., Kalavally, V., & Haque, S. (2023). Light exposure
704 behaviors predict mood, memory and sleep quality. *Scientific Reports*, 13(1),
705 12425. <https://doi.org/10.1038/s41598-023-39636-y>
- 706 Spitschan, M., Smolders, K., Vandendriessche, B., Bent, B., Bakker, J. P.,
707 Rodriguez-Chavez, I. R., & Vetter, C. (2022). Verification, analytical validation
708 and clinical validation (V3) of wearable dosimeters and light loggers. *Digital*
709 *Health*, 8, 20552076221144858.
- 710 Thomas, M. L. (2019). Advances in applications of item response theory to
711 clinical assessment. *Psychological Assessment*, 31(12), 1442.
- 712 Velicer, W. (1976). Determining the Number of Components from the Matrix of
713 Partial Correlations. *Psychometrika*, 41, 321–327.
714 <https://doi.org/10.1007/BF02293557>

- 715 Verriotto, J. D., Gonzalez, A., Aguilar, M. C., Parel, J.-M. A., Feuer, W. J., Smith,
716 A. R., & Lam, B. L. (2017). New methods for quantification of visual
717 photosensitivity threshold and symptoms. *Translational Vision Science &*
718 *Technology*, 6(4), 18–18.
- 719 Watkins, M. (2020). *A Step-by-Step Guide to Exploratory Factor Analysis with R*
720 *and RStudio*. <https://doi.org/10.4324/9781003120001>
- 721 Weinzaepflen, C., & Spitschan, M. (2021). *Enlighten your clock: How your body*
722 *tells time*. Open Science Framework. <https://doi.org/10.17605/OSF.IO/ZQXVH>
- 723 Widaman, K. F., & Reise, S. P. (1997). *Exploring the measurement invariance of*
724 *psychological instruments: Applications in the substance use domain*.
- 725 Worthington, R. L., & Whittaker, T. A. (2006). Scale Development Research: A
726 Content Analysis and Recommendations for Best Practices. *The Counseling*
727 *Psychologist*, 34(6), 806–838. <https://doi.org/10.1177/0011000006288127>
- 728 Xie, Y., Wu, X., Tao, S., Wan, Y., & Tao, F. (2022). Development and validation of
729 the self-rating of biological rhythm disorder for chinese adolescents.
730 *Chronobiology International*, 1–7.
731 <https://doi.org/10.1080/07420528.2021.1989450>
- 732 Yu, C. (2002). *Evaluating cutoff criteria of model fit indices for latent variable*
733 *models with binary and continuous outcomes* (Thesis). ProQuest
734 Dissertations Publishing.
- 735 Zumbo, B. D., Gadermann, A. M., & Zeisser, C. (2007). Ordinal versions of
736 coefficients alpha and theta for likert rating scales. *Journal of Modern Applied*
737 *Statistical Methods*, 6(1), 4.

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 ⁷	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)

⁷ 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.

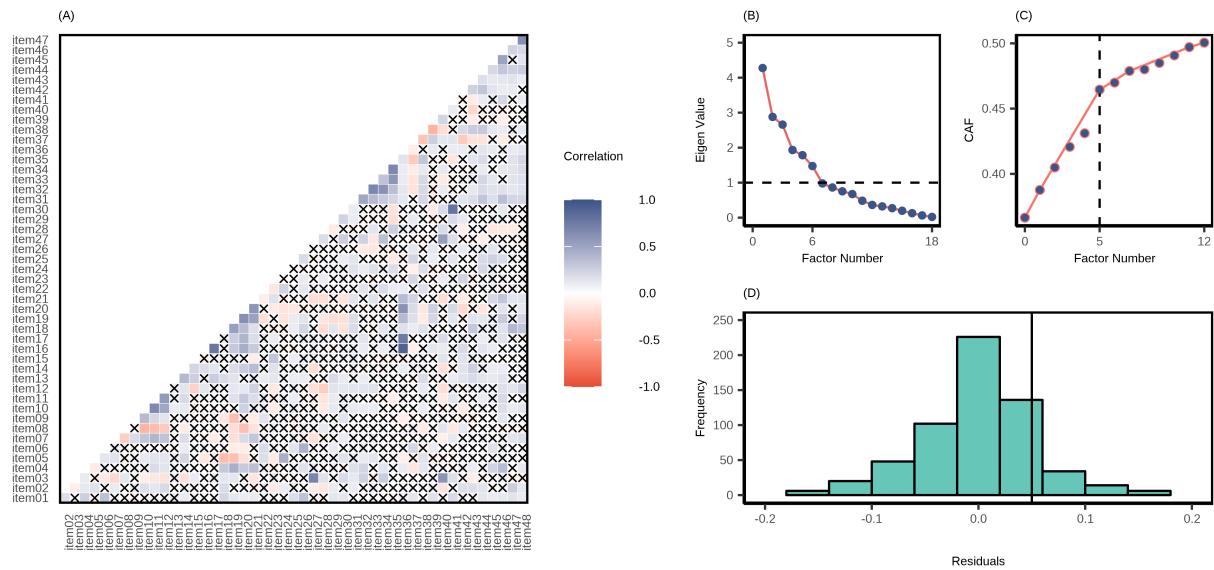


Figure 3. (A) Inter-item polychoric correlation coefficients for the 48 items. 4.9 % inter-item correlation coefficients were higher than $|.30|$. 'x' denotes non-significant correlation. (B) The Scree plot suggested six factors. (C) Hull method indicated that five factors were required to balance the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

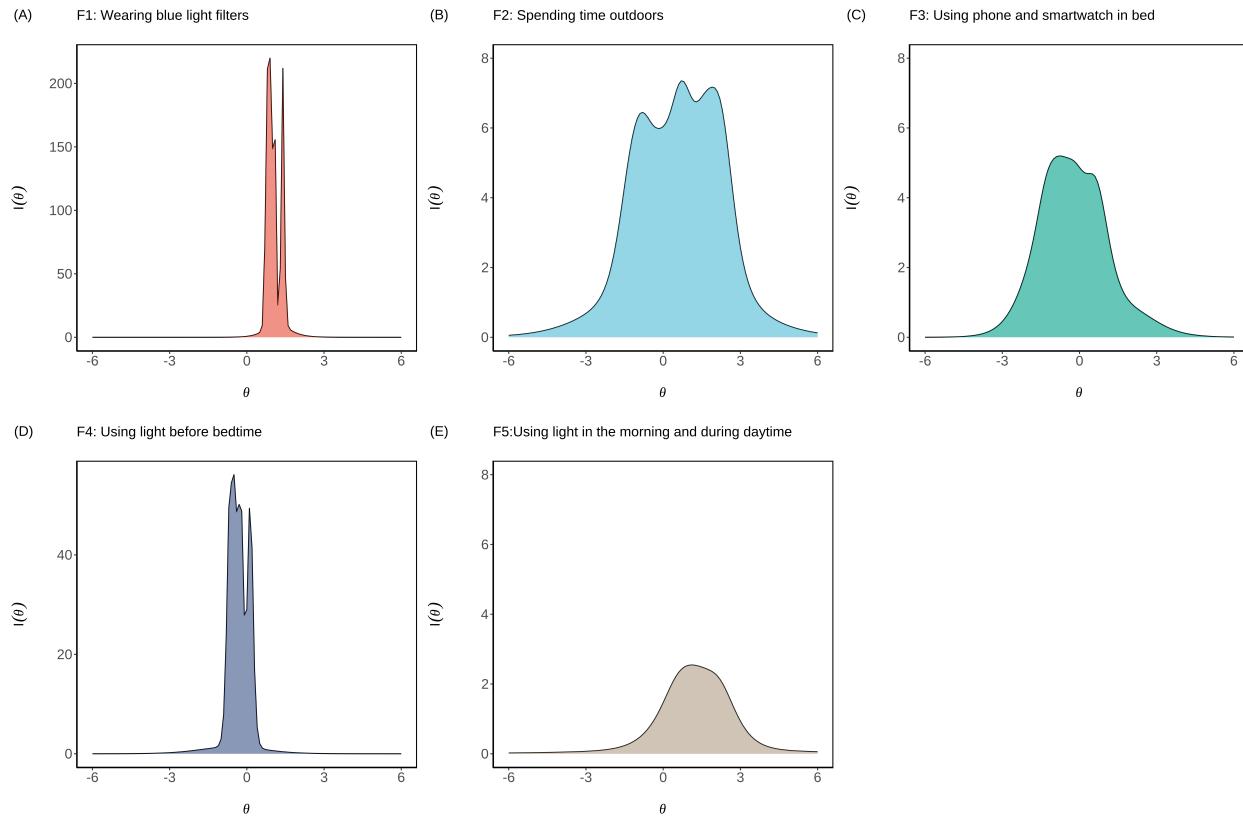


Figure 5. Test information curves for the five factors of LEBA: (A) wearing blue light filters (B) spending time outdoors (C) using a phone and smartwatch in bed (D) using light before bedtime (E) using light in the morning and during daytime. Along the x-axis, we plotted the underlying latent trait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

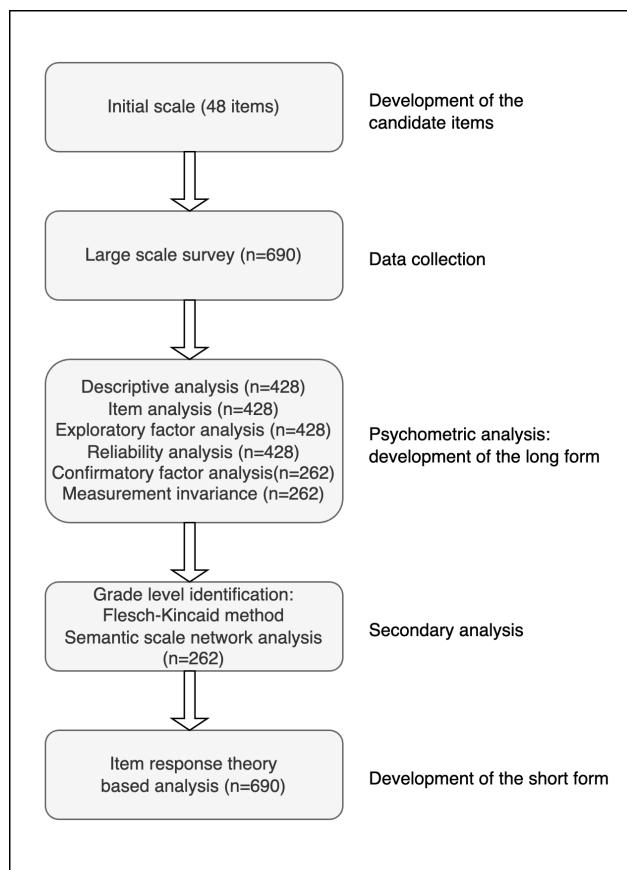


Figure 6. Flow chart of the LEBA (long and short form) development and evaluation.