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

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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 Behavior Assessment (LEBA).

An expert panel prepared the initial 48 item pool spanning different light exposure related behaviors. Responses, consisting rating the frequency of engaging in the per-item behavior 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=0.97, TLI=0.96, RMSEA=0.05, SRMR=0.09). The internal consistency reliability coefficient for the total instrument was, McDonald's Omega(total)=0.73. 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

- Light exposure is important
- Light exposure Behaviour is important
- Supplementary Table S1 Overview Existing Related Scales: items in total / items on light exposure (behaviour)
- Existing Scales: Review them in text
- None of these do light exposure behavior.

Methods

Data Collection

A quantitative cross-sectional fully anonymous online 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 anytime without being penalized. At the beginning of the survey, for the adult participants (>18 years) consent was recorded digitally. Underaged participants (<18 years) were urged to obtain assent from their parents/legal guardians. The entire survey was estimated to take <30 minutes. 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 ??.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 collections. At first we collected data for from 428 participants In the second round we collected data from another 262 participants 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 of our psychometric analysis. In our analysis we used R (version 4.1.0) (R Core Team, 2021). In the item generation and selection phase we had developed a 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). 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.

We conducted an initial item analysis and proceed to the exploratory factor analysis (EFA) with all 48 items using the data collected in our 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 factor extraction method with varimax rotation (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). We also conducted a EFA on non-merged response options data (**Supplementary File 3**)

For reliability estimation we used internal consistency reliability coefficient ordinal α. Though Cronbach's alpha coefficient 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 of nature (Gadermann, Guhn, & Zumbo, 2012; Zumbo, Gadermann, & Zeisser, 2007). Subsequently to get better estimates of reliability we reported ordinal alpha for each factors using polychoric-correlation matrix (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 from 0 to 1 and higher value represents better reliability.

To validated 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) on the data collected n our second round of data collection (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, SRMR and RMSEA.

We assessed the measurement invariance (MI) of our construct between native English speakers (n=129) and non native English speakers (n=133) among the CFA sample (n=262). MI evaluates whether a construct has the psychometric equivalence and same meaning across groups (Kline, 2015; Putnick & Bornstein, 2016). We used structural equation modelling framework 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, 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 (Dimitrov, 2010) thus allowing the superior invariance model to be accepted. (Widaman & Reise, 1997).

We also analysed possible semantic overlap of our developed tool 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. Additionally, to identify the educational grade level required to understand the items in our tool we subjected the tool to Flesch-Kincaid Grade Level (Flesch, 1948)

Lastly, we sought Item Response Theory (IRT) based analysis on developing a short form of LEBA. We fitted each factor of LEBA using the graded response model (Samejima, Liden, & Hambleton, 1997) to the combined EFA and CFA sample (n =690). IRT assesses the item quality by estimating item discrimination, item difficulty, item information, and test information (Baker, 2017). Item discrimination indicates the pattern of variation in the categorical responses with the changes in latent trait level (θ). Item information curve (IIC) indicates the amount of information an item carries along the latent trait continuum. Here, we reported the item discrimination parameter and categorize the items according to the suggestions of Baker (2017) : 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. 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 an the full-scale carry along the latent trait continuum. Item fit and person fit of the fitted IRT models were also analyzed to gather more evidence on validity and meaningfulness of our Tool (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 be 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

Initial development of items

After reviewing the literature, we identified several light exposure related scale. However, no scales specifically measuring the behavioural component of light exposure were found (**Supplementary Table 1**). As such, all authors in collaboration of 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 of instruments

Participants. 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, 1992; Schönbrodt & Perugini, 2013). To assess sampling adequacy for CFA, we followed the N:q rule (Bentler & Chou, 1987; Jackson, 2003; Kline, 2015; 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 Suppl. Table **??**.

Participants in our survey aged between 11 to 84 years [EFA sample: *min* = 11, *max* = 84; CFA sample: *min* = 12, *max* = 74], with an overall mean of ~ 32.95 years of age [Overall: *M* = 32.95, *SD* = 14.57; EFA: *M* = 32.99, *SD* = 15.11; CFA: *M* = 32.89, *SD* = 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. We tested all demographic variables in Table 1 for significant group differences between the EFA and CFA sample, applying Wilcoxon rank sum test for the continuous variable “Age” and Pearson’s χ^2 test for all other categorical variables via the gtsummary R package’s “add_p” function (Sjoberg et al., 2021a) . The p-values were corrected for multiple testing applying false discovery rate (FDR) via the “add_q” function of the same package. After p-value (FDR) correction for multiple testing, none of the demographic variables were significantly different between the EFA sample and the CFA sample (all q-values $q \geq$ Inf).

Descriptive Statistics. Figure 2 and Figure 3 summarize the response pattern of our total sample (n = 690) for all 48 items. Most of the items were skewed and violated normality assumption.

Item Analysis. **Supplementary Fig1** summarizes the univariate descriptive statistics for the 48 items among EFA sample (n =428. Our data violated both univariate normality (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). Due to these violations and ordinal nature of the response data polychoric correlations over Pearson’s correlations was chosen (Desjardins & Bulut, 2018). The corrected item-total correlation ranges between .03 -.48. However, no item was discarded based on descriptive statistics or item analysis.

Exploratory Factor 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 cutoff 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 @ref(fig:fig:efa-plot A) depicts the correlation matrix.

Scree plot (Figure **??** B) suggested a six-factor solution. However, the minimum average partial (MAP) (Velicer, 1976) method (**Supplementary Table 2**) and Hull method (Lorenzo-Seva et al., 2011) (Figure 4 D) 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 and gradually discarded problematic items. (cross-loading items and poor factor loading (<.30) items). 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. We further confirmed this five-factor latent structure by another EFA using varimax rotation with a minimum residual extraction method (**Supplementary Table 3**). Table 2 displays the factor-loading (structural coefficients) and communality of the items. The absolute value of the factor-loading ranged from .49 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 23 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 coded these two items.

Confirmatory Factor Analysis. **Supplementary Figure 2** depicts the response destrubition. Table 3 summarizes the CFA fit indices of our fitted model. Our fitted model attained acceptable fit (CFI =.94; TLI = .93); RMSEA = .06,[.05-.07, 90% CI]) with two imposed equity constrain on item pairs 32-33 [I dim my mobile phone screen within 1 hour before attempting to fall asleep.;I dim my computer screen within 1 hour before attempting to fall asleep.] and 16-17 [I wear blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day.;I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the day.]. Items pair 32-33 stemmed from the preference of dimming electric device's brightness before bed time and items pair 16 and 19 stemmed from the preference of using blue filtering or coloured glasses during the daytime. Nevertheless, SRMR value was higher than the guideline (SRMR = .12).

Further by allowing one pair of items (30-41) [I look at my smartwatch within 1 hour before attempting to fall asleep.;I look at my smartwatch when I wake up at night.] to covary their error variance and discarding two item (item 37 & 26) for very low r-square value, our model attained the best fit (CFI =.95; TLI = .95); RMSEA = .06[.05-.06, 90% CI]). Internal consistency ordinal α for the five factors of LEBA were .96, .83, .70, .69, .52 respectively. Internal consistency McDonald's ω_t coefficient for the total scale was .68. Figure 5 depicts the obtained CFA structure. Figure **??** 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 (For a detailed description these two groups see Sup. Table **??**). 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.

Semantic Analysis. "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 "WHO-Composite International Diagnostic Interview (CIDI): Insomnia"(WHO, 1990). The cosine similarities lie between .47 to .51. Flesch-Kincaid Grade Level (Flesch, 1948) analysis on the the 23 items of our scale indicated required educational grade level was 3.33 and with a age above 8.33.

Developing Short form of LEBA. 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 tool 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 5**). Examination of the item information curve (**Supplementary Figure 3**) indicated five items (1, 25, 38, 30, & 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.

We treated each factor of short-LEBA as an 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 tool 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, 2017).

Supplementary Table 6 summarizes the item fit indexes of the 18 items. All of the 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 out 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 tool to measure light exposure, they don't tell us much about the behavioural aspects pertaining to the light exposure. At present there is a dearth of validated tool to measure light exposure related behaviours. In that vein we have developed a subjective self-reported tool 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 large sample (n=428 to explore the latent structure. 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. As all the retained factors were meaningful and contributed essentially towards our aim we retained all five factors.

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

Conclusion

We developed a novel self-reported subjective tool-"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 measure different aspects of light exposure related behaviour.

Future Direction

Since, LEBA is the first of its kind, estimating convergent validity with other subjective tool was not possible. One way to establish the convergent validity of LEBA is to administer this subjective tool along which some objective measurement tools (e.g. personalised light dosimeter). Though such objective tools 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 tools 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 Partinipants (n=690)

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

[1] Mean (SD); n (%)

Table 2

Factor loadings and communality of the retained items in EFA using principal axis extraction method

item	Stem	PA1	PA2	PA3	PA4	PA5	Communality
item16	I wear blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day.	0.99					0.993
item36	I wear blue-filtering, orange-tinted, and/or red-tinted glasses within 1 hour before attempting to fall asleep.	0.94					0.899
item17	I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the day.	0.8					0.658
item11	I spend more than 3 hours per day (in total) outside.		0.79				0.642
item10	I spend between 1 and 3 hours per day (in total) outside.		0.76				0.592
item12	I spend as much time outside as possible.		0.65				0.465
item07	I go for a walk or exercise outside within 2 hours after waking up.		0.5				0.267
item08	I spend 30 minutes or less per day (in total) outside.		-0.49				0.252
item09	I spend between 30 minutes and 1 hour per day (in total) outside.		0.32				0.113
item27	I use my mobile phone within 1 hour before attempting to fall asleep.			0.8			0.658
item03	I look at my mobile phone screen immediately after waking up.			0.8			0.682
item40	I check my phone when I wake up at night.			0.65			0.464
item30	I look at my smartwatch within 1 hour before attempting to fall asleep.			0.45			0.353
item41	I look at my smartwatch when I wake up at night.			0.36			0.329

Table 2 continued

item	Stem	PA1	PA2	PA3	PA4	PA5	Communality
item33	I dim my computer screen within 1 hour before attempting to fall asleep.				0.74		0.555
item32	I dim my mobile phone screen within 1 hour before attempting to fall asleep.				0.73		0.624
item35	I use a blue-filter app on my computer screen within 1 hour before attempting to fall asleep.				0.66		0.454
item37	I purposely leave a light on in my sleep environment while sleeping.				-0.39		0.174
item38	I use as little light as possible when I get up during the night.				0.38		0.178
item46	I use tunable lights to create a healthy light environment.					0.6	0.422
item45	I use LEDs to create a healthy light environment.					0.59	0.374
item25	I use a desk lamp when I do focused work.					0.41	0.193
item04	I use an alarm with a dawn simulation light.					0.41	0.219
item01	I turn on the lights immediately after waking up.					0.4	0.17
item26	I turn on my ceiling room light when it is light outside.					0.35	0.165

Note. Only loading > .30 is reported

Table 3

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

Model	χ^2	df	CFI	TLI	RMSEA	RMSEA 90% Lower CI	RMSEA 90% Upper CI	SRMR
Model 1	448.51	222.00	.94	0.93	0.06	0.05	0.07	0.12
Model 2	415.45	231.00	.95	0.95	0.06	0.05	0.06	0.11

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

Table 4

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

	χ^2	df	CFI	TLI	RMSEA	RMSEA 90% Lower CI	RMSEA 90% Upper	$\Delta\ \chi^2$	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

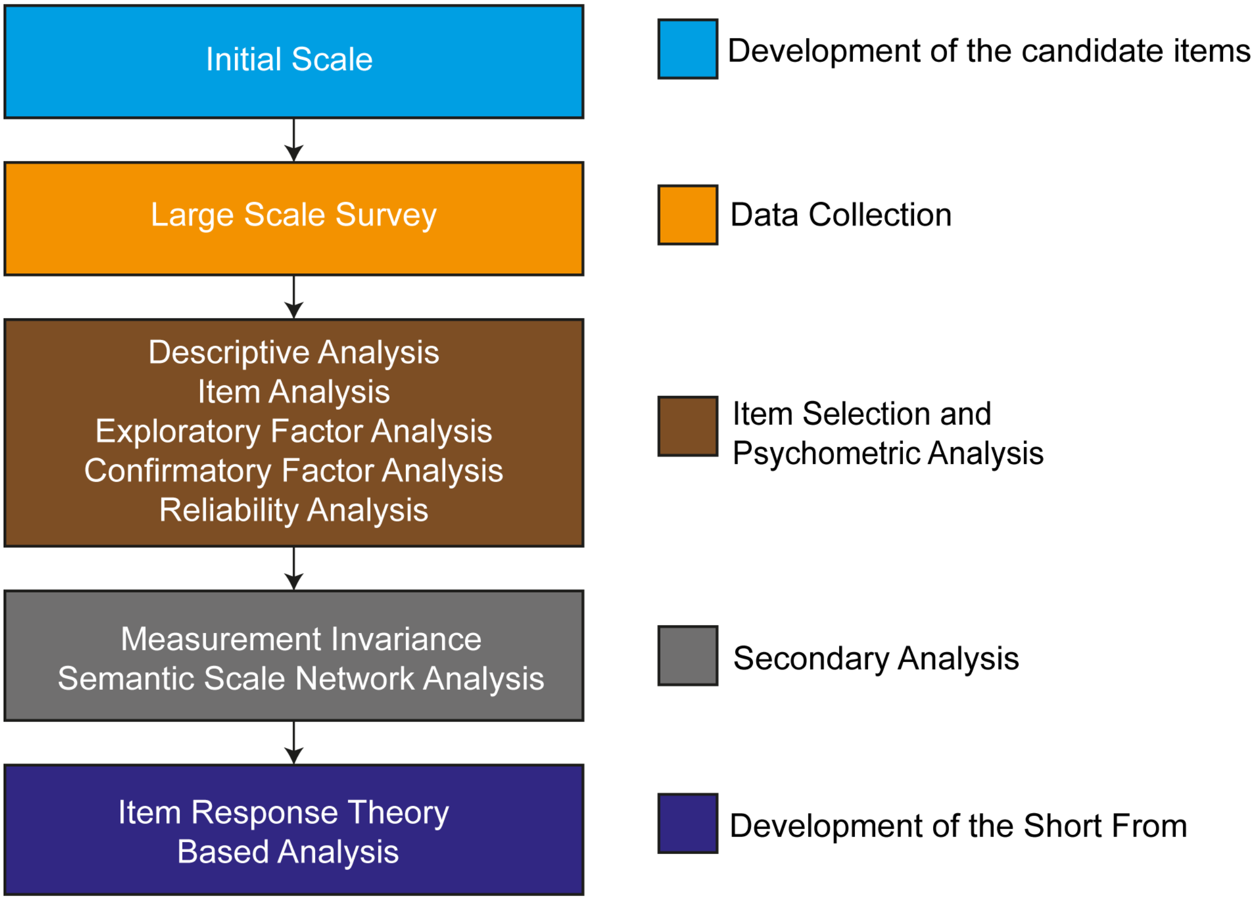
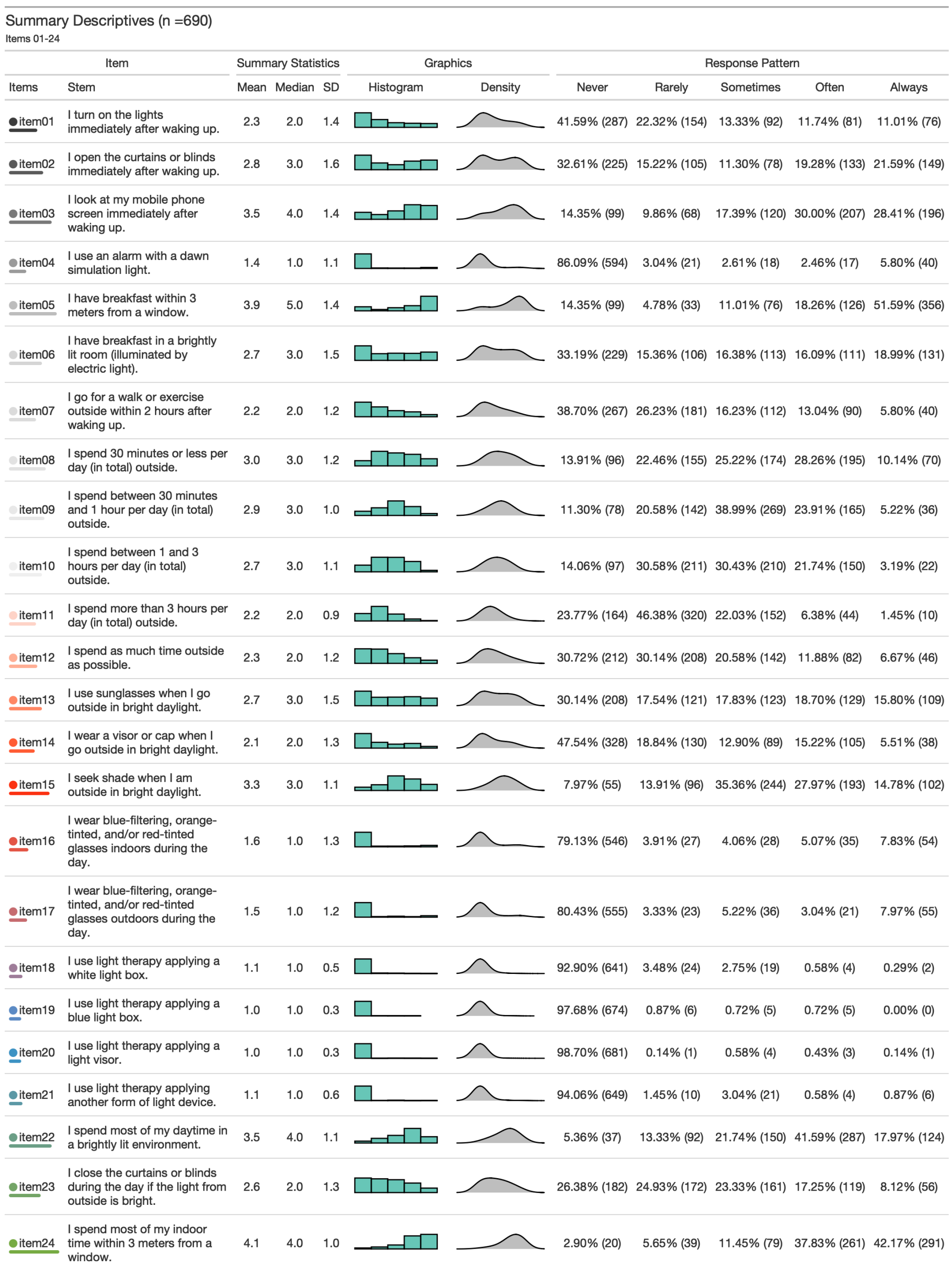


Figure 1. Development of long form (23-item) and short form (18-item) of LEBA.



Summary Descriptives (n =690)

Items 01-24

Item		Summary Statistics			Graphics		Response Pattern				
Items	Stem	Mean	Median	SD	Histogram	Density	Never	Rarely	Sometimes	Often	Always
item01	I turn on the lights immediately after waking up.	2.3	2.0	1.4			41.59% (287)	22.32% (154)	13.33% (92)	11.74% (81)	11.01% (76)
item02	I open the curtains or blinds immediately after waking up.	2.8	3.0	1.6			32.61% (225)	15.22% (105)	11.30% (78)	19.28% (133)	21.59% (149)
item03	I look at my mobile phone screen immediately after waking up.	3.5	4.0	1.4			14.35% (99)	9.86% (68)	17.39% (120)	30.00% (207)	28.41% (196)
item04	I use an alarm with a dawn simulation light.	1.4	1.0	1.1			86.09% (594)	3.04% (21)	2.61% (18)	2.46% (17)	5.80% (40)
item05	I have breakfast within 3 meters from a window.	3.9	5.0	1.4			14.35% (99)	4.78% (33)	11.01% (76)	18.26% (126)	51.59% (356)
item06	I have breakfast in a brightly lit room (illuminated by electric light).	2.7	3.0	1.5			33.19% (229)	15.36% (106)	16.38% (113)	16.09% (111)	18.99% (131)
item07	I go for a walk or exercise outside within 2 hours after waking up.	2.2	2.0	1.2			38.70% (267)	26.23% (181)	16.23% (112)	13.04% (90)	5.80% (40)
item08	I spend 30 minutes or less per day (in total) outside.	3.0	3.0	1.2			13.91% (96)	22.46% (155)	25.22% (174)	28.26% (195)	10.14% (70)
item09	I spend between 30 minutes and 1 hour per day (in total) outside.	2.9	3.0	1.0			11.30% (78)	20.58% (142)	38.99% (269)	23.91% (165)	5.22% (36)
item10	I spend between 1 and 3 hours per day (in total) outside.	2.7	3.0	1.1			14.06% (97)	30.58% (211)	30.43% (210)	21.74% (150)	3.19% (22)
item11	I spend more than 3 hours per day (in total) outside.	2.2	2.0	0.9			23.77% (164)	46.38% (320)	22.03% (152)	6.38% (44)	1.45% (10)
item12	I spend as much time outside as possible.	2.3	2.0	1.2			30.72% (212)	30.14% (208)	20.58% (142)	11.88% (82)	6.67% (46)
item13	I use sunglasses when I go outside in bright daylight.	2.7	3.0	1.5			30.14% (208)	17.54% (121)	17.83% (123)	18.70% (129)	15.80% (109)
item14	I wear a visor or cap when I go outside in bright daylight.	2.1	2.0	1.3			47.54% (328)	18.84% (130)	12.90% (89)	15.22% (105)	5.51% (38)
item15	I seek shade when I am outside in bright daylight.	3.3	3.0	1.1			7.97% (55)	13.91% (96)	35.36% (244)	27.97% (193)	14.78% (102)
item16	I wear blue-filtering, orange-tinted, and/or red-tinted glasses indoors during the day.	1.6	1.0	1.3			79.13% (546)	3.91% (27)	4.06% (28)	5.07% (35)	7.83% (54)
item17	I wear blue-filtering, orange-tinted, and/or red-tinted glasses outdoors during the day.	1.5	1.0	1.2			80.43% (555)	3.33% (23)	5.22% (36)	3.04% (21)	7.97% (55)
item18	I use light therapy applying a white light box.	1.1	1.0	0.5			92.90% (641)	3.48% (24)	2.75% (19)	0.58% (4)	0.29% (2)
item19	I use light therapy applying a blue light box.	1.0	1.0	0.3			97.68% (674)	0.87% (6)	0.72% (5)	0.72% (5)	0.00% (0)
item20	I use light therapy applying a light visor.	1.0	1.0	0.3			98.70% (681)	0.14% (1)	0.58% (4)	0.43% (3)	0.14% (1)
item21	I use light therapy applying another form of light device.	1.1	1.0	0.6			94.06% (649)	1.45% (10)	3.04% (21)	0.58% (4)	0.87% (6)
item22	I spend most of my daytime in a brightly lit environment.	3.5	4.0	1.1			5.36% (37)	13.33% (92)	21.74% (150)	41.59% (287)	17.97% (124)
item23	I close the curtains or blinds during the day if the light from outside is bright.	2.6	2.0	1.3			26.38% (182)	24.93% (172)	23.33% (161)	17.25% (119)	8.12% (56)
item24	I spend most of my indoor time within 3 meters from a window.	4.1	4.0	1.0			2.90% (20)	5.65% (39)	11.45% (79)	37.83% (261)	42.17% (291)

Figure 2. Summary descriptives and response pattern

Summary Descriptives (n =690)

Items 25-48

Item		Summary Statistics			Graphics		Response Pattern				
LEBA Items	Stem	Mean	Median	SD	Histogram	Density	Never	Rarely	Sometimes	Often	Always
item25	I use a desk lamp when I do focused work.	2.6	3.0	1.4			33.77% (233)	15.51% (107)	22.03% (152)	17.54% (121)	11.16% (77)
item26	I turn on my ceiling room light when it is light outside.	3.7	4.0	1.3			37.54% (259)	22.03% (152)	20.58% (142)	12.17% (84)	7.68% (53)
item27	I use my mobile phone within 1 hour before attempting to fall asleep.	3.9	4.0	1.3			7.54% (52)	9.71% (67)	10.00% (69)	31.59% (218)	41.16% (284)
item28	I use my computer/laptop/tablet within 1 hour before attempting to fall asleep.	3.7	4.0	1.2			5.07% (35)	13.19% (91)	17.39% (120)	35.36% (244)	28.99% (200)
item29	I watch television within 1 hour before attempting to fall asleep.	2.5	2.0	1.3			33.04% (228)	18.12% (125)	20.29% (140)	20.72% (143)	7.83% (54)
item30	I look at my smartwatch within 1 hour before attempting to fall asleep.	1.5	1.0	1.1			82.46% (569)	3.04% (21)	4.64% (32)	5.65% (39)	4.20% (29)
item31	I dim my room light within 1 hour before attempting to fall asleep.	3.0	3.0	1.6			31.30% (216)	10.43% (72)	12.03% (83)	20.14% (139)	26.09% (180)
item32	I dim my mobile phone screen within 1 hour before attempting to fall asleep.	3.5	4.0	1.6			24.20% (167)	5.94% (41)	9.42% (65)	15.65% (108)	44.78% (309)
item33	I dim my computer screen within 1 hour before attempting to fall asleep.	3.4	4.0	1.7			25.94% (179)	6.67% (46)	8.99% (62)	14.35% (99)	44.06% (304)
item34	I use a blue-filter app on my mobile phone screen within 1 hour before attempting to fall asleep.	3.4	5.0	1.8			34.06% (235)	2.90% (20)	4.20% (29)	7.83% (54)	51.01% (352)
item35	I use a blue-filter app on my computer screen within 1 hour before attempting to fall asleep.	3.8	5.0	1.7			24.64% (170)	2.17% (15)	5.07% (35)	8.26% (57)	59.86% (413)
item36	I wear blue-filtering, orange-tinted, and/or red-tinted glasses within 1 hour before attempting to fall asleep.	1.6	1.0	1.3			81.59% (563)	3.19% (22)	3.04% (21)	2.75% (19)	9.42% (65)
item37	I purposely leave a light on in my sleep environment while sleeping.	2.3	2.0	1.3			37.54% (259)	22.03% (152)	20.58% (142)	12.17% (84)	7.68% (53)
item38	I use as little light as possible when I get up during the night.	4.3	5.0	1.1			4.93% (34)	5.07% (35)	5.80% (40)	25.22% (174)	58.99% (407)
item39	I turn on the lights when I get up during the night.	2.0	2.0	1.1			37.97% (262)	37.10% (256)	14.78% (102)	6.52% (45)	3.62% (25)
item40	I check my phone when I wake up at night.	2.3	2.0	1.3			36.23% (250)	25.80% (178)	19.28% (133)	11.74% (81)	6.96% (48)
item41	I look at my smartwatch when I wake up at night.	1.3	1.0	0.8			86.96% (600)	4.35% (30)	4.64% (32)	2.90% (20)	1.16% (8)
item42	I close curtains or blinds to prevent light from entering the bedroom if I want to sleep.	4.0	5.0	1.4			13.62% (94)	5.07% (35)	8.41% (58)	15.51% (107)	57.39% (396)
item43	I use a sleep mask that covers my eyes.	1.7	1.0	1.2			69.86% (482)	9.28% (64)	10.00% (69)	4.20% (29)	6.67% (46)
item44	I modify my light environment to match my current needs.	3.4	4.0	1.3			14.49% (100)	7.68% (53)	20.29% (140)	34.93% (241)	22.61% (156)
item45	I use LEDs to create a healthy light environment.	2.1	1.0	1.5			57.25% (395)	6.38% (44)	13.77% (95)	11.88% (82)	10.72% (74)
item46	I use tunable lights to create a healthy light environment.	1.7	1.0	1.2			70.29% (485)	5.80% (40)	10.29% (71)	9.13% (63)	4.49% (31)
item47	I discuss the effects of light on my body with other people.	2.1	2.0	1.2			40.43% (279)	24.06% (166)	21.30% (147)	9.57% (66)	4.64% (32)
item48	I seek out knowledge on how to improve my light exposure.	2.5	2.0	1.3			26.81% (185)	23.33% (161)	28.12% (194)	12.46% (86)	9.28% (64)

Figure 3. Summary descriptives and response pattern

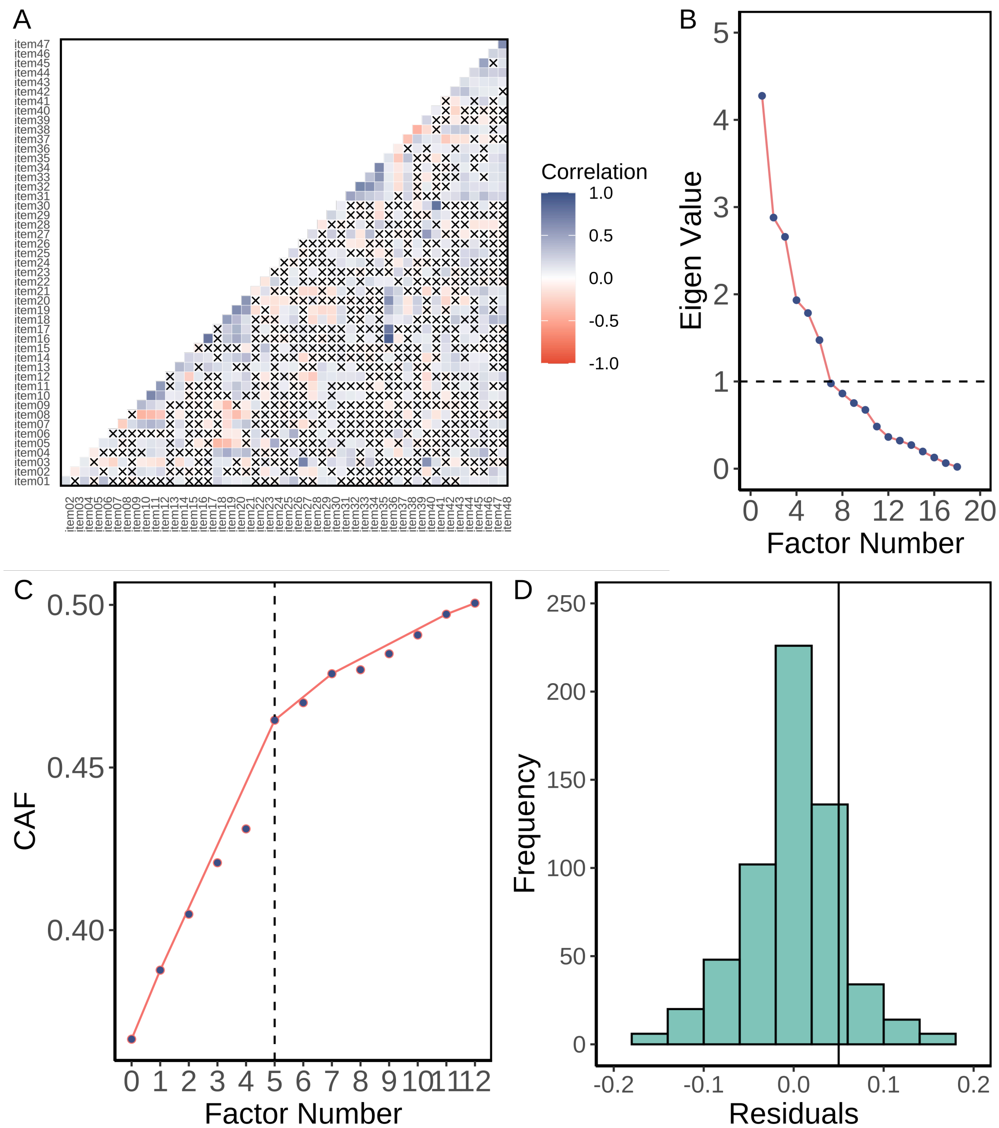


Figure 4. (A) Inter-item polychoric correlation coefficients for the 48 items. 4.9 % inter-item correlation coefficients were higher than |.30|. (B) Scree plot suggested six factors. (C) Hull method indicated 5 factors were required to balance the model fit and number of parameters. (D) Histogram of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

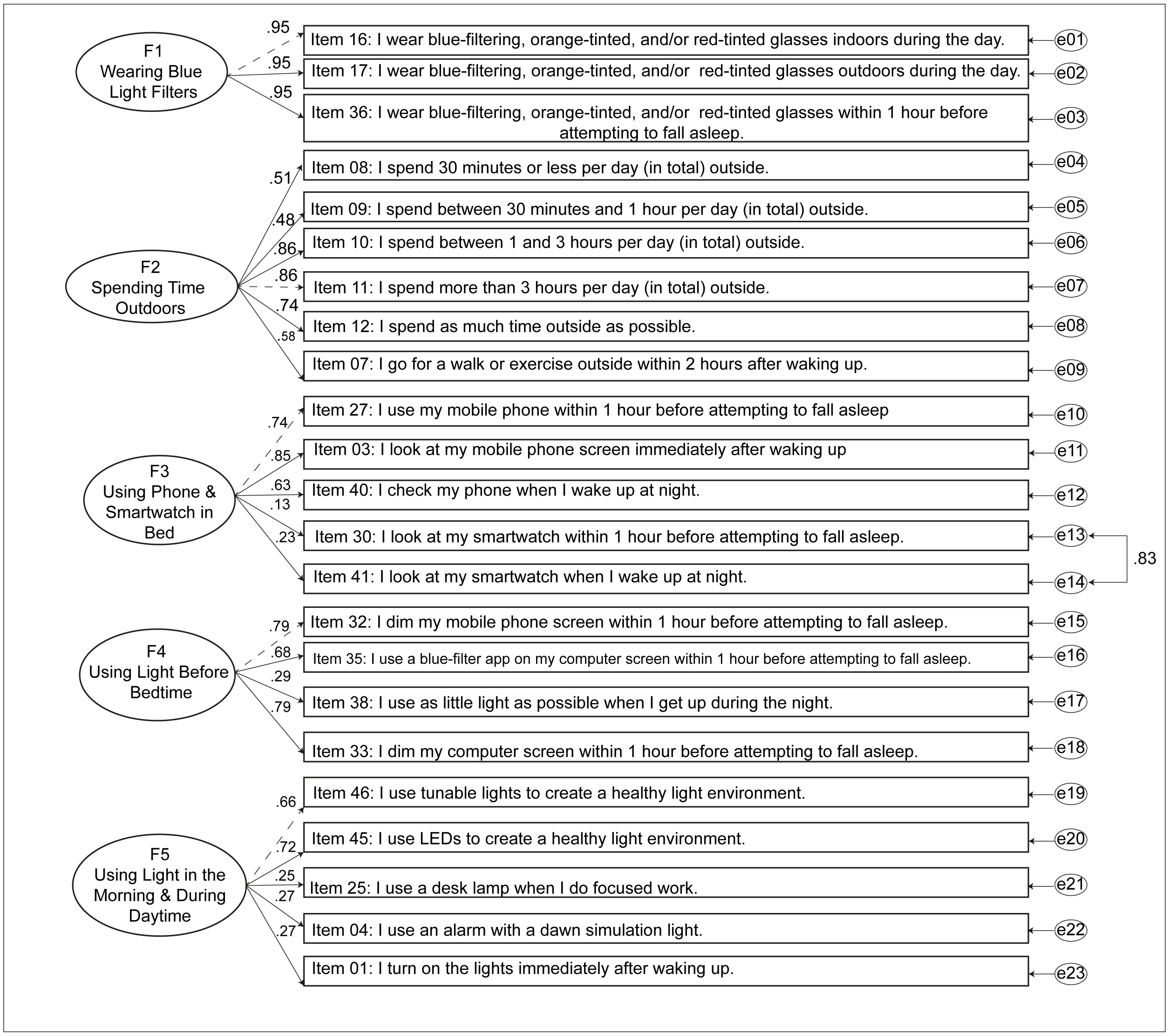


Figure 5. Five factor model of LEBA obtained by confirmatory factor analysis. By allowing item pair 41 and 30 to covary their error variance our model attained the best fit.

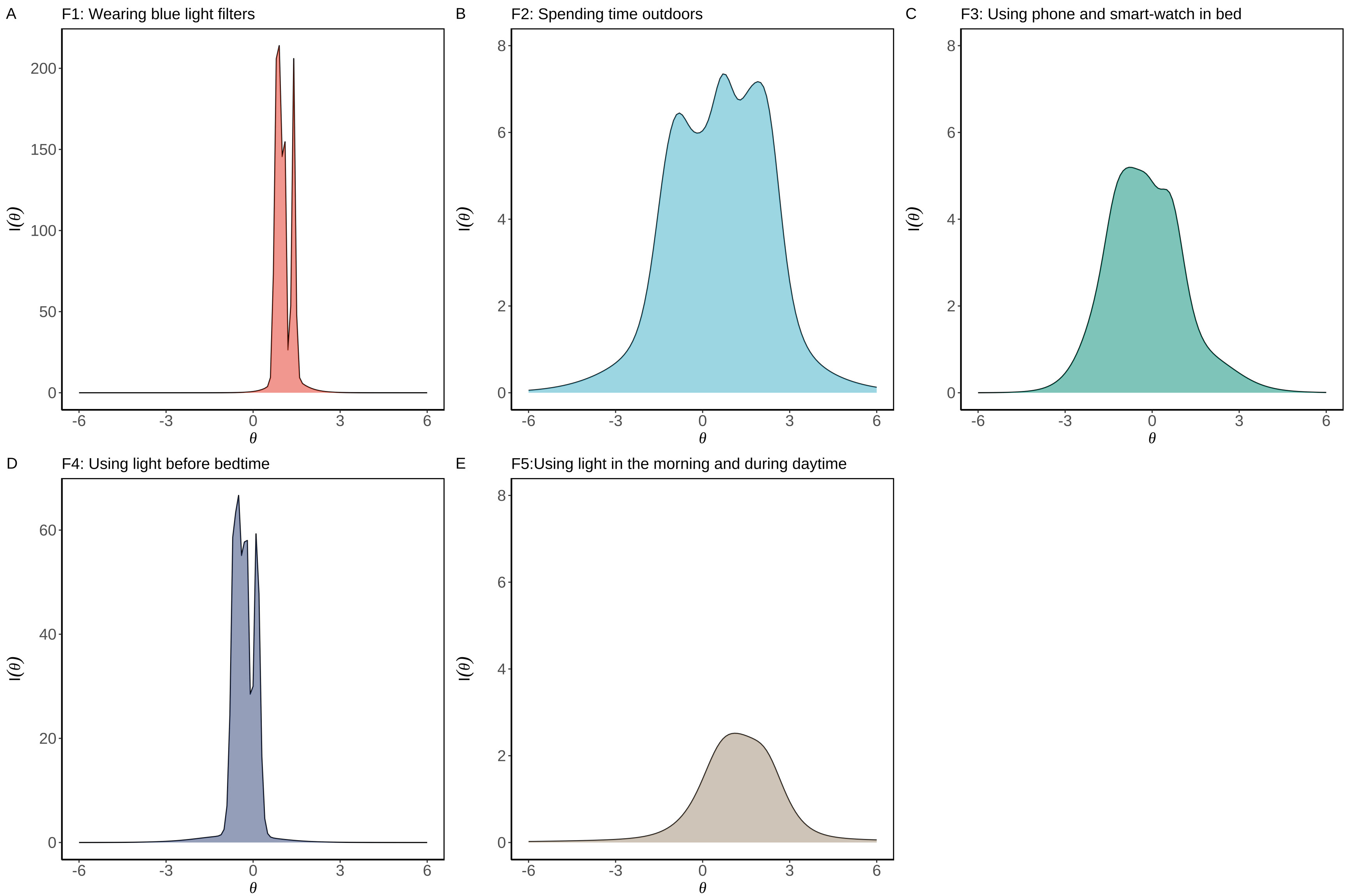


Figure 6. Test information curves for the five factors of LEBA: (a) wearing blue light filters (b) spending time outdoors (c) using phone and smartwatchin bed (d) using light before bedtime (e) using light in the morning andduring daytime. Along x-axis we plotted the underlying latent trait continumm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