

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

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53

Abstract

54 Light exposure is an essential driver of health and well-being. Our behaviour modulates
55 many aspects of light exposure, but how these light-related behaviours can be shaped to
56 optimise personal light exposure is currently unknown. Here, we present a novel,
57 self-reported and psychometrically validated instrument to capture light exposure-related
58 behaviour, the Light Exposure Behaviour Assessment (LEBA).

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

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

⁷⁹ *Keywords:* light exposure, light-related behaviours, non-visual effects of light,

⁸⁰ psychometrics

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83 *capture light exposure-related behaviours*

Introduction

Light exposure received by the eyes affects many facets of human health, well-being, and performance beyond visual sensation and perception (Boyce, 2022). The so-called non-image-forming (NIF) effects of light comprise light's circadian and non-circadian influence on several physiological and psychological functions, such as the secretion of melatonin, sleep, mood, pupil size, body temperature, alertness, and higher cognitive functions (i.a. reviewed in Bedrosian & Nelson, 2017; Blume, Garbazza, & Spitschan, 2019; Lok, Smolders, Beersma, & Kort, 2018; Paul & Brown, 2019; Santhi & Ball, 2020; Siraji, Kalavally, Schaefer, & Haque, 2021; Zele & Gamlin, 2020). With the introduction of artificial electric light, human behaviour has become somewhat independent of the natural light-dark cycle – people can now frequently choose when to be exposed to light or darkness. For example, they can decide whether to go outdoors and seek out sunlight, switch on/off light-emitting devices, use certain types of lights at home, or avoid specific light environments altogether. Additionally, when light sources can not be directly manipulated, sought out, or avoided (for example, at school, work, or in public places), there is still potential leeway to influence them behaviourally, for instance, by wearing sunglasses, directing one's gaze away or supplementing the situation with additional light sources. Although clearly yielding the potential for good, this agency is further associated with increased electric light exposure at night and indoor time during the day, compromising the natural temporal organisation of the light-dark cycle. For example, in the US, an average of 87% of the time is spent in enclosed buildings (Kleppeis et al., 2001), and more than 80% of the population is exposed to a night sky that is brighter than nights with a full moon due to electric light at night (Kristen J. Navara & Nelson, 2007a). An extensive body of scientific evidence

suggests that the imbalance of light and dark exposure disrupts humans' light-dependent physiological systems (Lunn et al., 2017). Subsequently, this disruption gives rise to a series of adverse health consequences, including the alteration of several hormonal rhythms, increased cancer rates, cardiovascular diseases, and metabolic disorders, such as obesity, and type II diabetes (Chellappa, Vujovic, Williams, & Scheer, 2019; see reviews by Lunn et al., 2017; Kristen J. Navara & Nelson, 2007b) These findings have sparked a significant call for assessment and guidance regarding healthy light exposure and timing – the latter was recently published as consensus-based experts' recommendations, postulating specific requirements for indoor light environments during the daytime, evening, and nighttime (T. M. Brown et al., 2022). Furthermore, building on earlier attempts (e.g. Hubalek, Zöschg, & Schierz, 2006), there was a recent push toward the development and use of portable light loggers to improve ambulant light assessment and gain more insight into the NIF effects of light on human health in field conditions (Duijnhoven, Aarts, Aries, Böhmer, & Rosemann, 2017; Stampfli et al., 2021; Webler, Chinazzo, & Andersen, 2021). Attached to different body parts (e.g., wrist, head on eye level, chest), these devices allow objectively measuring personal light exposure under real-world conditions and are valuable tools for field studies. Nevertheless, these devices also encompass limiting factors such as potentially being intrusive (e.g., when eye-level worn), yielding the risk of getting covered (e.g., when wrist- or chest-worn) and requiring (monetary) resources and expertise for acquisition and maintenance of the devices. On the other hand, several attempts have been made to quantify received light exposure subjectively with self-report questionnaires (cf. Supplementary Table 1), bypassing the cost and intrusiveness issues. However, subjective light intensity assessments pose a new set of challenges: The human visual system constantly adapts to brightness (Hurvich & Jameson, 1966), while the human non-visual light processing works largely subconsciously (Allen, Hazelhoff, Martial, Cajochen, & Lucas, 2018), making the self-report assessment of light properties potentially quite challenging.

especially for inexperienced laypeople. Retrospectively recalling the properties of a light source can further complicate such subjective evaluations. Moreover, measuring light properties alone does not yield any information about how individuals might behave differently regarding diverse light situations. These measurement limitations point to a couple of research challenges we aim to take on here: How can we gain insight into light exposure patterns via self-report but circumvent directly inquiring about the specific properties and intensity of a light source? And how can we simultaneously assess how people habitually interact with the received light? We propose that these challenges can be tackled by assessing light-exposure-related behaviour. We argue that, besides measuring received light exposure as intensity, it is also essential to understand people's behaviours concerning different light situations. Since, in many cases, humans have become their own agents regarding their exposure to light or darkness through artificial electric light, people's light exposure-related behaviours ultimately determine their light consumption and timing: People receive different light depending on their daily activities, including workplace habits, bedtime hygiene, pastime and social activities. The final objective of changing light-dark exposure patterns to avoid or mitigate negative health consequences from unhealthy habits will not just need an assessment of the lighting properties but the active change of behaviours related to light exposure. We argue that assessing these activities is a beneficial stepping stone for prospective behaviour change. Furthermore, people without light measurement expertise may find it easier to appraise and recall their behaviour concerning light exposure than subjectively assessing a light source's properties. To date, little effort has been made to understand and capture these activities. Supplementary Table 1 summarises the existing questionnaire literature assessing light exposure-related properties. However, only a few questions of these existing tools were associated with light exposure-related behaviour. For example, the "Munich Chronotype Questionnaire" [MCTQ; Roenneberg, Wirz-Justice, and Merrow (2003)], a popular self-report tool for identifying chronotypes via mid-sleep times,

162 includes questions about the individual's time spent outdoors on workdays and free days.
163 The Visual Light Sensitivity Questionnaire-8 (Verriotto et al., 2017) and Photosensitivity
164 Assessment Questionnaire (PAQ; Bossini et al. (2006)), a couple of self-report tools
165 measuring visual light sensitivity, contain single items which probe the preference for
166 specific light situations: "In the past month, how often did you need to wear dark glasses
167 on cloudy days or indoors?" (Verriotto et al., 2017); "I prefer rooms that are in
168 semi-darkness."; (Bossini et al., 2006). In addition, the "Pittsburgh Sleep Quality Index"
169 [PSQI; Buysse, Reynolds III, Monk, Berman, and Kupfer (1989)], a popular measure of
170 sleep quality, contains questions about sleep and wake-up times, which are relevant to
171 light exposure around bedtime. However, none of these questionnaires provides a
172 scaleable solution to capture light exposure-related behaviour in various physiologically
173 relevant lighting scenarios. To fill this gap, we here present the development process of
174 a novel self-report tool - the "Light Exposure Behavior Assessment" (LEBA) - for
175 capturing and quantifying diverse light exposure-related behaviours.

176 Methods

177 Data Collection

178 A quantitative cross-sectional, fully anonymous, geographically unconstrained
179 online survey was conducted via REDCap (Harris et al., 2019, 2009) by way of the
180 University of Basel sciCORE. Participants were recruited via the website
181 (<https://enlightenyourclock.org/participate-in-research>) of the science-communication
182 comic book "Enlighten your clock", co-released with the survey (Weinzaepflen &
183 Spitschan, 2021), social media (i.e., LinkedIn, Twitter, Facebook), mailing lists, word of
184 mouth, the investigators' personal contacts, and supported by the distribution of the
185 survey link via f.lux (F.lux Software LLC, 2021). The initial page of the online survey
186 provided information about the study, including that participation was voluntary and that

187 respondents could withdraw from participation at any time without being penalised.
188 Subsequently, consent was recorded digitally for the adult participants (>18 years), while
189 under-aged participants (<18 years) were prompted to obtain additional assent from their
190 parents/legal guardians. Filling in all questionnaires was estimated to take less than 30
191 minutes, and participation was not compensated. As a part of the demographic data,
192 participants provided information regarding age, sex, gender identity, occupational
193 status, COVID-19-related occupational setting, time zone/country of residence and
194 native language. The demographic characteristics of our sample are given in **Table 1**.
195 Participants were further asked to confirm that they participated in the survey for the first
196 time. Additionally, five attention check items (e.g., “We want to make sure you are paying
197 attention. What is 4+5?”) were included among the questionnaires to ensure high data
198 quality. All questions incorporating retrospective recall were aligned to a “past four
199 weeks” period.

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

203 Analytic Strategy

204 Figure 1 summarises the steps we followed while developing the LEBA. We
205 conducted all analyses with the statistical software environment R (R Core Team, 2021).
206 Firstly, we set an item pool of 48 items with a six-point Likert-type response format
207 (0-Does not apply/I don't know, 1-Never, 2-Rarely 3-Sometimes, 4-Often, 5-Always) for
208 our initial scale. Our purpose was to capture light exposure-related behaviour. In that
209 context, the first two response options: “Does not apply/I don't know” and “Never”,
210 provided similar information. As such, we collapsed them into one, making it a 5-point
211 Likert-type response format (1-Never, 2-Rarely, 3-Sometimes, 4-Often, 5-Always).

212 Secondly, the two rounds of data collection were administered. Thirdly, we
213 conducted descriptive and item analysis and proceeded to the exploratory factor analysis
214 (EFA) using the “psych” package (Revelle, 2021) on the data collected in the first round
215 (EFA sample; n=428), as a part of psychometric analysis. Prior to the EFA, the
216 necessary assumptions, including sample adequacy, normality assumptions, and quality
217 of correlation matrix, were assessed. As our data violated both the univariate and
218 multivariate normality assumption and yielded ordinal response data, we used a
219 polychoric correlation matrix in the EFA and employed “principal axis” (PA) as the factor
220 extraction method (Desjardins & Bulut, 2018; Watkins, 2020). We applied a combination
221 of methods, including a Scree plot (Cattell, 1966), minimum average partials method
222 (Velicer, 1976), and Hull method (Lorenzo-Seva, Timmerman, & Kiers, 2011) to identify
223 factor numbers. To determine the latent structure, we followed the common guidelines:
224 (i) no factors with fewer than three items (ii) no factors with a factor loading <0.3 (iii) no
225 items with cross-loading > .3 across factors (Bandalos & Finney, 2018).

226 For reliability estimation, the “psych” package was applied (Revelle, 2021). Though
227 Cronbach’s internal consistency coefficient alpha is widely used for estimating internal
228 consistency, it tends to deflate the estimates for Likert-type data since the calculation is
229 based on the Pearson-correlation matrix, which requires response data to be continuous
230 in nature (Gadermann, Guhn, & Zumbo, 2012; Zumbo, Gadermann, & Zeisser, 2007).
231 Subsequently, we reported ordinal alpha for each factor obtained in the EFA (Zumbo et
232 al., 2007) to get better reliability estimates. We also estimated the internal consistency
233 reliability of the total scale using McDonald’s ω_t coefficient, which was suggested as a
234 better reliability estimate for multidimensional constructs (Dunn, Baguley, & Brunsden,
235 2014; Sijtsma, 2009). Both ordinal alpha and McDonald’s ω_t coefficient values range
236 between 0 to 1, where higher values represent better reliability.

237 To validate the latent structure obtained in the EFA, we conducted a categorical
238 confirmatory factor analysis (CFA) with the weighted least squares means and variance

adjusted (WLSMV) estimation (Desjardins & Bulut, 2018), using the “lavaan” package (Rosseel, 2012) on the data collected in the second round (CFA sample; n=262). 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 .95 or above/ between .90-.95 and above (iii) root mean square error of approximation (RMSEA): close to .06 or below, (iv) Standardized root mean square (SRMR): close to .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.

We then assessed the measurement invariance (MI) of our scale between native English speakers (n=129) and non-native English speakers (n=133) in the CFA sample (n=262). MI evaluates whether a construct has the psychometric equivalence and the same meaning across groups (Kline, 2016; Putnick & Bornstein, 2016). We used the structural equation modelling framework applying the “lavaan” package (Rosseel, 2012) to assess the measurement invariance. We successively compared four nested models: configural, metric, scalar, and residual models using the χ^2 difference test ($\Delta\chi^2$). Among MI models, the configural model is the least restrictive, and the residual model is the most restrictive. A non-significant $\Delta\chi^2$ test between two nested measurement invariance models indicates mode fit does not significantly decrease for the superior model, thus allowing the superior invariance model to be accepted (Dimitrov, 2010; Widaman & Reise, 1997).

Fourthly, as secondary analysis, we identified the educational grade level required to understand the items in our scale with the Flesch-Kincaid grade level identification method (Flesch, 1948) applying the “koRpus” (Michalke, 2021) package. Correspondingly, we analysed possible semantic overlap of our developed scale using the “Semantic Scale Network” (SSN) engine (Rosenbusch, Wanders, & Pit, 2020). The

²⁶⁶ SSN detects semantically related scales and provides a cosine similarity index ranging
²⁶⁷ between -.66 to 1 (Rosenbusch et al., 2020). Pairs of scales with a cosine similarity
²⁶⁸ index value of 1 indicate full semantical similarity, suggesting redundancy.

²⁶⁹ Lastly, we derived a short form of the LEBA employing an Item Response Theory
²⁷⁰ (IRT) based analysis. We fitted each factor of the LEBA to the combined EFA and CFA
²⁷¹ sample (n=690) using the graded response model (Samejima, Liden, & Hambleton,
²⁷² 1997) via the “mirt” package (Chalmers, 2012). IRT assesses the item quality by
²⁷³ estimating the item discrimination, item difficulty, item information curve, and test
²⁷⁴ information curve (Baker & Kim, 2017). Item discrimination indicates how well a
²⁷⁵ particular item can differentiate between participants across the given latent trait
²⁷⁶ continuum (θ). Item difficulty corresponds to the latent trait level at which the probability
²⁷⁷ of endorsing a particular response option is 50%. The item information curve (IIC)
²⁷⁸ indicates the amount of information an item carries along the latent trait continuum.
²⁷⁹ Here, we reported the item difficulty and discrimination parameter and categorize the
²⁸⁰ items based on their item discrimination index: none = 0; very low = 0.01 to 0.34; low =
²⁸¹ 0.35 to 0.64; moderate = 0.65 to 1.34 ; high = 1.35 to 1.69; very high >1.70 (Baker &
²⁸² Kim, 2017). We discarded the items with a relatively flat item information curve
²⁸³ (information <.2) to derive the short form of LEBA. We also assessed the precision of the
²⁸⁴ short LEBA utilizing the Test information curve (TIC). TIC indicates the amount of
²⁸⁵ information a particular scale carries along the latent trait continuum. Additionally, the
²⁸⁶ item and person fit of the fitted IRT models were analysed to gather more evidence on
²⁸⁷ the validity and meaningfulness of our scale (Desjardins & Bulut, 2018). The item fit was
²⁸⁸ evaluated using the RMSEA value obtained from Signed- χ^2 index implementation,
²⁸⁹ where an RMSEA value $\leq .06$ was considered an adequate item fit. The person fit was
²⁹⁰ estimated employing the standardized fit index Zh statistics (Drasgow, Levine, &
²⁹¹ Williams, 1985). Here, Zh < -2 was considered as a misfit (Drasgow et al., 1985).

292 **Ethical Approval**

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

299 **Data Availability**

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

305 **Results**

306 **Development of the Initial Scale**

307 An expert panel comprising all authors – researchers from chronobiology, light
308 research, neuroscience and psychology – developed a comprehensive item pool of 48
309 items. The 48 items were examined independently based on their relevance and
310 representativeness of the construct “Light Exposure Related Behaviour” by each panel
311 member, and modifications were suggested as required. The author team discussed the
312 suggestions and amended the items as indicated, thus creating a 48-item scale.

313 **Anonymous Online Survey**

314 Table 1 summarises the survey participants' demographic characteristics. Only
315 participants completing the full LEBA questionnaire were included. Thus, there are no
316 missing values in the item analyses. (XXX??) participants were excluded from the
317 analysis due to not passing at least one of the "attention check" items. For the EFA, a
318 sample of at least 250-300 is recommended (Comrey & Lee, 2013; Schönbrodt &
319 Perugini, 2013). To assess sampling adequacy for CFA, we followed the N:q rule
320 (Bentler & Chou, 1987; Jackson, 2003; Kline, 2016; Worthington & Whittaker, 2006),
321 where at least ten participants per item are required to earn trustworthiness of the result.
322 Both our EFA and CFA sample size exceeded these requirements. Participants indicated
323 filling out the online survey from various geographic locations, including 74 countries and
324 28 time zones. For a complete list of geographic locations, see **Supplementary Table 2**.

325 Participants in our survey were aged between 11 to 84 years, with an overall mean
326 of ~ 32.95 years of age [Overall: 32.95 ± 14.57 ; EFA: 32.99 ± 15.11 ; CFA: 32.89 ± 13.66]. In
327 total, 325 (47%) of the participants indicated female sex, 351 (51%) indicated male, and
328 14 (2.0%) indicated other sex. Overall, 49 (7.2%) participants reported a gender-variant
329 identity. In a "Yes/No" question regarding native language, 320 (46%) of respondents
330 [EFA: 191 (45%); CFA: 129 (49%)] indicated to be native English speakers. For their
331 "Occupational Status", more than half of the overall sample reported that they currently
332 work, whereas 174 (25%) reported that they go to school, and 120 (17%) responded that
333 they do "Neither". With respect to the COVID-19 pandemic, we asked participants to
334 indicate their occupational setting during the last four weeks: In the overall sample 303
335 (44%) of the participants indicated that they were in a home office/ home schooling
336 setting, while 109 (16%) reported face-to-face work/schooling. Lastly, 147 (21%) overall
337 reported a combination of home- and face-to-face work/schooling, whereas 131 (19%)
338 filled in the "Neither (no work or school, or on vacation)" response option.

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

340 **Descriptive Statistics and Item Analysis.** Figure 2 and Figure 3 summarise the
341 response patterns of our total sample (n=690) for all 48 items. Most of the items
342 appeared skewed. The Shapiro–Wilk test of univariate normality (Shapiro & Wilk, 1965)
343 and Mardia test of multivariate normality (Mardia, 1970) indicated that our data violated
344 both univariate and multivariate normality. The multivariate skew was 488.40 (p <0.001),
345 and the multivariate kurtosis was 2,808.17 (p <0.001).

346 **Supplementary Figure 1** summarises the univariate descriptive statistics for the 48
347 items in the EFA sample (n=428). Likewise, our data violated the univariate (Shapiro &
348 Wilk, 1965) and multivariate normality assumptions (Mardia, 1970). The multivariate
349 skew was 583.80 (p <0.001) and the multivariate kurtosis yielded a value of 2,749.15 (p
350 <0.001). The corrected item-total correlation ranged between .03 and .48. However, no
351 item was discarded based on descriptive statistics or item analysis.

352 **Exploratory Factor Analysis and Reliability Analysis.** We checked the sampling
353 adequacy by applying Kaiser-Meyer-Olkin (KMO) measures of sampling adequacy on
354 the EFA sample (n=428) (Kaiser, 1974). The overall KMO value for 48 items was 0.63,
355 which exceeded the cut-off value (.50), indicating an adequate sample size (Hutcheson,
356 1999). Additionally, Bartlett's test of sphericity (Bartlett, 1954), χ^2 (1128)=5042.86, p <
357 .001 implied that the correlations between items were adequate for conducting the EFA.
358 However, only 4.96% of the inter-item correlation coefficients were greater than |.30|.,
359 and the inter-item correlation coefficients ranged between -.44 to .91. Figure 4-A depicts
360 the respective correlation matrix.

361 Inspection via the Scree plot (Figure 4-B) suggested a six-factor solution, whereas
362 the minimum average partial (MAP) method (Velicer, 1976) (Supplementary Table 3) and
363 Hull method (Lorenzo-Seva et al., 2011) (Figure 4-C) implied a five-factor solution for
364 the LEBA questionnaire. As a result, we tested both five-factor and six-factor solutions.

365 Applying varimax rotation, we conducted three rounds of EFA with the initial 48
366 items and gradually discarded problematic items (cross-loading items and items with
367 factor loading <.30). Finally, a five-factor EFA solution with 25 items was accepted with
368 all factor-loading higher than .30 and no cross-loading greater than .30. Table 2 displays
369 the factor-loading (structural coefficients) and communality of the items. The absolute
370 values of the factor-loadings ranged from .32 to .99 indicating strong coefficients. The
371 commonalities ranged between .11 and .99. However, the histogram of the absolute
372 values of nonredundant residual correlations (Figure 4-D) displayed that 26% of
373 correlations were greater than the absolute value of .05, indicating a possible
374 under-factoring. (Desjardins & Bulut, 2018). Subsequently, we fitted a six-factor solution,
375 wherefrom a factor with only two salient variables emerged, thus disqualifying the
376 six-factor solution (Supplementary Table 4).

377 In the five-factor solution, the first factor contained three items and explained
378 10.25% of the total variance with an internal reliability coefficient ordinal $\alpha = .94$. All the
379 items in this factor encapsulated the individual's preference for using blue light filters in
380 different light environments. The second factor contained six items and explained 9.93%
381 of the total variance with an internal reliability coefficient ordinal $\alpha = .76$. Items under this
382 factor incorporated the individuals' hours spent outdoor. The third factor contained five
383 items and explained 8.83% of the total variance. Items under this factor covered the
384 specific behaviours of using a phone and smartwatch in bed. The internal consistency
385 reliability coefficient was ordinal $\alpha = .75$. The fourth factor comprised five items and
386 explained 8.44% of the total variance with an internal consistency coefficient, ordinal $\alpha =$
387 .72. These five items investigated the behaviours related to the individual's light
388 exposure before bedtime. The fifth factor encompassed six items and explained 6.14%
389 of the total variance. This factor captured the individual's morning and daytime light
390 exposure-related behaviour. The internal consistency reliability yielded ordinal $\alpha = .62$.

391 Lastly, we examined the factor's interpretability in the five-factor solution and

392 weighed it against the psychometric properties as we considered it essential to attain a
393 balance between the two. As we deemed the five derived factors interpretable and
394 relevant concerning our aim to capture light exposure-related behaviour, we retained all
395 of them with 25 items for our confirmatory factor analysis (CFA), despite the apparent
396 lower reliability of the fifth factor. Two of the items showed negative factor-loading (items
397 44 and 21). Upon re-inspection, we recognized these items to be negatively correlated to
398 the respective factor, and thus, we reverse-scored these two items in the CFA analysis.
399 The internal consistency coefficient McDonald's ω_t for the total scale was 0.77.

400 **Confirmatory Factor Analysis.** Table 3 compares the CFA fit indices of the original
401 CFA five-factor model with 25 and the post-hoc modified model with 23 items,
402 respectively. The 25-item model attained an acceptable fit ($CFI = .92$; $TLI = .91$; $RMSEA = .07$ [.06-.07, 90% CI]) with two imposed equity constraints on item pairs 32-33 [item 32:
404 I dim my mobile phone screen within 1 hour before attempting to fall asleep; item 33: I
405 dim my computer screen within 1 hour before attempting to fall asleep] and 16-17 [item
406 16: I wear blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day;
407 item 17: I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the
408 day]. Item pair 32-33 describes the preference for dimming the electric devices'
409 brightness before bedtime, whereas item pair 16-17 represents the preference for using
410 blue filtering or coloured glasses during the daytime. Given the similar nature of captured
411 behaviours within each item pair, we accepted the imposed equity constraints.
412 Nevertheless, the SRMR value exceeded the guideline recommendation ($SRMR = .12$).

413 In order to improve the model fit, we conducted a post-hoc model modification.
414 Firstly, the modification indices suggested cross-loadings between item 37 and 26 [item
415 37: I purposely leave a light on in my sleep environment while sleeping; item 26: I turn
416 on my ceiling room light when it is light outside], which were hence discarded. Secondly,
417 items 30 and 41 [item 30: I look at my smartwatch within 1 hour before attempting to fall
418 asleep; item 41: I look at my smartwatch when I wake up at night] showed a tendency to

419 co-vary in their error variance ($MI = 141.127$, $p < .001$). By allowing the latter pair of items
420 (30 & 41) to co-vary, the model's error variance attained an improved fit ($CFI = .95$; $TLI =$
421 $.95$); $RMSEA = .06$ [.05-.06, 90% CI]; $SRMR = .11$). Internal consistency ordinal α for the
422 five factors of the LEBA were $.96$, $.83$, $.70$, $.69$, $.52$, respectively.

423 Accordingly, we accept the five-factor model with 23 items, finalizing the long Form
424 of LEBA (see Supplementary File 1). The Internal consistency McDonald's ω_t coefficient
425 for the total scale yielded $.68$. Figure 5 depicts the obtained CFA structure, while
426 Supplementary Figure 2 depicts the data distribution and endorsement pattern of the
427 retained 23 items in our CFA sample.

428 **Measurement Invariance.** Our CFA sample consisted of 129 native English
429 speakers and 133 non-native English speakers, whose demographic data are contrasted
430 in Supplementary Table 5. As shown in Table 4, the employed five-factor model
431 generated acceptable fit indices over all of the fitted MI models. The model fit did not
432 significantly decrease across the nested models, implying the acceptability of the highest
433 measurement invariance model (residual model).

434 Secondary Analysis: Grade Level Identification and Semantic Scale Network Analysis

435 A grade level identification and Semantic Scale analysis were additionally
436 administered to assess the LEBA's (23 items) language-based accessibility and its'
437 semantic relation to other questionnaires. The results of the Flesch-Kincaid grade level
438 analysis (Flesch, 1948) displayed a required educational grade level of 3.33 with age
439 above 8.33 years, implying that the LEBA instrument should be understandable for
440 students of grade four at least 8.33 years old. Furthermore, the Semantic Scale Network
441 (SSN) analysis (Rosenbusch et al., 2020) indicated that the LEBA appeared most
442 strongly related to scales about sleep: The "Sleep Disturbance Scale For Children"
443 (Bruni et al., 1996) and the "Composite International Diagnostic Interview (CIDI):
444 Insomnia" (Robins et al., 1988). The cosine similarity yielded values between $.47$ to $.51$.

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

446 In order to derive a short form of the LEBA instrument, we fitted each factor of the
447 LEBA with the graded response model (Samejima et al., 1997) to the combined EFA and
448 CFA sample ($n=690$). The resulting item discrimination parameters of the scale fell into
449 categories of “very high” (10 items), “high” (4 items), “moderate” (4 items), and “low” (5
450 items), indicating a good range of discrimination along the latent trait level (θ)
451 (**Supplementary Table 6**). An examination of the item information curve (**Supplementary**
452 **Figure 3**) revealed five items (1, 25, 30, 38, & 41) with relatively flat curves ($I(\theta) <.20$).
453 We discarded those items, culminating in a short form of LEBA with five factors and 18
454 items (**Supplementary File 2**).

455 Subsequently, we treated each factor of the short-LEBA as a unidimensional
456 construct and obtained five test information curves (TICs). As (Figure 6). illustrates, the
457 TICs of the first and fifth factors peaked on the right side of the centre of their latent
458 traits, while the TICs of the other three factors were roughly centred on the respective
459 trait continuum (θ). This points out that the LEBA short-scale estimates the light
460 exposure-related behaviour most precisely near the centre of the trait continuum for the
461 second, third and fourth factors and, in contrast, to the right of the centre for the first and
462 fifth factors (Baker & Kim, 2017).

463 Finally, **Supplementary Table 7** summarises the item fit indexes of the LEBA short
464 form. All 18 items yielded RMSEA value $\leq .06$, indicating adequate fit to the fitted IRT
465 model. Furthermore, **Supplementary Figure 4** depicts the person fit Z_h statistics
466 histogram for the five IRT models. Z_h statistics are larger than -2 for most participants,
467 suggesting a good person fit regarding the selected IRT models.

468

Discussion

469 Nowadays, in many industrialized countries, most of the time is spent in enclosed
470 buildings (Klepeis et al., 2001), where people's received light is determined not only by
471 the natural light-dark cycle but by exposure to artificial light sources. Accordingly, people
472 receive varying light intensities at different times, ultimately depending on their
473 light-related behavioural habits. As established by extensive evidence, the timing,
474 duration and intensity of light exposure, among other light properties, affect many
475 aspects of human health, well-being, and performance (i.a. reviewed in Bedrosian &
476 Nelson, 2017; Blume et al., 2019; Lok et al., 2018; Paul & Brown, 2019; Santhi & Ball,
477 2020; Siraji et al., 2021; Zele & Gamlin, 2020). Thus, there is a clear need for guidance
478 (see T. M. Brown et al., 2022) and assessment regarding healthy light exposure and
479 consequentially healthy light-related behaviour. In reviewing the literature, we found that
480 a handful of previously introduced instruments assess aspects of light exposure by
481 self-report (see **Supplementary Table 1**). Even fewer assessment tools have yet partially
482 probed behavioural aspects of received light like the estimated time spent outside
483 [MCTQ; Roenneberg et al. (2003)] or the preference for specific light situations (e.g. "I
484 prefer rooms that are in semi-darkness."); PAQ Bossini et al. (2006)). However, none of
485 these questionnaires systematically and thoroughly captures behaviours that modify light
486 exposure across different lighting scenarios. With the present LEBA tool, we have
487 developed two versions of a self-report scale that can capture light exposure-related
488 behaviour in multiple dimensions.

489 The 48 initially generated items were applied in a large-scale geographically
490 unconstrained cross-sectional survey, yielding (n=690) complete datasets. Moreover, to
491 assure high data quality, this included only data where the five "attention check items"
492 throughout the survey were passed. As a result, data was recorded from 74 countries
493 and 28 time zones, including native and non-native English speakers from a

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

497 Data collected in the first round was used to explore the latent structure (EFA
498 sample; n=428). The exploratory factor analysis revealed a highly interpretable
499 five-factor solution (“Wearing blue light filters”, “Spending time outdoors”, “Using phone
500 and smartwatch in bed”, “Using light before bedtime”, and “Using light in the morning and
501 during daytime”) with 25 items. The total scale exhibited satisfactory internal consistency
502 (McDonald’s $\omega_t = 0.77$).

503 Our CFA analysis (CFA sample; n=262) confirmed the five-factor structure we
504 obtained in our EFA, thus providing evidence for structural validity.(CFI=.95; TLI=.95;
505 RMSEA=.06 [.05-.06, 90% CI]; SRMR=.11). In this model, we discarded two additional
506 items (item 26 & 37) for possible cross-loadings. The internal consistency coefficients
507 ordinal alpha for the five factors and the total scale were again satisfactory (Ordinal
508 alpha ranged between 0.52 to 0.96; McDonald’s $\omega_t = .68$).

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

520 while the CIDI and the SDSC capture various clinically relevant sleep problems and
521 related activities, the LEBA aims to assess light-exposure-related behaviour. Since light
522 exposure at night has been shown to influence sleep negatively (T. M. Brown et al.,
523 2022; Santhi & Ball, 2020), this overlap confirms our aim to measure the physiologically
524 relevant aspects of light-exposure-related behaviour. Nevertheless, the general
525 objectives of the complete questionnaires and the LEBA differ evidently.

526 Lastly, we derived a short version of the LEBA (18 items) using IRT analysis. We
527 fitted a graded response model to the combined EFA and CFA sample ($n=690$) and
528 discarded five items (1, 25, 30, 38, & 41) with relatively flat item information curve $[I(\theta)]$
529 $<.20$. The resulting test information curves suggest that the short-LEBA is a
530 psychometrically sound measure with adequate coverage of underlying traits and can be
531 applied to capture different extents of light exposure-related behaviours reliably.

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

537 ##Known Limitations

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

- 539 • In the five factor-solution derived from the Exploratory factor analysis, the internal
540 consistency reliability coefficient ordinal alpha ranged between .62-.94, though only
541 the fifth factor ("Using light in the morning and during daytime") yielded internal
542 reliability coefficients below .70 .62. As a rule of thumb, reliability coefficients
543 higher than .70 are regarded as "satisfactory". However, for scales with less than
544 20 items and at the early developmental stage, a value of .50 is considered
545 acceptable (Dall'Oglio et al., 2010; Field, 2015; Nunnally, 1978). Furthermore, the

546 full LEBA scale exhibited satisfactory internal consistency (McDonald's $\alpha=0.77$),
547 while all factors were highly interpretable regarding a common behavioural theme.
548 Thus, we decided to proceed with the five-factor solution.

- 549 • During the post-hoc model modification, as part of the confirmatory factor analysis,
550 we discarded two items (item 26 & 37) for possible cross-loadings, as
551 demonstrated in the data. However, two additional items covaried in their error
552 variance. By allowing the latter pair (30 & 41) to covary, the model's error variance
553 attained an improved fit (cf. Figure 5). A possible explanation for the covariation is
554 that many respondents might not have used a smartwatch at all, resulting in similar
555 response patterns between these two items. Thus, though rather unconventional,
556 we decided to accept this post-hoc modification to our five-factor model.
- 557 • The habitual patterns queried in the developed scales might not exhaustively
558 represent all relevant light-exposure-related behaviours. For instance, it is
559 conceivable that additional light-related activities not included in the LEBA depend
560 on the respondents' profession/occupation, geographical context, and
561 socio-economic status. However, we generated the initial item pool with an
562 international team of researchers and followed a thorough psychometric analysis.
563 Therefore, we are confident that the developed LEBA scales can serve as a good
564 starting point for exploring the behavioural aspects of light exposure in more depth.
- 565 • As with all studies relying on retrospective self-report data, individuals filling in the
566 LEBA may have difficulties precisely recalling the inquired light-related behaviours.
567 In the interest of bypassing a substantial memory component, we limited the recall
568 period to four weeks and chose response options that do not require exact memory
569 recall. In contrast to directly assessing light properties via self-report, we assume
570 that reporting behaviours might be more manageable for inexperienced laypeople,
571 as the latter does not rely on existing knowledge about light sources. The
572 accessibility of the LEBA is also reflected in the "grade level identification" findings

573 suggesting a minimum age of 8.33 years and an educational grade of four or
574 higher. We argue that measuring light-related behaviours via self-report is crucial
575 because these behaviours will hardly be as observable by anyone else or
576 measurable with other methods (like behavioural observations) with reasonable
577 effort.

578 Future Directions

579 To our knowledge, the LEBA is the first questionnaire characterising light
580 exposure-related behaviour in a scalable manner. Thus, estimating convergent validity
581 with similar subjective scales was impossible. Alternatively, the validity of the LEBA
582 could be evaluated by administering it conjointly with objective field measurements of
583 light exposure (e.g. with portable light loggers, see literature review). By this route, one
584 could study how the (subjectively measured) light exposure-related behavioural patterns
585 translate into (objectively measured) received light exposure. Additionally, developing
586 daily recall scales of light-related behaviour could provide a more detailed behavioural
587 assessment to supplement the LEBA's broader (four-week) measurement approach.
588 Comparing the LEBA scores to 24-hour recall scores could provide helpful information
589 about how light exposure-related behaviour assessment is related between different time
590 perspectives. Moreover, light-exposure-related behaviour might depend on the
591 respondents' profession, geographical location, housing conditions, socio-economic
592 status, or other contextual factors. As the current data is limited to our international
593 online survey context, future research should apply the LEBA across more variable
594 populations and contexts. On the other hand, this will require the development of
595 cross-cultural adaptations and translations into other languages of the LEBA scale,
596 which should be targeted in prospective studies. Finally, in the future, applying the LEBA
597 scales should not just be limited to gathering information in cross-sectional quantitative
598 studies but allow for individual behaviour profiling. For instance, the LEBA could be

599 applied in a clinical context as part of Cognitive Behavioural Therapy for Insomnia
600 (CBT-I). More specifically, it could be used to supplement the sleep hygiene aspects of
601 CBT-I, as receiving light exposure at different times has implications for sleep (Santhi &
602 Ball, 2020). This match was also evident in the semantic relationship between the LEBA
603 and two scales capturing sleep problems (CIDI: Insomnia;@robins1988composite &
604 SDSC; Bruni et al. (1996)) found in the semantic similarity analysis. However, before
605 applying the LEBA in such contexts in the future, more work is certainly needed to
606 understand light exposure-related behaviour and its' relationship to relevant health
607 outcomes measured subjectively and objectively.

608 Conclusion

609 With the “Light exposure behaviour assessment”(LEBA), we developed a novel,
610 internally consistent and structurally valid 23-item self-report scale for capturing light
611 exposure-related behaviour in five scalable factors. In addition, an 18-item short-form of
612 the LEBA was derived using IRT analysis, yielding adequate coverage across the
613 underlying trait continuum. Applying the LEBA scales can provide insights into light
614 exposure-related habits on a population-based level. Furthermore, it can serve as a
615 good starting point to profile individuals based on their light exposure-related behaviour
616 determining their light consumption and timing.

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Table 1

Demographic Characteristics of Participants (n=690).

Variable	Overall, N = 690	1. EFA Sample, N = 428	2. CFA Sample, N = 262
Age	32.95 (14.57)	32.99 (15.11)	32.89 (13.66)
Sex			
Female	325 (47%)	189 (44%)	136 (52%)
Male	351 (51%)	230 (54%)	121 (46%)
Other	14 (2.0%)	9 (2.1%)	5 (1.9%)
Gender-Variant Identity	49 (7.2%)	33 (7.8%)	16 (6.2%)
Native English Speaker	320 (46%)	191 (45%)	129 (49%)
Occupational Status			
Work	396 (57%)	235 (55%)	161 (61%)
School	174 (25%)	122 (29%)	52 (20%)
Neither	120 (17%)	71 (17%)	49 (19%)
Occupational setting			
Home office/Home schooling	303 (44%)	194 (45%)	109 (42%)
Face-to-face work/Face-to-face schooling	109 (16%)	68 (16%)	41 (16%)
Combination of home- and face-to-face- work/schooling	147 (21%)	94 (22%)	53 (20%)
Neither (no work or school, or in vacation)	131 (19%)	72 (17%)	59 (23%)

¹ Mean (SD); n (%)

Table 2

Factor loadings and communality of the retained items in EFA using principal axis extraction method (n=482).

item	Stem	PA1	PA2	PA3	PA4	PA5	Communality
item16	I wear blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day.	0.99					0.99
item36	I wear blue-filtering, orange-tinted, and/or red-tinted glasses within 1 hour before attempting to fall asleep.	0.94					0.90
item17	I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the day.	0.8					0.66
item11	I spend more than 3 hours per day (in total) outside.		0.79				0.64
item10	I spend between 1 and 3 hours per day (in total) outside.		0.76				0.59
item12	I spend as much time outside as possible.		0.65				0.47
item07	I go for a walk or exercise outside within 2 hours after waking up.		0.5				0.27
item08	I spend 30 minutes or less per day (in total) outside.		-0.49				0.25
item09	I spend between 30 minutes and 1 hour per day (in total) outside.		0.32				0.11
item27	I use my mobile phone within 1 hour before attempting to fall asleep.		0.8				0.66
item03	I look at my mobile phone screen immediately after waking up.		0.8				0.68
item40	I check my phone when I wake up at night.		0.65				0.46
item30	I look at my smartwatch within 1 hour before attempting to fall asleep.		0.45				0.35
item41	I look at my smartwatch when I wake up at night.		0.36				0.33

Table 2 continued

item	Stem	PA1	PA2	PA3	PA4	PA5	Communality
item33	I dim my computer screen within 1 hour before attempting to fall asleep.				0.74		0.56
item32	I dim my mobile phone screen within 1 hour before attempting to fall asleep.				0.73		0.62
item35	I use a blue-filter app on my computer screen within 1 hour before attempting to fall asleep.				0.66		0.45
item37	I purposely leave a light on in my sleep environment while sleeping.				-0.39		0.17
item38	I use as little light as possible when I get up during the night.				0.38		0.18
item46	I use tunable lights to create a healthy light environment.				0.6		0.42
item45	I use LEDs to create a healthy light environment.				0.59		0.37
item25	I use a desk lamp when I do focused work.				0.41		0.19
item04	I use an alarm with a dawn simulation light.				0.41		0.22
item01	I turn on the lights immediately after waking up.				0.4		0.17
item26	I turn on my ceiling room light when it is light outside.				0.35		0.16

Note. Only loading > .30 is reported.

Table 3

Confirmatory Factor Analysis model fit indices of the two model: (a) Model 1: five factor model with 25 items (b) Model 2: five factor model with 23 items. Model 2 attained the best fit.

Model	χ^2	df	CFI	TLI	RMSEA	RMSEA 90% Lower CI	RMSEA 90% Upper CI	SRMR
Model 1	Model 1	Model 1	Model 1	Model 1	Model 1	Model 1	Model 1	Model 1
Model 2	Model 2	Model 2	Model 2	Model 2	Model 2	Model 2	Model 2	Model 2

Note. df: Degrees of Freedom; CFI: Comparative Fit Index; TLI: Tucker Lewis Index; RMSEA: Root Mean Square Error of Approximation; CI: Confidence Interval; SRMR: Standardized Root Mean Square.

Table 4

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

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

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

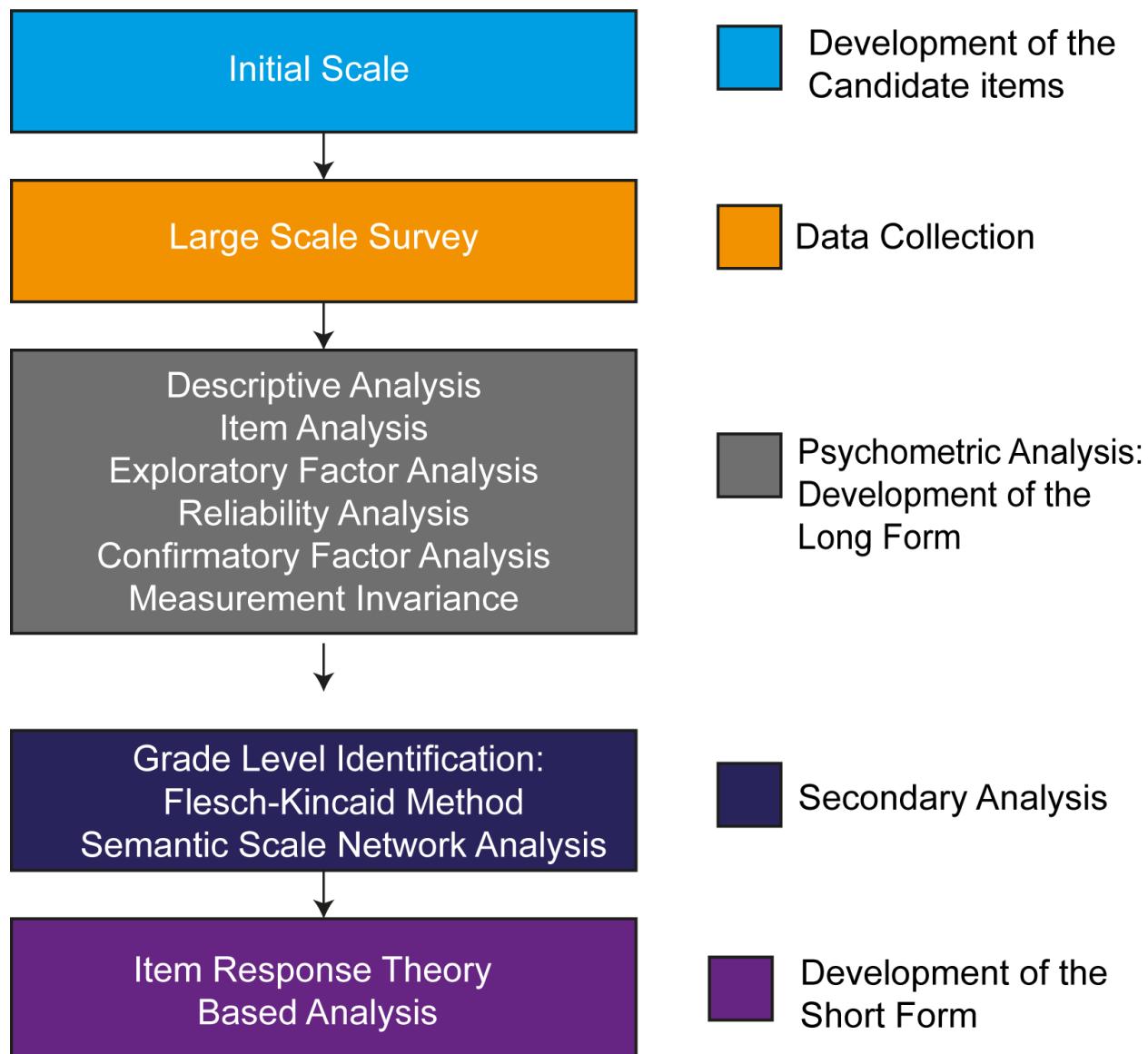


Figure 1. Flow chart of the LEBA (long and short form) development and evaluation.

Summary Descriptives (n=690)											
Items	Item	Summary Statistics			Graphics		Response Pattern				
		Mean	SD	SW ¹	Histogram	Density	Never	Rarely	Sometimes	Often	Always
●item01	I turn on the lights immediately after waking up.	2.3	1.4	0.82*			41.59% (287)	22.32% (154)	13.33% (92)	11.74% (81)	11.01% (76)
●item02	I open the curtains or blinds immediately after waking up.	2.8	1.6	0.84*			32.61% (225)	15.22% (105)	11.30% (78)	19.28% (133)	21.59% (149)
●item03	I look at my mobile phone screen immediately after waking up.	3.5	1.4	0.86*			14.35% (99)	9.86% (68)	17.39% (120)	30.00% (207)	28.41% (196)
●item04	I use an alarm with a dawn simulation light.	1.4	1.1	0.40*			86.09% (594)	3.04% (21)	2.61% (18)	2.46% (17)	5.80% (40)
●item05	I have breakfast within 3 meters from a window.	3.9	1.4	0.74*			14.35% (99)	4.78% (33)	11.01% (76)	18.26% (126)	51.59% (356)
●item06	I have breakfast in a brightly lit room (illuminated by electric light).	2.7	1.5	0.85*			33.19% (229)	15.36% (106)	16.38% (113)	16.09% (111)	18.99% (131)
●item07	I go for a walk or exercise outside within 2 hours after waking up.	2.2	1.2	0.84*			38.70% (267)	26.23% (181)	16.23% (112)	13.04% (90)	5.80% (40)
●item08	I spend 30 minutes or less per day (in total) outside.	3.0	1.2	0.91*			13.91% (96)	22.46% (155)	25.22% (174)	28.26% (195)	10.14% (70)
●item09	I spend between 30 minutes and 1 hour per day (in total) outside.	2.9	1.0	0.91*			11.30% (78)	20.58% (142)	38.99% (269)	23.91% (165)	5.22% (36)
●item10	I spend between 1 and 3 hours per day (in total) outside.	2.7	1.1	0.91*			14.06% (97)	30.58% (211)	30.43% (210)	21.74% (150)	3.19% (22)
●item11	I spend more than 3 hours per day (in total) outside.	2.2	0.9	0.86*			23.77% (164)	46.38% (320)	22.03% (152)	6.38% (44)	1.45% (10)
●item12	I spend as much time outside as possible.	2.3	1.2	0.87*			30.72% (212)	30.14% (208)	20.58% (142)	11.88% (82)	6.67% (46)
●item13	I use sunglasses when I go outside in bright daylight.	2.7	1.5	0.87*			30.14% (208)	17.54% (121)	17.83% (123)	18.70% (129)	15.80% (109)
●item14	I wear a visor or cap when I go outside in bright daylight.	2.1	1.3	0.79*			47.54% (328)	18.84% (130)	12.90% (89)	15.22% (105)	5.51% (38)
●item15	I seek shade when I am outside in bright daylight.	3.3	1.1	0.91*			7.97% (55)	13.91% (96)	35.36% (244)	27.97% (193)	14.78% (102)
●item16	I wear blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day.	1.6	1.3	0.51*			79.13% (546)	3.91% (27)	4.06% (28)	5.07% (35)	7.83% (54)
●item17	I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the day.	1.5	1.2	0.49*			80.43% (555)	3.33% (23)	5.22% (36)	3.04% (21)	7.97% (55)
●item18	I use light therapy applying a white light box.	1.1	0.5	0.27*			92.90% (641)	3.48% (24)	2.75% (19)	0.58% (4)	0.29% (2)
●item19	I use light therapy applying a blue light box.	1.0	0.3	0.12*			97.68% (674)	0.87% (6)	0.72% (5)	0.72% (5)	0.00% (0)
●item20	I use light therapy applying a light visor.	1.0	0.3	0.08*			98.70% (681)	0.14% (1)	0.58% (4)	0.43% (3)	0.14% (1)
●item21	I use light therapy applying another form of light device.	1.1	0.6	0.24*			94.06% (649)	1.45% (10)	3.04% (21)	0.58% (4)	0.87% (6)
●item22	I spend most of my daytime in a brightly lit environment.	3.5	1.1	0.88*			5.36% (37)	13.33% (92)	21.74% (150)	41.59% (287)	17.97% (124)
●item23	I close the curtains or blinds during the day if the light from outside is bright.	2.6	1.3	0.89*			26.38% (182)	24.93% (172)	23.33% (161)	17.25% (119)	8.12% (56)
●item24	I spend most of my indoor time within 3 meters from a window.	4.1	1.0	0.79*			2.90% (20)	5.65% (39)	11.45% (79)	37.83% (261)	42.17% (291)

¹ Shapiro-Wilk test

Figure 2. Summary descriptives and response pattern observed in the large-scale survey for item 01-24. All items violated normality assumption.

Summary Descriptives (n=690)											
Item		Summary Statistics			Graphics		Response Pattern				
LEBA Items	Item Stem	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 3. Summary descriptives and response pattern observed in the large-scale survey for item 25-48. All items violated normality assumption.

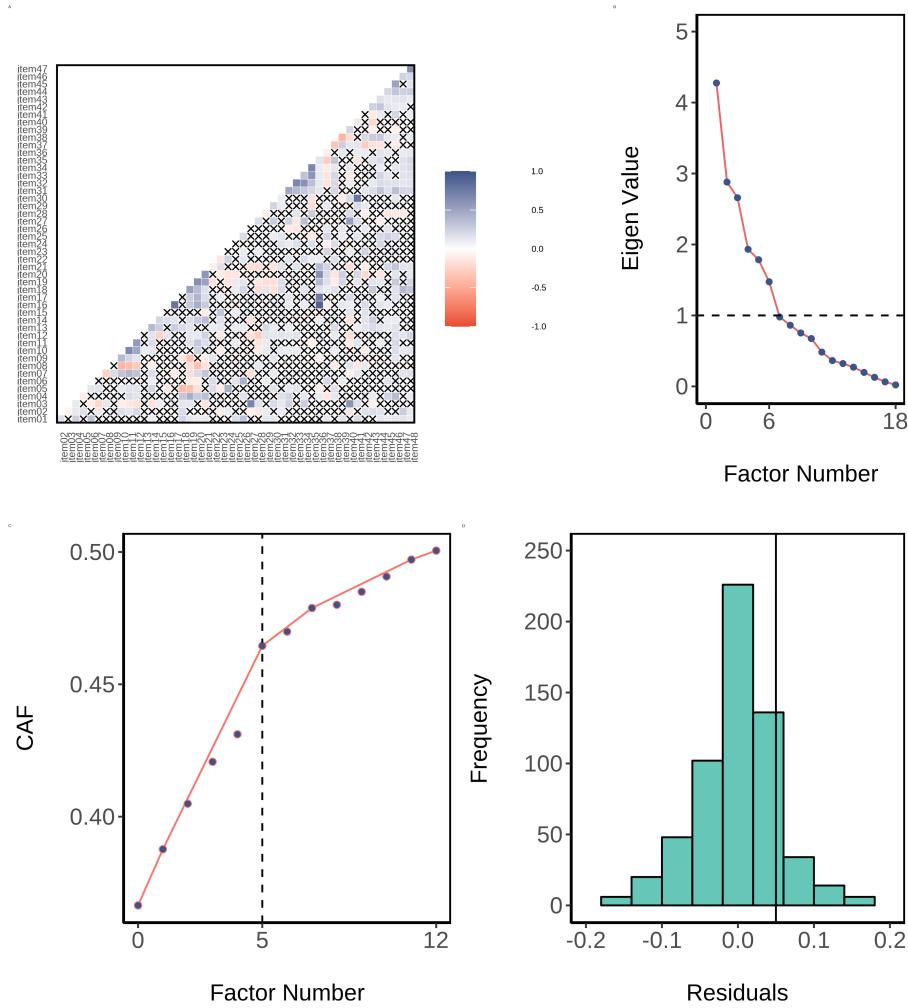


Figure 4. (A) Inter-item polychoric correlation coefficients for the 48 items. 4.9 % inter-item correlation coefficients were higher than $|.30|$. ‘x’ denotes a non-significant item-total correlation. (B) The Scree plot suggested six factors. (C) Hull method indicated that five factors were required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



Figure 5. 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.

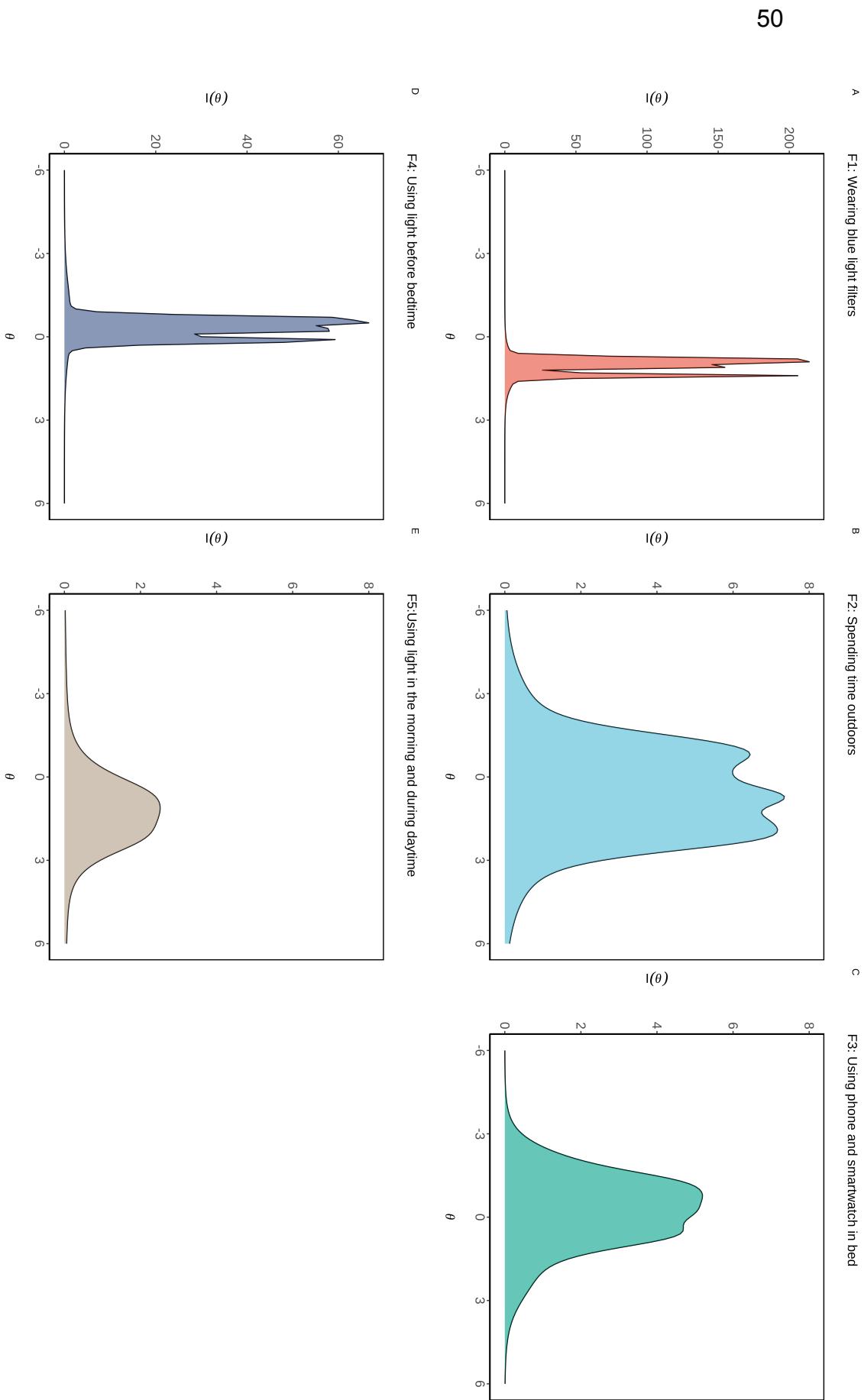


Figure 6. Test information curves for the five factors of LEBA: (a) wearing blue light filters (b) spending time outdoors (c) using a phone and smartwatch in bed (d) using light before bedtime (e) using light in the morning and during daytime. Along the x-axis, we plotted the underlying latent trait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