

¹ *Light Exposure Behavior Assessment (LEBA): Development of a novel instrument to capture light exposure-related behaviours*

³ **Mushfiqul Anwar Siraj^{1,*}, Rafael Robert Lazar^{2, 3,*}, Juliëtte van Duijnhoven^{4, 5}, Luc**
⁴ **Schlängen^{5, 6}, Shamsul Haque¹, Vineetha Kalavally⁷, Céline Vetter^{8, 9}, Gena**
⁵ **Glickman¹⁰, Karin Smolders^{5, 6}, & Manuel Spitschan^{11, 12, 13}**

⁶ ¹ Monash University, Department of Psychology, Jeffrey Cheah School of Medicine and
⁷ Health Sciences, Malaysia

⁸ ² Psychiatric Hospital of the University of Basel (UPK), Centre for Chronobiology, Basel,
⁹ Switzerland

¹⁰ ³ University of Basel, Transfaculty Research Platform Molecular and Cognitive
¹¹ Neurosciences, Basel, Switzerland

¹² ⁴ Eindhoven University of Technology, Department of the Built Environment, Building
¹³ Lighting, Eindhoven, Netherlands

¹⁴ ⁵ Eindhoven University of Technology, Intelligent Lighting Institute, Eindhoven,
¹⁵ Netherlands

¹⁶ ⁶ Eindhoven University of Technology, Department of Industrial Engineering and
¹⁷ Innovation Sciences, Human-Technology Interaction, Eindhoven, Netherlands

¹⁸ ⁷ Monash University, Department of Electrical and Computer Systems Engineering,
¹⁹ Selangor, Malaysia

²⁰ ⁸ University of Colorado Boulder, Department of Integrative Physiology, Boulder, USA

²¹ ⁹ XIMES GmbH, Vienna, Austria

²² ¹⁰ Uniformed Services University of the Health Sciences, Department of Psychiatry,
²³ Bethesda, USA

²⁴ ¹¹ Translational Sensory & Circadian Neuroscience, Max Planck Institute for Biological
²⁵ Cybernetics, Tübingen, Germany

²⁶ ¹² TUM Department of Sport and Health Sciences (TUM SG), Technical University of
²⁷ Munich, Munich, Germany

²⁸ ¹³ University of Oxford, Department of Experimental Psychology, Oxford, United Kingdom
²⁹ * Joint first author

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40 Lazar: Data curation, Investigation, Project administration, Visualization, Writing –
41 original draft, Writing – review & editing;; Juliëtte van Duijnhoven: Conceptualization,
42 Methodology, Investigation, Writing – review & editing; Luc Schlangen:
43 Conceptualization, Methodology, Investigation, Writing – review & editing; Shamsul
44 Haque: Conceptualization, Supervision, Writing – review & editing; Vineetha Kalavally:
45 Supervision, Writing – review & editing; Céline Vetter: Conceptualization, Writing –
46 review & editing; Gena Glickman: Conceptualization, Methodology, Writing – review &
47 editing; Karin Smolders: Conceptualization, Methodology, Writing – review & editing;
48 Manuel Spitschan: Conceptualization, Data curation, Investigation, Project
49 administration, Visualization, Methodology, Writing – original draft, Writing – review &
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51

Abstract

52 Light exposure is an important driver of health and well-being. Many aspects of light
53 exposure are modulated by our behaviour. How these light-related behaviours can be
54 shaped to optimise personal light exposure is currently unknown. Here, we present a
55 novel, self-reported and psychometrically validated instrument to capture light
56 exposure-related behaviour, the Light Exposure Behavior Assessment (LEBA).

57 An expert panel prepared the initial 48 item pool spanning different light exposure
58 related behaviors. Responses, consisting rating the frequency of engaging in the
59 per-item behavior on a 5-point Likert type scale were collected in an online survey
60 yielding responses from a geographically unconstrained sample (690 completed
61 responses, 74 countries, 28 time zones). Exploratory factor analysis (EFA) on an initial
62 subset of our sample ($n=428$) rendered a five-factor solution with 25 items (Wearing blue
63 light filters, spending time outdoors, using phone and smart-watch in bed, using light
64 before bedtime, using light in the morning and during daytime). In a confirmatory factor
65 analysis (CFA) performed on an independent subset of participants ($n=262$), we
66 removed two further items to attain the best fit for the five-factor solution ($CFI=0.97$,
67 $TLI=0.96$, $RMSEA=0.05$, $SRMR=0.09$). The internal consistency reliability coefficient for
68 the total instrument was, McDonald's Omega(total)=0.73. Measurement model
69 invariance analysis between native and non-native English speakers showed our model
70 attained the highest level of invariance (residual invariance; $CFI=0.95$, $TLI =0.95$,
71 $RMSEA=0.05$). Lastly, a short form of LEBA ($n=18$) was developed using Item Response
72 Theory on the complete sample ($n=690$).

73 The psychometric properties of the LEBA instrument indicate the usability to
74 measure the light exposure-related behaviours across a variety of settings and may offer
75 a scalable solution to characterise light exposure-related behaviours in remote samples.
76 The LEBA instrument will be available under the open-access CC-BY-NC-ND license.

⁷⁷ *Keywords:* light exposure, light-related behaviours, non-visual effects of light,

⁷⁸ psychometrics

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81 *capture light exposure-related behaviours*

Introduction

- Light exposure is important
 - Light exposure Behaviour is important
 - Supplementary Table S1: Overview Existing Related Scales
 - Existing Scales: Review them in text
 - None of these do light exposure behaviour.

Methods

89 Data Collection

A quantitative cross-sectional fully anonymous online large scale survey was conducted via REDCap (Harris et al., 2019, 2009) by way of the University of Basel sciCORE. Participants were recruited via the website (<https://enlightenyourclock.org/participate-in-research>) of the science-communication comic-book “Enlighten your clock” co-released with the survey (Weinzaepflein & Spitschan, 2021), social media (i.e., LinkedIn, Twitter, Facebook), mailing lists, word of mouth, the investigators’ personal contacts, and supported by distribution of the survey link via f.lux (F.lux Software LLC, 2021). The landing page of the online survey had the explanatory statements where we mentioned participation was voluntary and that respondents could withdraw from participation anytime without being penalized. At the beginning of the survey, for the adult participants (>18 years) consent was recorded digitally. Underaged participants (<18 years) were urged to obtain assent from their parents/legal guardians. The entire survey was estimated to take <30 minutes.

103 Participants were not compensated. As a part of the demographic information
104 participants provided information regarding age, sex, gender identity, occupational
105 status, COVID-19 related occupational setting, time zone/country of residence and
106 native language. The demographic characteristics of our sample are given in Table 1. To
107 ensure high data quality, five attention check items were included in the survey (e.g.,
108 “We want to make sure you are paying attention. What is 4+5?”). Participants were
109 asked to confirm that they were participating the survey for the first time. Questions
110 incorporating retrospective recall were all aligned to the period of “past four weeks.”

111 We conducted two rounds of data collections. At first we collected data from from
112 428 participants. In the second round we collected data from another 262 participants
113 making a total sample of 690. The data analysed in this study was collected between 17
114 May 2021 and 3 September 2021.

115 Analytic Strategy

116 Figure 1 summarizes the steps we followed while developing LEBA. In our analysis
117 we used R statistical tool (R Core Team, 2021). First, we developed a item pool of 48
118 items with six-point Likert type response format (0-Does not apply/I don't know, 1-Never,
119 2-Rarely 3-Sometimes, 4-Often, 5-Always) for our initial scale. Our purpose was to
120 capture light exposure related behaviour. In that context, the first two response options:
121 “Does not apply/I don't know” and “Never” were providing similar information. As such
122 we collapsed them into one, making it a 5 point Likert type response format.

123 Second, for data collection we conducted a large scale survey. Third, with the data
124 collected on the first round of the large scale survey (EFA sample; n=428) we conducted
125 descriptive and item analysis and proceeded to the exploratory factor analysis (EFA).
126 Prior to the EFA, necessary assumptions, including sample adequacy, normality
127 assumptions, quality of correlation matrix were assessed. Our data violated both the
128 univariate and multivariate normality assumptions. Due to these violations and the

129 ordinal nature of our response data, in EFA we used polychoric correlation matrix and
130 employed principal axis (PA) as factor extraction method (Desjardins & Bulut, 2018;
131 Watkins, 2020). We used a combination of factor identification method including Scree
132 plot (Cattell, 1966), minimum average partials method (Velicer, 1976), and Hull method
133 (Lorenzo-Seva, Timmerman, & Kiers, 2011) to identify factor numbers. To determine the
134 latent structure, we followed the common guidelines : (i) no factors with fewer than three
135 items (ii) no factors with a factor loading <0.3 (iii) no items with cross-loading > .3 across
136 factors (Bandalos & Finney, 2018).

137 Though Cronbach's internal consistency coefficient alpha is widely used for
138 estimating internal consistency, it has a tendency to deflate the estimates for Likert-type
139 data since the calculation is based on Pearson-correlation matrix which requires
140 response data to be continuous in nature (Gadermann, Guhn, & Zumbo, 2012; Zumbo,
141 Gadermann, & Zeisser, 2007). Subsequently to get better estimates of reliability we
142 reported ordinal alpha for each factors obtained in EFA using polychoric-correlation
143 matrix (Zumbo et al., 2007). We also estimated the internal consistency reliability of the
144 total scale using McDonald's ω_t coefficient which is a better reliability estimate for
145 multidimensional constructs (Dunn, Baguley, & Brunsden, 2014; Sijtsma, 2009). Both
146 ordinal alpha and McDonald's ω_t coefficient value range from 0 to 1 and higher value
147 represents better reliability.

148 To validate the latent structure obtained in EFA, We conducted a categorical
149 confirmatory factor analysis (CFA) with weighted least square with mean and variance
150 adjusted (WLSMV) estimator (Desjardins & Bulut, 2018) on the data collected in the
151 second round of data collection (CFA sample; n=262). We assessed the model fit using
152 common model fit guidelines: (i) χ^2 test statistics: a non-significant test statistics is
153 required to accept the model (ii) comparative fit index (CFI) and Tucker Lewis index
154 (TLI): close to .95 or above/ between .90-.95 and above (iii) root mean square error of
155 approximation (RMSEA): close to .06 or below, (iv) Standardized root mean square

156 (SRMR): close to .08 or below (Hu & Bentle, 1999; Schumacker & Lomax, 2004).
157 However, the χ^2 test is sensitive to sample size (Brown, 2015) and SRMR does not work
158 well with ordinal data (Yu, 2002) As such, we judged the model fit using CFI, TLI and
159 RMSEA.

160 We assessed the measurement invariance (MI) of our scale between native
161 English speakers (n=129) and non native English speakers (n=133) in the CFA sample
162 (n=262). MI evaluates whether a construct has the psychometric equivalence and same
163 meaning across groups (Kline, 2015; Putnick & Bornstein, 2016). We used structural
164 equation modelling framework to assess the measurement invariance. We successively
165 compared four nested models: configural, metric, scalar, and residual models using the
166 χ^2 difference test ($\Delta\chi^2$). Among MI models, configural model is the least restrictive
167 model and residual model is the most restrictive model. A non-significant $\Delta\chi^2$ test
168 between two nested measurement invariance models indicates mode fit does not
169 significantly decrease for the superior model thus allowing the superior invariance model
170 to be accepted (Dimitrov, 2010; Widaman & Reise, 1997).

171 Fourth, as secondary analysis we analysed possible semantic overlap of our
172 developed tool using “Semantic Scale Network” (SSN) engine (Rosenbusch, Wanders, &
173 Pit, 2020) and identified the the educational grade level required to understand the items
174 in our tool using Flesch-Kincaid Grade Level identification method (Flesch, 1948). The
175 SSN detects semantically related scales and provides cosine similarity index ranging
176 between -.66 to 1 (Rosenbusch et al., 2020). Pair of scales with a cosine similarity index
177 value of 1 indicates they are perfectly semantically similar scales indicating redundancy.

178 Fifth, we developed a short form of LEBA using Item Response Theory (IRT) based
179 analysis. We fitted each factor of LEBA using the graded response model (Samejima,
180 Liden, & Hambleton, 1997) to the combined EFA and CFA sample (n =690). IRT
181 assesses the item quality by estimating item discrimination, item difficulty, item

182 information curve, and test information curve (Baker, 2017). Item discrimination indicates
183 how well a particular item can differentiate between participants across the given latent
184 trait continuum (θ). Item difficulty corresponds to the latent trait level at which the
185 probability of endorsing a particular response option is 50%. Item information curve (IIC)
186 indicates the amount of information an item carries along the latent trait continuum.

187 Here, we reported the item discrimination parameter and categorize the items according
188 to the suggestions of Baker (2017) : none = 0; very low =0.01 to 0.34; low = 0.35 to 0.64;
189 moderate = 0.65 to 1.34 ; high = 1.35 to 1.69; very high >1.70. We discarded the items
190 with relatively flat item information curve (information <.2) to develop the short form of
191 LEBA. We also assessed the precision of the short LEBA using Test information curve
192 (TIC). TIC indicates the amount of information an the full-scale carry along the latent trait
193 continuum. Item fit and person fit of the fitted IRT models were also analyzed to gather
194 more evidence on validity and meaningfulness of our Tool (Desjardins & Bulut, 2018).
195 Item fit was evaluated using the RMSEA value obtained from Signed- χ^2 index
196 implementation, RMSEA value $\leq .06$ was considered adequate item fit. Person fit was
197 estimated using standardized fit index Zh statistics (Drasgow, Levine, & Williams, 1985).
198 Zh < -2 was considered as a misfit (Drasgow et al., 1985).

199 **Ethical approval**

200 By reason of using fully anonymous online survey data, the present research
201 project does not fall under the scope of the Human Research Act, making an
202 authorisation from the ethics committee redundant. Nevertheless, the cantonal ethics
203 commission (Ethikkommission Nordwest- und Zentralschweiz, EKNZ) reviewed our
204 proposition (project ID Req-2021-00488) and issued an official clarification of
205 responsibility.

206 **Data Availability**

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

212 **Results**

213 **Initial Scale**

214 After reviewing the literature, we identified several light exposure related scale.
215 However, no scale specifically measuring the behavioural component of light exposure
216 were found (**Supplementary Table 1**). As such, an expert panel developed a
217 comprehensive item pool of 48 items. The expert panel composed of all authors and
218 researchers from the fields of chronobiology, light research, neuroscience and
219 psychology. The 48 items were then judged based on their relevance and
220 representativeness of the construct “Light Exposure Related Behaviour” by the expert
221 panel. The panel members independently judged each of the items in terms of their
222 relevance and representativeness and suggested required modification, if there is any.
223 The author team acknowledged the suggestions and amended the items as required
224 thus creating a 48-item scale.

225 **Large-scale survey of scale**

226 Table 1 summarizes the survey participants’ demographic characteristics. Only
227 participants completing the full LEBA questionnaire were included, thus there are no
228 missing values in the item analyses. (XX??) participants were excluded from analysis

229 due to not passing at least one of the “attention check” items. For EFA, a sample of
230 250-300 is recommended (Comrey & Lee, 1992; Schönbrodt & Perugini, 2013). To
231 assess sampling adequacy for CFA, we followed the N:q rule (Bentler & Chou, 1987;
232 Jackson, 2003; Kline, 2015; Worthington & Whittaker, 2006), where ten participants per
233 item is required to earn trustworthiness of the result. Both our EFA and CFA sample size
234 exceeded these requirements. We collected data from 74 countries (28 time
235 zones). Participants reported a diverse range of geographic location Participants
236 indicated filling out the online survey from a diverse range of geographic locations. For a
237 complete list of geographic locations, see Supplementary Table 2.

238 Participants in our survey aged between 11 to 84 years [EFA sample: *min* = 11,
239 *max* = 84; CFA sample: *min* = 12, *max* = 74], with an overall mean of ~ 32.95 years of
240 age [Overall: *M* = 32.95, *SD* = 14.57; EFA: *M* = 32.99, *SD* = 15.11; CFA: *M* = 32.89, *SD*
241 = 13.66]. In total 325 (47%) of the participants indicated female sex [EFA: 189 (44%);
242 CFA: 136 (52%)], 351 (51%) indicated male [EFA: 230 (54%); CFA: 121 (46%)] and 14
243 (2.0%) indicated other sex [EFA: 9 (2.1%), CFA: 5 (1.9%)]. Overall, 49 (7.2%) [EFA: 33
244 (7.8%); CFA: 16 (6.2%)] participants indicated a gender-variant identity. In a “Yes/No”
245 question regarding native language, 320 (46%) of respondents [EFA: 191 (45%); CFA:
246 129 (49%)] indicated to be native English speakers. For their “Occupational Status,”
247 more than half of the overall sample reported that they currently work [Overall: 396
248 (57%); EFA: 235 (55%); CFA: 161 (61%)], whereas 174 (25%) [EFA: 122 (29%); CFA: 52
249 (20%)] reported that they go to school and 120 (17%) [EFA: 71 (17%); CFA: 49 (19%)]
250 responded that they do “Neither.” With respect to the COVID-19 pandemic we asked
251 participants to indicate their occupational setting during the last four weeks: In the overall
252 sample 303 (44%) [EFA: 194 (45%); CFA: 109 (42%)] of the participants indicated that
253 they were in a home office/ home schooling setting, while 109 (16%) overall [EFA: 68
254 (16%); CFA: 41 (16%)] reported face-to-face work/schooling. Lastly, 147 (21%) overall
255 [EFA: 94 (22%); CFA: 53 (20%)] reported a combination of home- and face-to-face

256 work/schooling, whereas 131 (19%) overall [EFA: 72 (17%); CFA: 59 (23%)] filled in the
257 "Neither (no work or school, or on vacation)" response option.

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

259 **Descriptive Statistics.** Figure 2 and Figure 3 summarize the response pattern of
260 our total sample ($n = 690$) for all 48 items. Most of the items were skewed.

261 **Item Analysis.** Supplementary Figure 1 summarizes the univariate descriptive
262 statistics for the 48 items among EFA sample ($n = 428$). Our data violated both univariate
263 normality (Shapiro & Wilk, 1965) and multivariate normality assumptions (Mardia, 1970).
264 Multivariate skew was 583.80 ($p < 0.001$) and multivariate kurtosis was 2,749.15 (p
265 < 0.001). The corrected item-total correlation ranges between .03 -.48. However, no item
266 was discarded based on descriptive statistics or item analysis.

267 **Exploratory Factor Analysis.** Sampling adequacy was checked using
268 Kaiser-Meyer-Olkin (KMO) measures of sampling adequacy using the EFA sample (n
269 = 428) (Kaiser, 1974). The overall KMO value for 48 items was 0.63 which was above the
270 cutoff value (.50) indicating adequate sample size (Hutcheson, 1999). Bartlett's test of
271 sphericity (Bartlett, 1954), $\chi^2 (1128) = 5042.86$, $p < .001$ indicated the correlations
272 between items are adequate for conducting the EFA. However only 4.96% of the
273 inter-item correlation coefficients were greater than |.30|. The inter-item correlation
274 coefficients ranged between -.44 to .91. Figure 4-A depicts the correlation matrix.

275 Scree plot (Figure 4-B) suggested a six-factor solution. However, the minimum
276 average partial (MAP) (Velicer, 1976) method (Supplementary Table 3) and Hull method
277 (Lorenzo-Seva et al., 2011) (Figure 4C) suggested a five-factor solution. As a result, we
278 tested both five-factor and six-factor solutions.

279 With the initial 48 items we conducted three rounds of EFA and gradually discarded
280 problematic items (cross-loading items and poor factor loading (<.30) items). Finally, a

281 five-factor EFA solution with 25 items was accepted with all factor-loading higher than
282 .30 and no cross-loading greater than .30. Table 2 displays the factor-loading (structural
283 coefficients) and communality of the items. The absolute value of the factor-loading
284 ranged from .32 to .99 indicating strong coefficients. The commonalities ranged between
285 .11 to .99. However, the histogram of the absolute values of non-redundant
286 residual-correlations (Figure 4D) showed 26% correlations were greater than the
287 absolute value of .05, indicating a possible under-factoring. (Desjardins & Bulut, 2018).
288 Subsequently, we fitted a six-factor solution. However, a factor emerged with only two
289 salient variables, thus disqualifying the six-factor solution (**Supplementary Table 4**).

290 In the five-factor solution, the first factor contained three items and explained
291 10.25% of the total variance with an internal reliability coefficient ordinal $\alpha = .94$. All the
292 items in this factor stemmed from the individual's preference of using blue light filters in
293 different light environments. The second factor contained six items and explained 9.93%
294 of the total variance with an internal reliability coefficient ordinal $\alpha = .76$. Items under this
295 factor investigated individuals' hours spent outdoor. The third factor contained five items
296 and explained 8.83% of the total variance. Items under this factor dealt with the specific
297 behaviours pertaining to using phone and smart-watch in bed. The internal consistency
298 reliability coefficient was, ordinal $\alpha = .75$. The fourth factor contained five items and
299 explained 8.44% of the total variance with an internal consistency coefficient, ordinal $\alpha =$
300 .72. These five items investigated the behaviours related to individual's light exposure
301 before bedtime. Lastly, the fifth factor contained six items and explained 6.14% of the
302 total variance. This factor captured individual's morning and daytime light exposure
303 related behaviour. The internal consistency reliability was, ordinal $\alpha = .62$. It is essential
304 to attain a balance between psychometric properties and interpretability of the common
305 themes when exploring the latent structure. As all of the emerged factors are highly
306 interpretable and relevant towards our aim to capture light exposure related behaviour,
307 regardless of the apparent low reliability of the fifth factor, we retain all the five-factors

308 with 23 items for our confirmatory factor analysis (CFA). Two items showed negative
309 factor-loading (items 44 and 21). Upon inspection, it was understood that these items
310 are negatively correlated to the respective common theme, and thus in the CFA analysis,
311 we reverse coded these two items.

312 **Confirmatory Factor Analysis and Reliability Analysis.** Table 3 summarizes the
313 CFA fit indices of our fitted model. Our fitted model attained acceptable fit ($CFI = .94$; TLI
314 $= .93$; $RMSEA = .06$, [.05-.07, 90% CI]) with two imposed equity constrain on item pairs
315 32-33 [I dim my mobile phone screen within 1 hour before attempting to fall asleep.; I dim
316 my computer screen within 1 hour before attempting to fall asleep.] and 16-17 [I wear
317 blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day.; I wear
318 blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the day.]. Items
319 pair 32-33 stemmed from the preference of dimming electric device's brightness before
320 bed time and items pair 16 and 19 stemmed from the preference of using blue filtering or
321 coloured glasses during the daytime. Nevertheless, SRMR value was higher than the
322 guideline ($SRMR = .12$). Further by allowing one pair of items (30-41) [I look at my
323 smartwatch within 1 hour before attempting to fall asleep.; I look at my smartwatch when I
324 wake up at night.] to covary their error variance and discarding two item (item 37 & 26)
325 for very low r-square value, our model attained the best fit ($CFI = .95$; $TLI = .95$); $RMSEA$
326 $= .06$, [.05-.06, 90% CI]). Internal consistency ordinal α for the five factors of LEBA were
327 .96, .83, .70, .69, .52 respectively. Internal consistency McDonald's ω_t coefficient for the
328 total scale was .68. Figure 5 depicts the obtained CFA structure. Supplementary Figure
329 2 depicts the data distribution and endorsement pattern of the retained 23 items in our
330 CFA sample.

331 **Measurement Invariance.** In our CFA sample we had 129 native English speakers
332 and 133 non-native English speakers (For a detailed description these two groups see
333 Sup. Table ??). Table 4 indicates our fitted model had acceptable fit indices for all of the
334 fitted MI models. The model fit did not significantly decrease across the nested models

335 indicating the acceptability of the highest measurement invariance model : residual
336 model.

337 **Secondary Analysis: Semantic Scale Network and Grade Level**

338 “Semantic Scale Network”(SSN) analysis (Rosenbusch et al., 2020) indicated that
339 LEBA (23 items) appeared most strongly related to scales about sleep: “Sleep
340 Disturbance Scale For Children” (Bruni et al., 1996) and “WHO-Composite International
341 Diagnostic Interview (CIDI): Insomnia”(WHO, 1990). The cosine similarities lie between
342 .47 to .51. Flesch-Kincaid Grade Level (Flesch, 1948) analysis on the the 23 items of our
343 scale indicated required educational grade level was 3.33 and with a age above 8.33.

344 **Developing Short form of LEBA**

345 We fitted each factor of LEBA with the graded response model (Samejima et al.,
346 1997) to the combined EFA and CFA sample ($n = 690$). Item discrimination parameters of
347 our tool fell in very high (10 items), high (4 items), moderate (4 items), and low (5 items)
348 categorizes indicating a good range of discrimination along the latent trait level (θ)
349 (Supplementary Table 5). Examination of the item information curve (Supplementary
350 Figure 3) indicated five items (1, 25, 38, 30, & 41) had relatively flat information curves
351 ($I(\theta) < .20$). We discarded those items which yielded a short form of LEBA with 5 factors
352 and 18 items.

353 We treated each factor of short-LEBA as an unidimensional construct and obtain 5
354 TICs (Figure 6). These information curves indicated except the first and fifth factors, the
355 other three factor’s TICs are roughly centred on the centre of the trait continuum (θ).The
356 first and fifth factor had a peak to the right side of the centre of latent trait.Thus we
357 conferred the LEBA tool estimated the light exposure related behaviour with precision
358 near the centre of trait continuum for 2nd, 3rd and 4th factors and near the right side of

³⁵⁹ the centre of trait continuum for 1st and 5th factors (Baker, 2017).

360 Supplementary Table 6 summarizes the item fit indexes of the 18 items. All of the
361 items had RMSEA value $\leq .06$ indicating adequate fit of the items to the fitted IRT model.
362 Supplementary Figure 4 depicts the person fit Z_h statistics histogram of our fitted
363 models. Z_h statistics are larger than -2 for most participants, suggesting a good person
364 fit of the selected IRT models.

Discussion

366 Though there are lots of validated tool to measure light exposure, they don't tell us
367 much about the behavioural aspects pertaining to the light exposure. At present there is
368 a dearth of validated tool to measure light exposure related behaviours. In that vein we
369 have developed a subjective self-reported tool that can capture light exposure related
370 behaviour in different dimensions.

371 Authors along with an expert panel generated 48 items and evaluated their quality
372 and relevance and made necessary amendments. A large scale geographically
373 unconstrained quantitative cross-sectional survey was conducted yielding responses
374 from large sample ($n=428$) to explore the latent structure. Exploratory factor analysis
375 revealed a five factor solution with 25 items. (“Wearing blue light filters,” “Spending time
376 outdoors,” “Using phone and smart-watch in bed,” “Using light before bedtime,” and
377 “Using light in the morning and during daytime”). The internal consistency reliability
378 coefficient ordinal alpha ranged between .62-.94. As all the retained factors were
379 meaningful and contributed essentially towards our aim we retained all five factors.

LEBA can be used to profile individuals based on their light exposure related behaviours, which can facilitate the development process of individual interventions to promote health. All the five factors of LEBA may identify 'problematic' behaviours that are opposed to good light hygiene.

384 Conclusion

385 We developed a novel self-reported subjective tool-“Light exposure behaviour
386 assessment”(LEBA) to capture light exposure related behaviour. We developed 48
387 items, judged the relevance and content of the items and conducted a large scale
388 geographically unrestricted cross-sectional survey. Our EFA gave a five solution with 25
389 items. A CFA with this 25-item scale again offered a five-factor solution, but this time two
390 more item was discarded. The 23-item “LEBA” was found reliable (internal consistency)
391 and valid (structural validity). A short-form of LEBA was developed using IRT analysis.
392 IRT analysis gave a 18-item scale with a good coverage across the underlying trait
393 continuum. Hence, we could recommend that LEBA can be used to measure different
394 aspects of light exposure related behaviour.

395 Future Direction

396 Since, LEBA is the first of its kind, estimating convergent validity with other
397 subjective tool was not possible. One way to establish the convergent validity of LEBA is
398 to administer this subjective tool along which some objective measurement tools
399 (e.g. personalised light dosimeter). Though such objective tools do not directly capture
400 light exposure related behaviour, potential insight can be drawn by understanding the
401 behaviour pattern and light exposure. Also, light exposure related behaviours can be
402 dependent upon the socio-economic status as behaviours can be modulated by
403 available tools individual have on their disposal. Our analysis did not consider
404 socio-economic status, as we didn't measure it. Investigating the properties of LEBA
405 while considering different socio-economic status would be a valuable addition.

406
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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

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					0.993
item36	I wear blue-filtering, orange-tinted, and/or red-tinted glasses within 1 hour before attempting to fall asleep.	0.94					0.899
item17	I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the day.	0.8					0.658
item11	I spend more than 3 hours per day (in total) outside.		0.79				0.642
item10	I spend between 1 and 3 hours per day (in total) outside.		0.76				0.592
item12	I spend as much time outside as possible.		0.65				0.465
item07	I go for a walk or exercise outside within 2 hours after waking up.		0.5				0.267
item08	I spend 30 minutes or less per day (in total) outside.		-0.49				0.252
item09	I spend between 30 minutes and 1 hour per day (in total) outside.		0.32				0.113
item27	I use my mobile phone within 1 hour before attempting to fall asleep.		0.8				0.658
item03	I look at my mobile phone screen immediately after waking up.		0.8				0.682
item40	I check my phone when I wake up at night.		0.65				0.464
item30	I look at my smartwatch within 1 hour before attempting to fall asleep.		0.45				0.353
item41	I look at my smartwatch when I wake up at night.		0.36				0.329

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		0.555
item32	I dim my mobile phone screen within 1 hour before attempting to fall asleep.				0.73		0.624
item35	I use a blue-filter app on my computer screen within 1 hour before attempting to fall asleep.				0.66		0.454
item37	I purposely leave a light on in my sleep environment while sleeping.				-0.39		0.174
item38	I use as little light as possible when I get up during the night.				0.38		0.178
item46	I use tunable lights to create a healthy light environment.				0.6		0.422
item45	I use LEDs to create a healthy light environment.				0.59		0.374
item25	I use a desk lamp when I do focused work.				0.41		0.193
item04	I use an alarm with a dawn simulation light.				0.41		0.219
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		0.165

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
Model 1	448.51	222.00	.94	0.93	0.06	0.05	0.07	0.12
Model 2	415.45	231.00	.95	0.95	0.06	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

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

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

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

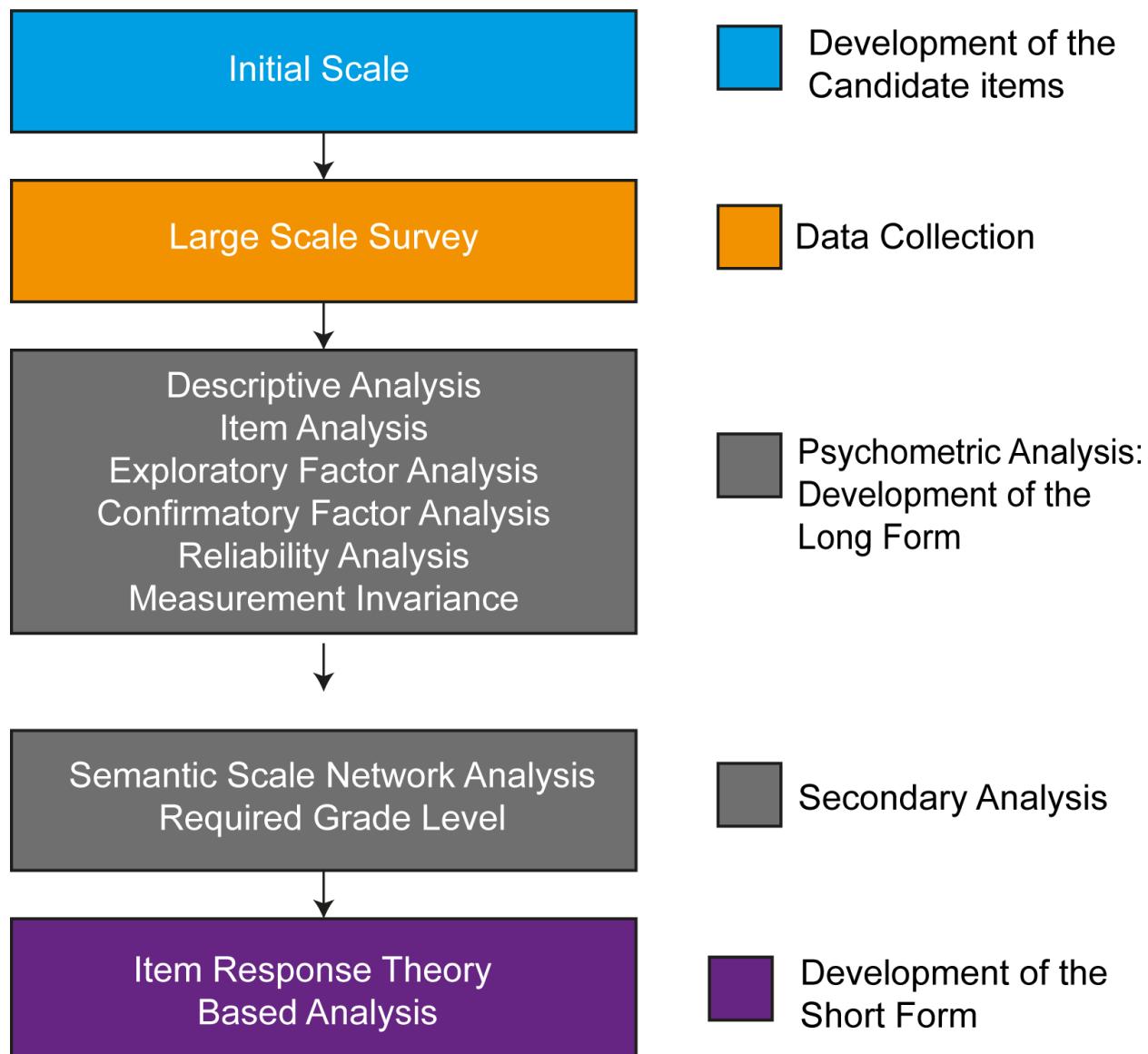


Figure 1. Flow chart of the LEBA (long and short form) development and evaluation.

Summary Descriptives (n =690)

Items 01-24

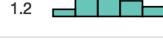
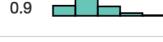
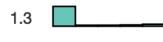
Items	Item	Summary Statistics			Graphics		Response Pattern				
		Mean	Median	SD	Histogram	Density	Never	Rarely	Sometimes	Often	Always
●item01	I turn on the lights immediately after waking up.	2.3	2.0	1.4			41.59% (287)	22.32% (154)	13.33% (92)	11.74% (81)	11.01% (76)
●item02	I open the curtains or blinds immediately after waking up.	2.8	3.0	1.6			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	4.0	1.4			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	1.0	1.1			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	5.0	1.4			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	3.0	1.5			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	2.0	1.2			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	3.0	1.2			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	3.0	1.0			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	3.0	1.1			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	2.0	0.9			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	2.0	1.2			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	3.0	1.5			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	2.0	1.3			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	3.0	1.1			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	1.0	1.3			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	1.0	1.2			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	1.0	0.5			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	1.0	0.3			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	1.0	0.3			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	1.0	0.6			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	4.0	1.1			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	2.0	1.3			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	4.0	1.0			2.90% (20)	5.65% (39)	11.45% (79)	37.83% (261)	42.17% (291)

Figure 2. Summary descriptives and response pattern

Summary Descriptives (n =690)

Items 25-48

LEBA Items	Item Stem	Summary Statistics			Graphics		Response Pattern				
		Mean	Median	SD	Histogram	Density	Never	Rarely	Sometimes	Often	Always
●item25	I use a desk lamp when I do focused work.	2.6	3.0	1.4			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	4.0	1.3			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	4.0	1.3			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	4.0	1.2			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	2.0	1.3			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	1.0	1.1			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	3.0	1.6			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	4.0	1.6			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	4.0	1.7			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	5.0	1.8			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	5.0	1.7			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	1.0	1.3			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	2.0	1.3			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	5.0	1.1			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	2.0	1.1			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	2.0	1.3			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	1.0	0.8			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	5.0	1.4			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	1.0	1.2			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	4.0	1.3			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	1.0	1.5			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	1.0	1.2			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	2.0	1.2			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	2.0	1.3			26.81% (185)	23.33% (161)	28.12% (194)	12.46% (86)	9.28% (64)

Figure 3. Summary descriptives and response pattern

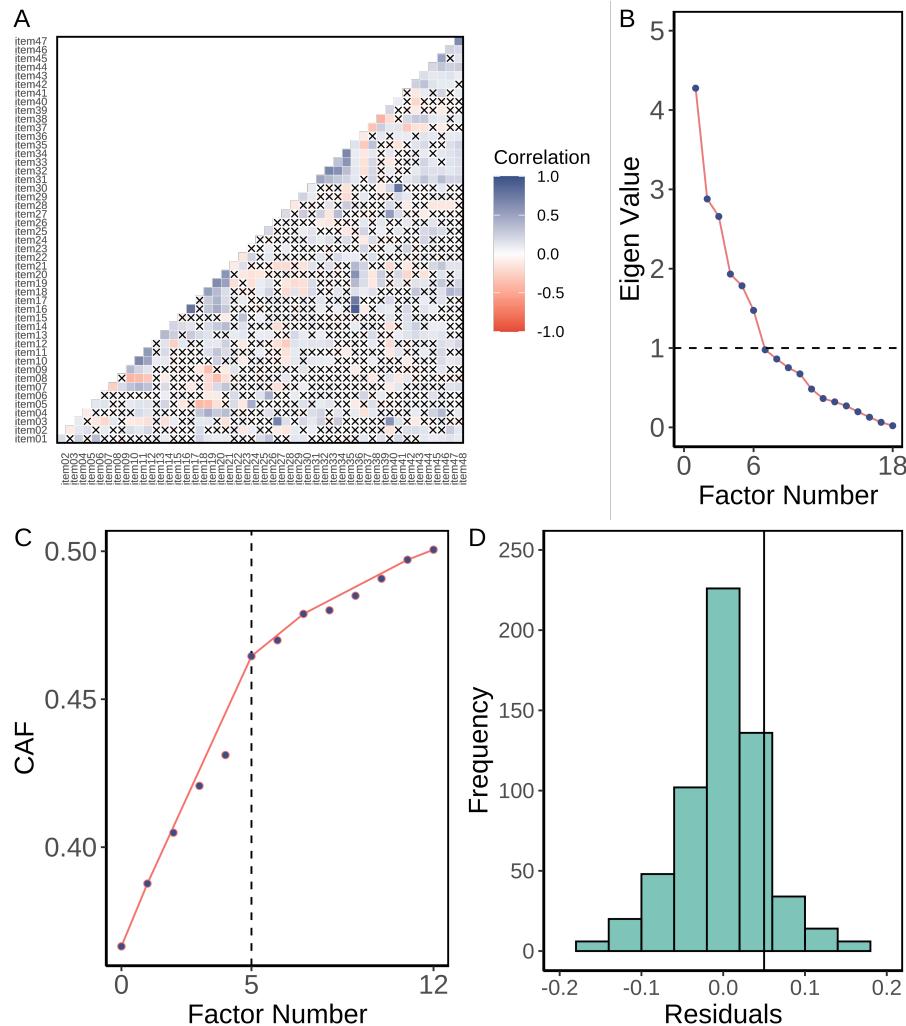


Figure 4. (A) Inter-item polychoric correlation coefficients for the 48 items. 4.9 % inter-item correlation coefficients were higher than $|.30|$. 'x' denotes non-significant item-total correlation. (B) Scree plot suggested six factors. (C) Hull method indicated 5 factors were required to balance the model fit and number of parameters. (D) Histogram of nonredundant residual correlations indicated 26% of inter-item correlations were higher than .05, hinting a possible under factoring.

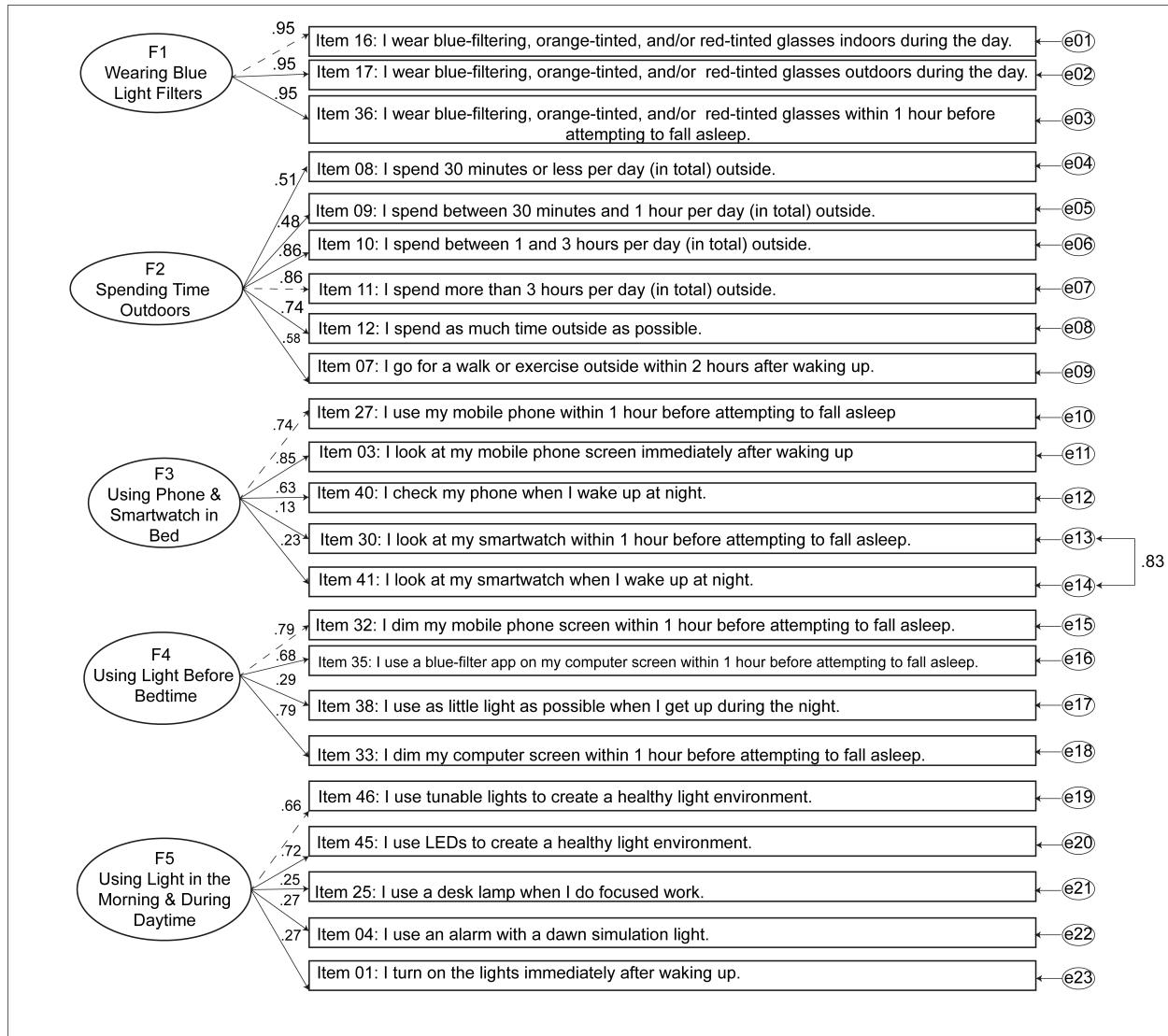


Figure 5. Five factor model of LEBA obtained by confirmatory factor analysis. By allowing item pair 41 and 30 to covary their error variance our model attained the best fit.

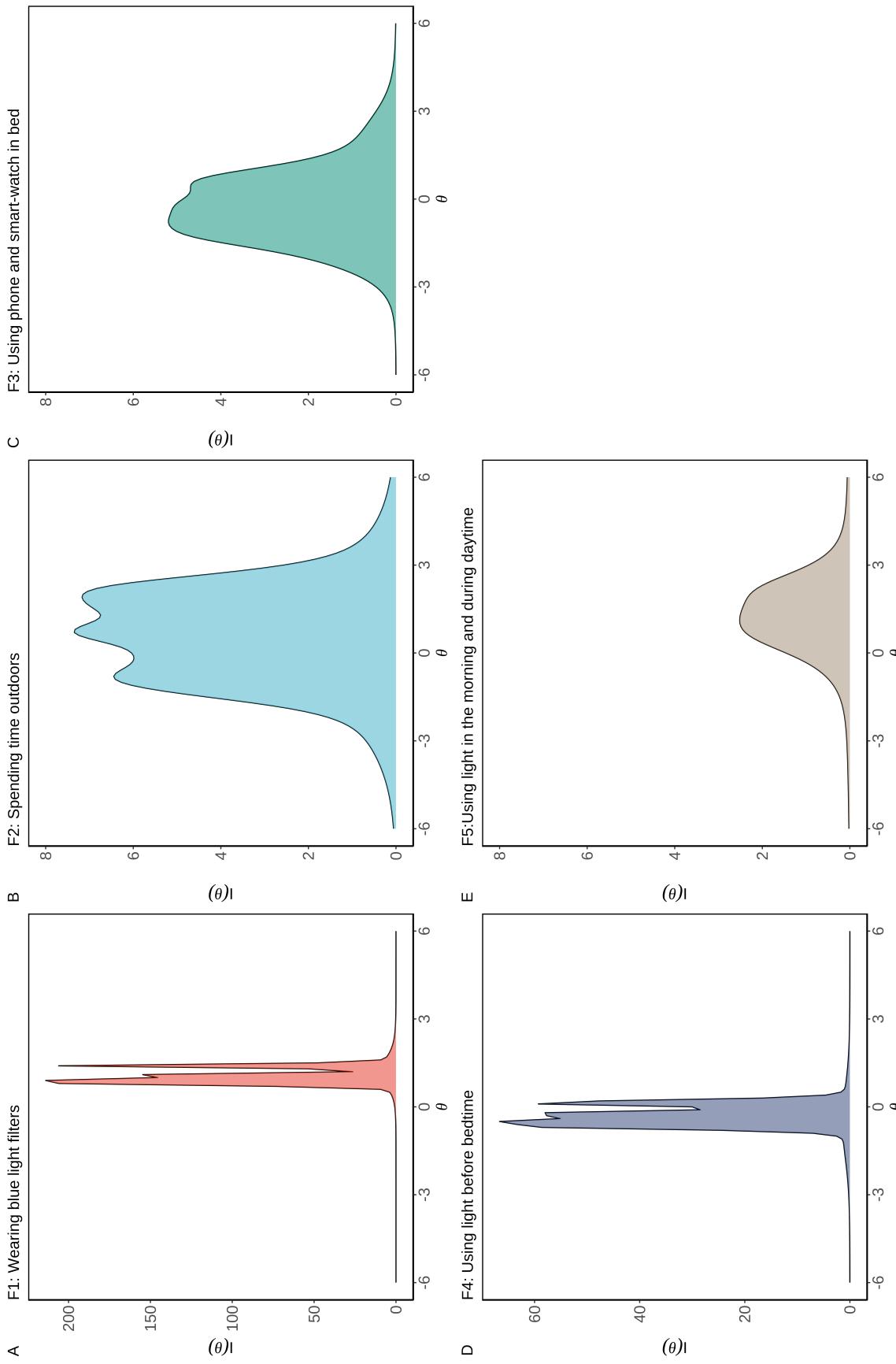


Figure 6. Test information curves for the five factors of LEBA: (a) wearing blue light filters (b) spending time outdoors (c) using phone and smartwatch in bed (d) using light before bedtime (e) using light in the morning and during daytime. Along x-axis we plotted the underlying latent trait continuum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