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

Mushfiqul Anwar Siraji[1, *], Rafael Robert Lazar[2, 3, *], Juliëtte van Duijnhoven[4, 5], Luc Schlangen[5, 6], Shamsul Haque[1], Vineetha Kalavally[7], Céline Vetter[8, 9], Gena Glickman[10], Karin Smolders[5,6], & Manuel Spitschan[11, 12, 13]

[1] Monash University, Department of Psychology, Jeffrey Cheah School of Medicine and Health Sciences, Malaysia

[2] Psychiatric Hospital of the University of Basel (UPK), Centre for Chronobiology, Basel, Switzerland

[3] University of Basel, Transfaculty Research Platform Molecular and Cognitive Neurosciences, Basel, Switzerland

[4] Eindhoven University of Technology, Department of the Built Environment, Building Lighting, Eindhoven, Netherlands

[5] Eindhoven University of Technology, Intelligent Lighting Institute, Eindhoven, Netherlands

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

[7] Monash University, Department of Electrical and Computer Systems Engineering, Selangor, Malaysia

[8] University of Colorado Boulder, Department of Integrative Physiology, Boulder, USA

[9] XIMES GmbH, Vienna, Austria
[10] Uniformed Services University of the Health Sciences, Department of Psychiatry, Bethesda, USA
[11] Translational Sensory & Circadian Neuroscience, Max Planck Institute for Biological Cybernetics, Tübingen, Germany
[12] TUM Department of Sport and Health Sciences (TUM SG), Technical University of Munich, Munich, Germany
[13] University of Oxford, Department of Experimental Psychology, Oxford, United Kingdom
[*] Joint first author

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Abstract

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

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

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

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

Word count: X

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Introduction

Our circadian rhythm is in sync with the earth's 24-hour rotation cycle. In this synchronization, light plays the vital role. Light sends signals to the master oscillator of our brain, the suprachiasmatic nuclei (SCN), via the third class of photoreceptors-intrinsically photosensitive retinal ganglion cells (ipRGCs) (Berson, Dunn, & Takao, 2002; Lucas et al., 2014; Provencio, Cooper, & Foster, 1998), thus entraining our biological clock (Duffy & Wright Jr, 2005). However, the temporal properties of light exposure, i.e., the time of day and the duration of light exposure, play a vital role in our health and well-being. These influences of light are known as non-image-forming (NIF) effects of light and include several physiological and psychological aspects such as secretion of melatonin, modulation of pupil size, skin temperature, alertness and other higher cognitive functions (Cajochen, Zeitzer, Czeisler, & Dijk, 2000; Lok, Smolders, Beersma, & Kort, 2018; Siraji, Kalavally, Schaefer, & Haque, 2021). Wrong light exposure at an inappropriate time of day may lead to sleep disturbances (Chellappa et al., 2013; Santhi et al., 2012). Evening and nighttime bright light exposure may cause suppression of melatonin (Gooley et al., 2011) and may cause a phase shift in the internal biological clock, thus, desynchronizing the body clock with nature's day-night circle. This reorganization of the body clock can create a series of adverse effects, including alteration of rhythmicity of several hormones, increased stress, cancer, and metabolic disruption, including obesity, type II diabetes, and heart diseases (Navara & Nelson, 2007)

With the increased use of electric light, the natural temporal organization of the dark-light cycle has been compromised. People are exposed to light more than ever. Furthermore, nighttime electric light exposure is significantly increased day by day. In the

US, 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 (Navara & Nelson, 2007). Our circadian clock signals the start of our melatonin secretion in our body based on the darkness of the night (Pauley, 2004). Since nights are no longer pure dark, most of the light-dependent systems of our body are disrupted. For example, studies suggest that electric monochromatic blue light exposure as low as 0.1 lux, which is almost equivalent to the brightness of full moonlight, may reduce the melatonin level (Brainard, 2002). In turn, such changes in melatonin levels influence metabolism, immunity, fertility, and other hormonal balance, including adrenaline and thyroid hormone (Prendergast, Nelson, & Zucker, 2002).

In recent years, the focus has been given in understanding the pathways underlying these influences of light. ipRGCs are mostly responsible for signalling the SCN when the ambient light changes (Gooley, Lu, Fischer, & Saper, 2003). Additionally, ipRGCs also send signals to different brain regions, closely associated with our sleep, attention and emotion, thus influencing our work performance, sleep quality and mood (For a detailed discussion, see (Lok et al., 2018; Siraji et al., 2021)). However, it is also essential to understand the behaviours people are engaging in, which ultimately quantify our light consumption. People are getting different types of light exposure due to their different daily life activities, including workplace habits, bedtime hygiene, pastimes, and other social activities. Currently, little effort has been made to understand and capture these behaviours. Supplementary Table 1 summarizes relevant questionnaires to understand different light exposure related properties. Only a few questions of these questionnaires were related to light exposure related behaviour. For example, “Munich Chronotype Questionnaire” (Roenneberg, Wirz-Justice, & Merrow, 2003), a self-reporting chronotype identifier, has questions about time spent outdoors and the work environment. Popularly used “Pittsburgh Sleep Quality Index” (Buysse, Reynolds III, Monk, Berman, & Kupfer, 1989), a measure of sleep quality, also has questions about sleeping and wake-up time.

However, none of these questionnaires provides a scaleable solution to capture light exposure related behaviour. To fill this gap, here we have reported the development process of a novel tool- “Light Exposure Behavior Assessment” (LEBA), to capture and quantify different light exposure related behaviour. LEBA will allow us to capture different light exposure related behaviour and gain insight into how different behaviour changes one’s light exposure. Understanding these light exposure related behaviour will help us provide a personalized light diet to decrease the effects of inappropriate light exposure.

Methods

Data Collection

A quantitative cross-sectional fully anonymous geographically unconstrained 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 (Weinzaepflen & 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 any time without being penalized. At the beginning of the survey, for the adult participants (>18 years) consent was recorded digitally. Under-aged participants (<18 years) were urged to obtain assent from their parents/legal guardians. The entire survey was estimated to take less than 30 minutes. Participants were not compensated. As a part of the demographic information participants provided information regarding age, sex, gender identity, occupational status, COVID-19 related occupational setting, time zone/country of residence and native language. The demographic characteristics of our sample are given in Table 1. To ensure high data quality, five attention check items were included in the survey (e.g., “We want to make sure you are paying attention. What is 4+5?”). Participants were asked to confirm that they were participating the survey for the first time. Questions incorporating retrospective recall were all aligned to the period of “past four weeks.”

We conducted two rounds of data collection. At first, we collected data from 428 participants (EFA sample). In the second round we collected data from another 262 participants (CFA sample) making a total sample of 690. The data analysed in this study was collected between 17 May 2021 and 3 September 2021.

Analytic Strategy

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

Second, for data collection we conducted two rounds of large-scale survey. **Third**, as a part of psychometric analysis, we conducted descriptive and item analysis and proceeded to the exploratory factor analysis (EFA) using “psych” package (Revelle, 2021) on the data collected in the first round (EFA sample; n=428). Prior to the EFA, necessary assumptions, including sample adequacy, normality assumptions, quality of correlation matrix were assessed. Our data violated both the univariate and multivariate normality assumptions. Due to these violations and the ordinal nature of our response data, in EFA we used polychoric correlation matrix and employed principal axis (PA) as the factor extraction method (Desjardins & Bulut, 2018; Watkins, 2020). We used a combination of factor identification method including Scree plot (Cattell, 1966), minimum average partials method (Velicer, 1976), and Hull method (Lorenzo-Seva, Timmerman, & Kiers, 2011) to identify factor numbers. To determine the latent structure, we followed the common guidelines : (i) no factors with fewer than three items (ii) no factors with a factor loading <0.3 (iii) no items with cross-loading > .3 across factors (Bandalos & Finney, 2018).

For reliability estimation “psych” package was used (Revelle, 2021). Though Cronbach’s internal consistency coefficient alpha is widely used for estimating internal consistency, it has a tendency to deflate the estimates for Likert-type data since the calculation is based on Pearson-correlation matrix which requires response data to be continuous in nature (Gadermann, Guhn, & Zumbo, 2012; Zumbo, Gadermann, & Zeisser, 2007). Subsequently to get better estimates of reliability we reported ordinal alpha for each factors obtained in EFA (Zumbo et al., 2007). We also estimated the internal consistency reliability of the total scale using McDonald’s ω_t coefficient which is a better reliability estimate for multidimensional constructs (Dunn, Baguley, & Brunsden, 2014; Sijtsma, 2009). Both ordinal alpha and McDonald’s ω_t coefficient value range between 0 to 1 and higher value represents better reliability.

To validate the latent structure obtained in EFA, We conducted a categorical confirmatory factor analysis (CFA) with weighted least square with mean and variance adjusted (WLSMV) estimator (Desjardins & Bulut, 2018) using “lavaan” package (Rosseel, 2012) on the data collected in the second round (CFA sample; n=262). We assessed the model fit using common 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 (Brown, 2015) and SRMR does not work well with ordinal data (Yu, 2002) As such, we judged the model fit using CFI, TLI and RMSEA.

We 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 structural equation modelling framework using “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 model and residual model is the most restrictive model. 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).

Fourth, as secondary analysis we identified the educational grade level required to understand the items in our scale using Flesch-Kincaid grade level identification method (Flesch, 1948) using “koRpus” (Michalke, 2021) package. Also, we analysed possible semantic overlap of our developed scale using “Semantic Scale Network” (SSN) engine (Rosenbusch, Wanders, & Pit, 2020). The SSN detects semantically related scales and provides cosine similarity index ranging between -.66 to 1 (Rosenbusch et al., 2020). Pair of scales with a cosine similarity index value of 1 indicates they are perfectly semantically similar scales indicating redundancy.

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

Ethical Approval

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

Data Availability

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

Results

Development of the Initial Scale

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

Large-scale Survey

Table 1 summarizes the survey participants’ demographic characteristics. Only participants completing the full LEBA questionnaire were included, thus there are no missing values in the item analyses. (XX??) participants were excluded from analysis due to not passing at least one of the “attention check” items. For EFA, a sample of 250-300 is recommended (Comrey & Lee, 2013; Schönbrodt & Perugini, 2013). To assess sampling adequacy for CFA, we followed the N:q rule (Bentler & Chou, 1987; Jackson, 2003; Kline, 2016; Worthington & Whittaker, 2006), where ten participants per item is required to earn trustworthiness of the result. Both our EFA and CFA sample size exceeded these requirements. We collected data from 74 countries (28 time zones). Participants reported a diverse range of geographic location Participants indicated filling out the online survey from a diverse range of geographic locations. For a complete list of geographic locations, see **Supplementary Table 2**.

Participants in our survey aged between 11 to 84 years [EFA sample: 11 to 84; CFA sample: 12 to 74], with an overall mean of ~ 32.95 years of age [Overall: 32.95±14.57; EFA: 32.99±15.11; CFA: 32.89±13.66]. In total 325 (47%) of the participants indicated female sex [EFA: 189 (44%); CFA: 136 (52%)], 351 (51%) indicated male [EFA: 230 (54%); CFA: 121 (46%)] and 14 (2.0%) indicated other sex [EFA: 9 (2.1%), CFA: 5 (1.9%)]. Overall, 49 (7.2%) [EFA: 33 (7.8%); CFA: 16 (6.2%)] participants indicated a gender-variant identity. In a “Yes/No” question regarding native language, 320 (46%) of respondents [EFA: 191 (45%); CFA: 129 (49%)] indicated to be native English speakers. For their “Occupational Status,” more than half of the overall sample reported that they currently work [Overall: 396 (57%); EFA: 235 (55%); CFA: 161 (61%)], whereas 174 (25%) [EFA: 122 (29%); CFA: 52 (20%)] reported that they go to school and 120 (17%) [EFA: 71 (17%); CFA: 49 (19%)] responded that they do “Neither.” With respect to the COVID-19 pandemic we asked participants to indicate their occupational setting during the last four weeks: In the overall sample 303 (44%) [EFA: 194 (45%); CFA: 109 (42%)] of the participants indicated that they were in a home office/ home schooling setting, while 109 (16%) overall [EFA: 68 (16%) ; CFA: 41 (16%)] reported face-to-face work/schooling. Lastly, 147 (21%) overall [EFA: 94 (22%) ; CFA: 53 (20%)] reported a combination of home- and face-to-face work/schooling, whereas 131

(19%) overall [EFA: 72 (17%); CFA: 59 (23%)] filled in the “Neither (no work or school, or on vacation)” response option.

Psychometric Analysis: Development of the Long Form

Descriptive Statistics and Item Analysis. Figure 2 and Figure 3 summarize the response pattern of our total sample (n=690) for all 48 items. Most of the items appeared skewed.The Shapiro–Wilk test of univariate normality (Shapiro & Wilk, 1965) and Mardia test of multivariate normality (Mardia, 1970) indicated our data violated both univariate and multivariate normality. Multivariate skew was 488.40 ($p < 0.001$) and multivariate kurtosis was 2,808.17 ($p < 0.001$).

Supplementary Figure 1 summarizes the univariate descriptive statistics for the 48 items in the EFA sample (n=428). Here also our data violated univariate (Shapiro & Wilk, 1965) and multivariate normality assumptions (Mardia, 1970). Multivariate skew was 583.80 ($p < 0.001$) and multivariate kurtosis was 2,749.15 ($p < 0.001$). The corrected item-total correlation ranges between .03 -.48. However, no item was discarded based on descriptive statistics or item analysis.

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

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

With the initial 48 items we conducted three rounds of EFA with varimax rotation and gradually discarded problematic items (cross-loading items and items with factor loading <.30). Finally, a five-factor EFA solution with 25 items was accepted with all factor-loading higher than .30 and no cross-loading greater than .30. Table 2 displays the factor-loading (structural coefficients) and communality of the items. The absolute value of the factor-loading ranged from .32 to .99 indicating strong coefficients. The commonalities ranged between .11 to .99. However, the histogram of the absolute values of non-redundant residual-correlations (Figure 4-D) showed 26% correlations were greater than the absolute value of .05, indicating a possible under-factoring. (Desjardins & Bulut, 2018). Subsequently, we fitted a six-factor solution. However, a factor emerged with only two salient variables, thus disqualifying the six-factor solution (**Supplementary Table 4**).

In the five-factor solution, the first factor contained three items and explained 10.25% of the total variance with an internal reliability coefficient ordinal α = .94. All the items in this factor stemmed from the individual's preference of using blue light filters in different light environments. The second factor contained six items and explained 9.93% of the total variance with an internal reliability coefficient ordinal α = .76. Items under this factor investigated individuals' hours spent outdoor. The third factor contained five items and explained 8.83% of the total variance. Items under this factor dealt with the specific behaviours pertaining to using phone and smart-watch in bed. The internal consistency reliability coefficient was, ordinal α = .75. The fourth factor contained five items and explained 8.44% of the total variance with an internal consistency coefficient, ordinal α = .72. These five items investigated the behaviours related to individual's light exposure before bedtime. Lastly, the fifth factor contained six items and explained 6.14% of the total variance. This factor captured individual's morning and daytime light exposure related behaviour. The internal consistency reliability was, ordinal α = .62. It is essential to attain a balance between psychometric properties and interpretability of the common themes when exploring the latent structure. As all of the emerged factors are highly interpretable and relevant towards our aim to capture light exposure related behaviour, regardless of the apparent low reliability of the fifth factor, we retain all the five-factors with 25 items for our confirmatory factor analysis (CFA). Two items showed negative factor-loading (items 44 and 21). Upon inspection, it was understood that these items are negatively correlated to the respective common theme, and thus in the CFA analysis, we reverse scored these two items. Internal consistency coefficient McDonald's ω_t for the total scale was 0.77.

Confirmatory Factor Analysis. Table 3 summarizes the CFA fit indices of our fitted model. Our fitted model attained acceptable fit (CFI =.92; TLI = .91; RMSEA = .07 [.06-.07, 90% CI]) with two imposed equity constrain on item pairs 32-33 [item 32: I dim my mobile phone screen within 1 hour before attempting to fall asleep; item 33: I dim my computer screen within 1 hour before attempting to fall asleep] and 16-17 [item 16: I wear blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day; item 17: I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the day]. Item pair 32-33 stemmed from the preference of dimming electric device's brightness before bed time and item pair 16-17 stemmed from the preference of using blue filtering or coloured glasses during the daytime. Given the similar nature of behaviour these item pair were capturing, we accepted the equity constrain imposed. Nevertheless, SRMR value was higher than the guideline (SRMR = .12).

To improve model fit we conducted a post-hoc model modification. Modification indices indicated the possibility of cross-loading of the item 37 and 26 [item 37: I purposely leave a light on in my sleep environment while sleeping; item 26: I turn on my ceiling room light when it is light outside] thus discarded. Also, item 30 and 41 [item 30: I look at my smart-watch within 1 hour before attempting to fall asleep; item 41: I look at my smart-watch when I wake up at night] showed a tendency to co-vary in their error variance (MI = 141.127, p<.001). By allowing this pair of items (30 & 41) to covary their error variance our model attained the best fit (CFI =.95; TLI = .95); RMSEA = .06 [.05-.06, 90% CI]; SRMR = .11). Internal consistency ordinal α for the five factors of LEBA were .96, .83, .70, .69, .52 respectively. As such, we accept this model thus finalizing the long Form of LEBA with 23 items. The items are provided in the **Supplementary File 1**. Internal consistency McDonald's ω_t coefficient for the total scale was .68. Figure 5 depicts the obtained CFA structure. **Supplementary Figure 2** depicts the data distribution and endorsement pattern of the retained 23 items in our CFA sample.

Measurement Invariance. In our CFA sample we had 129 native English speakers and 133 non-native English speakers. **Supplementary Table 5** summarizes the demographic descriptions native and non-native English speakers.Table 4 indicates our fitted model had acceptable fit indices for all of the fitted MI models. The model fit did not significantly decrease across the nested models indicating the acceptability of the highest measurement invariance model: residual model.

Secondary Analysis: Grade Level Identification and Semantic Scale Network Analysis

Flesch-Kincaid grade level (Flesch, 1948) analysis on the 23 items indicated required educational grade level was 3.33 and with a age above 8.33 years. This indicated our scale will be understandable to students of grade four and aged at least 8.33 years. Semantic Scale Network (SSN) analysis (Rosenbusch et al., 2020) indicated that LEBA (23 items) appeared most strongly related to scales about sleep: "Sleep Disturbance Scale For Children" (Bruni et al., 1996) and "Composite International Diagnostic Interview (CIDI): Insomnia"(Robins et al., 1988). The cosine similarities lie between .47 to .51.

Developing Short form of LEBA: IRT Based Analysis

We fitted each factor of LEBA with the graded response model (Samejima et al., 1997) to the combined EFA and CFA sample (n=690). Item discrimination parameters of our scale fell in very high (10 items), high (4 items), moderate (4 items), and low (5 items) categorizes indicating a good range of discrimination along the latent trait level (θ) (**Supplementary Table 6**). Examination of the item information curve (**Supplementary Figure 3**) indicated five items (1, 25, 30, 38, & 41) had relatively flat information curves (I(θ) <.20). We discarded those items which yielded a short form of LEBA with 5 factors and 18 items (**Supplementary File 2**).

We treated each factor of short-LEBA as a unidimensional construct and obtain 5 TICs (Figure 6). These information curves indicated except the first and fifth factors, the other three factor's TICs are roughly centred on the centre of the trait continuum (θ). The first and fifth factor had a peak to the right side of the centre of latent trait.Thus we conferred the LEBA scale estimated the light exposure related behaviour with precision near the centre of trait continuum for 2nd, 3rd and 4th factors and near the right side of the centre of trait continuum for 1st and 5th factors (Baker & Kim, 2017).

Supplementary Table 7 summarizes the item fit indexes of the 18 items. All items had RMSEA value $\leq$.06 indicating adequate fit of the items to the fitted IRT model. **Supplementary Figure 4** depicts the person fit Zh statistics histogram of our fitted models. Zh statistics are larger than -2 for most participants, suggesting a good person fit of the selected IRT models.

Discussion

Though there are lots of validated scale to measure light exposure, they don't tell us much about the behavioural aspects pertaining to the light exposure. In that vein we have developed a subjective self-reported scale that can capture light exposure related behaviour in different dimensions.

Authors along with an expert panel generated 48 items and evaluated their quality and relevance and made necessary amendments. A large-scale geographically unconstrained quantitative cross-sectional survey was conducted yielding responses from a large sample (n=690). Data collected on the first round was used to explore the latent structure (EFA sample; n=428). Exploratory factor analysis revealed a five factor solution with 25 items. (“Wearing blue light filters,” “Spending time outdoors,” “Using phone and smart-watch in bed,” “Using light before bedtime,” and “Using light in the morning and during daytime”). The internal consistency reliability coefficient ordinal alpha ranged between .62-.94. Except for the fifth factor the internal reliability coefficients were above .70. For the fifth factor it was .62. As a rule of thumb reliability coefficient higher than .70 is considered to be satisfactory. However for scales with less than 20 items and at the early developmental stage, a value of .50 is also acceptable (Dall’Oglio et al., 2010; Field, 2015; Nunnally, 1978). Also all of the factors were highly interpretable in terms of a common theme and contributed essentially towards our aim to capture light exposure related behaviour. This eventually led us to accept the obtained five-factor structure. The total scale exhibited satisfactory internal consistency (McDonald’s ω_t=0.77).

Our CFA analysis (CFA sample; n=262) confirmed the five factor structure we obtained in our EFA thus provided evidence of structural validity.(CFI=.95; TLI=.95); RMSEA=.06 [.05-.06, 90% CI]; SRMR=.11). However, in this model we discarded two items (item 26 & 37) for possible cross-loadings. Also, we accepted one pair of items (item 30 & 41) to covary their error variance . This item-pair was capturing smart-watch based light exposure behaviour. In retrospect, it seemed plausible that not having a smart-watch may lead the respondent to answer in a similar fashion for these two items. Thus, we decided to accept the modification to our model. The internal consistency coefficients ordinal alpha for the five factors and the total scale were also satisfactory

(Ordinal alpha ranged between 0.52 to 0.96; McDonald's ω_t=.68). On this same data set our measurement invariance analysis indicated the underlying construct of our scale "Light exposure related behaviour" was equivalent across native and non-native English speakers. This indicated the applicability of LEBA on both native and non-native English Speakers. However, this decisions brought up another question to be answered, what was the required grade level to understand the items of our scale? To answer this question we ran secondary analysis where we identified the grade level required using Flesch-Kincaid grade level identification method. Our scale would appear understandable to those who were at least a grade four student and had a age of at least 8.33 years. As a secondary analysis we also assessed the semantic similarity of our scale to the scales recorded in the "Semantic Scale Network" database (Rosenbusch et al., 2020). "LEBA" was related to "Sleep Disturbance Scale For Children" (SDSC) (Bruni et al., 1996) and "Composite International Diagnostic Interview (CIDI): Insomnia"(Robins et al., 1988). Upon inspecting the item contents we found items under "Using phone and smart-watch in bed" and "Using light before bedtime" have semantic overlap with the items of SDSC and CIDI. However, the aim of those scale and ours were different. Items in those two scales were looking into behaviours related to sleep whereas our aim was to capture light exposure related behaviour.

lastly, we developed a short-LEBA (18 items) using IRT analysis. We fitted a graded response model model to the combined EFA and CFA sample (n=690). We discarded five items (1, 25, 30, 38, & 41) with relatively flat item information curve [I(θ) <.20]. Test information curves indicated short form of LEBA is a psychometrically sound measure with adequate coverage of underlying traits to capture different extents of light exposure related behaviours with precision. Item fit index and person fit index for all five fitted model were acceptable providing evidence of validity of our models. Items had diverse item discrimination parameters indicating a good range of discrimination- the ability to differentiate respondents with different levels of the light exposure related behaviour.

Based on all the gathered evidences, we can say 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.

Conclusion

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

Future Direction

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

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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	566.80	267.00	.92	0.91	0.07	0.06	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	$\Delta\ \chi^2$	Δ df*	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.

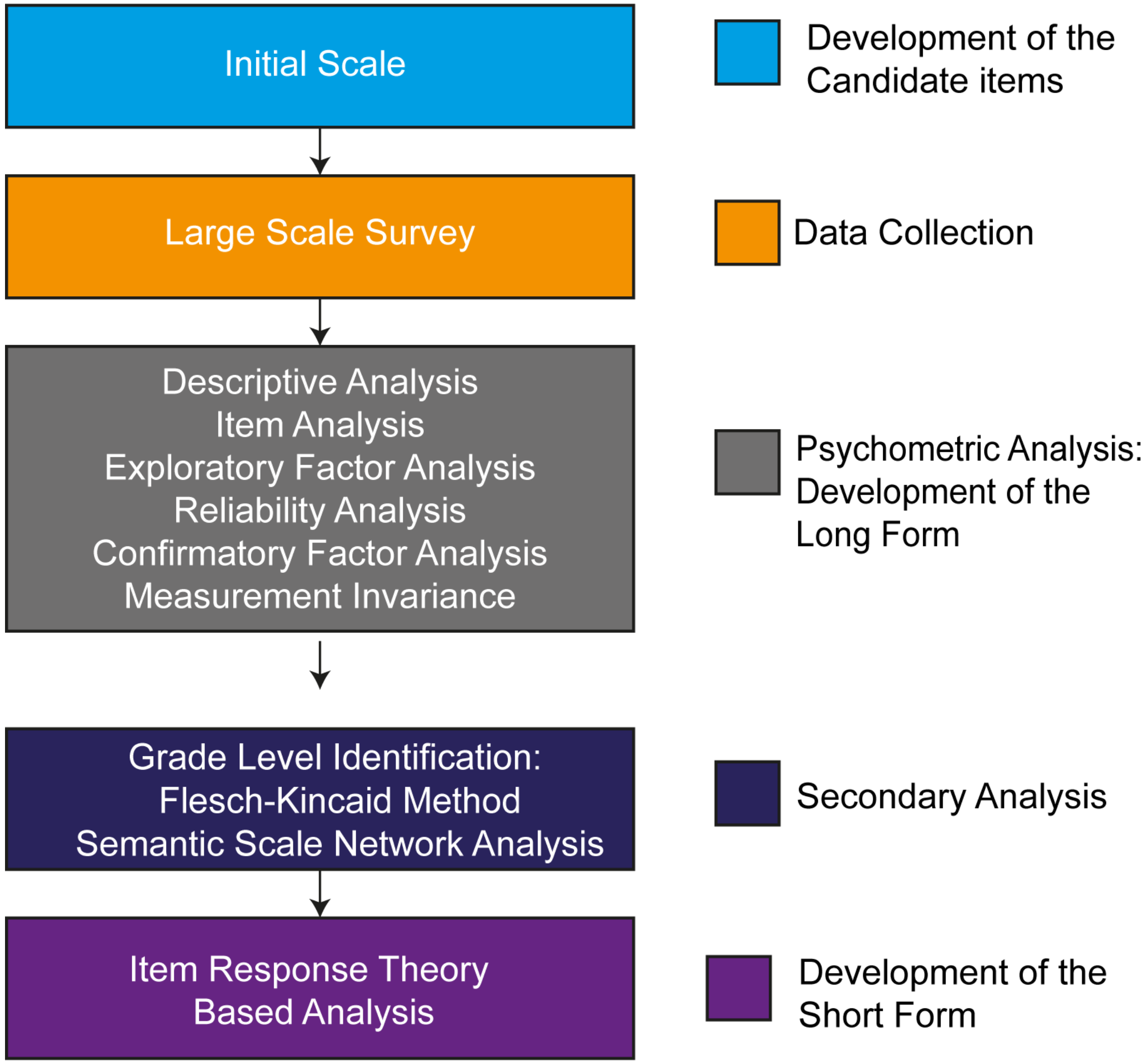

Figure 1. Flow chart of the LEBA (long and short form) development and evaluation.

Summary Descriptives (n=690)

Items 01-24

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

† **Shapiro–Wilk test**

Figure 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)

Items 25-48

Item		Summary Statistics			Graphics		Response Pattern				
LEBA Items	Stem	Mean	SD	SW[†]	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)

[†] **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.

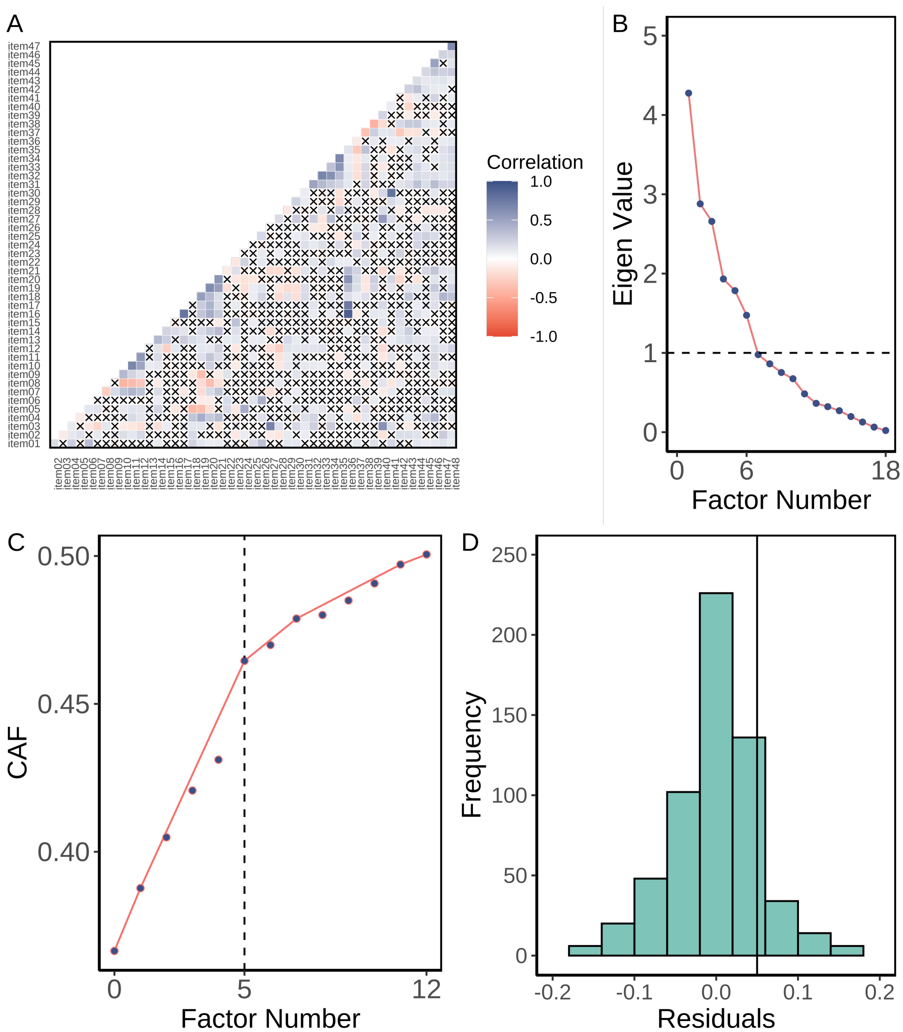

Figure 4. (A) Inter-item polychoric correlation coefficients for the 48 items. 4.9 % inter-item correlation coefficients were higher than |.30|. ‘x’ denotes non-significant item-total correlation. (B) Scree plot suggested six factors. (C) Hull method indicated 5 factors were required to balance the model fit and number of parameters. (D) Histogram of nonredundent 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.

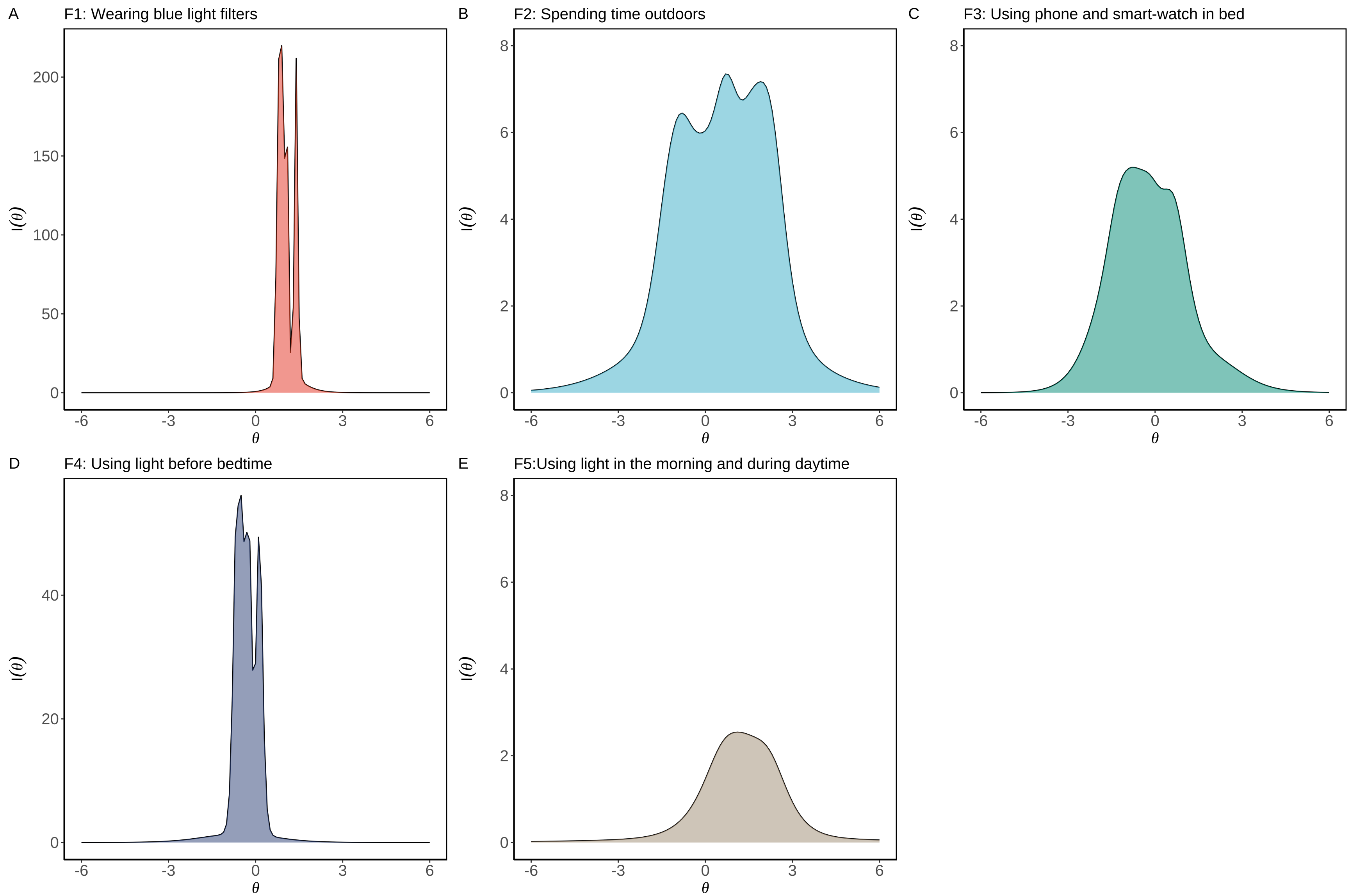

Figure 6. Test information curves for the five factors of LEBA: (a) wearing blue light filters (b) spending time outdoors (c) using phone and smart-watch in bed (d) using light before bedtime (e) using light in the morning and during daytime. Along x-axis we plotted the underlying latent trait continuum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