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

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- 15 Preparation, Data Visualization.
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18 Abstract

One or two sentences providing a **basic introduction** to the field,

20 comprehensible to a scientist in any discipline.

Two to three sentences of **more detailed background**, comprehensible

to scientists in related disciplines.

One sentence clearly stating the **general problem** being addressed by

24 this particular study.

One sentence summarizing the main result (with the words "here we

26 **show**" or their equivalent).

Two or three sentences explaining what the **main result** reveals in direct

comparison to what was thought to be the case previously, or how the main

result adds to previous knowledge.

One or two sentences to put the results into a more **general context**.

Two or three sentences to provide a **broader perspective**, readily

comprehensible to a scientist in any discipline.

Keywords: keywords

Word count: X

33

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

37 Introduction

38 Methods

39 Participants

This line is just a test for pushing in the github repo.

41 Material

40

42 Procedure

Our study had four objectives. First, to develop an instrument to assess individual's light exposure behavior. Second, to conduct an exploratory factor analysis(EFA) to understand the latent structure. Third to gather structural validity evidence for the latent structure obtained in EFA. Lastly, we gathered item information using Item response theory (IRT)(Baker, 2017)

Data Collection. Timeline of data collection, ethical approval, mode of data collection, how consent was recorded.

Item generation and Content Validity: Expert Panel Review. How we developed the 48 items?

2 Analytic Strategies

We used R (version 4.1.0), including several R-packages for our analyses.

Necessary assumptions of EFA, 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 we used polychoric 57 correlation matrix (C. Desjardins & Bulut, 2018) for the EFA. We employed 58 principal axis (pa) a factor extraction method with varimax rotation. PA is 59 apparently robust to the normality assumption violations (Watkins, 2020). The 60 obtained latent structure was confirmed by minimum residuals extraction 61 method as well. We used a combination factor indentification method including 62 scree plot(Cattell, 1966), Horn's parallel analysis (Horn, 1965), minimum average partials method(Velicer, 1976), and hull method (Lorenzo-Seva, 64 Timmerman, & Kiers, 2011) to identify factor numbers. Additionally, to identify 65 the simple structure we followed the following guidelines recommended by 66 psychometricians (i) no factors with fewer than three items (ii) no factors with a factor loading <0.3 (iii) no items with cross-loading greater than .3 across factors (Bandalos & Finney, 2018; Child, 2006; Mulaik, 2009; Watkins, 2020)

Results 70

Sampling adequacy was investigated by Kaiser-Meyer-Olkin (KMO) measures of sampling adequacy(Kaiser, 1974). The overall KMO vale for 23 items was 0.63 which was above the cutoff value of .50 indicating a mediocre sample (Hutcheson, 1999).

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Table1 summarizes the univariate descriptive statistics for the 48 items. 76 some of the items were skewed with high Kurtosis values. The Shapiro-Wilk test of normality (Shapiro & Wilk, 1965) indicated all the items violated normality assumptions. Multivariate normality assumptions were investigated by Marida's test (Mardia, 1970). Multivariate skew = 583.80 (p < 0.001) and multivariate

kurtosis = 2,749.15 (p <0.001) indicated multivariate normality assumptions violation. Due to these violations and ordinal nature of the response data polychoric correlations over Pearson's correlations was chosen (C. Desjardins & Bulut, 2018). Bartlett's test of sphericity (Bartlett, 1954), χ^2 (1128) = 5042.86, p < .001] indicated the correlations between items are adequate for the EFA. However only 4.96% of the inter-item correlation coefficients were greater than .30 in the obtained matrix. The inter item correlation ranged between .44 to .91. The corrected item-total correlations ranged between .10 to .44.

Scree plot (Fig3) suggested a six-factor solution. Horn's parallel analysis 89 (Horn, 1965), like the Monte Carlo study, draws several sets of random data 90 with the same number of participants as the original data set and compares 91 the mean eigenvalues among the simulated and original data sets to retain 92 optimal factors. This extraction method also supported a five-factor model. In 93 our data set parallel analysis with 500 iterations indicated six-factor solution. 94 However, In MAP method (Velicer, 1976) and Hull method (Lorenzo-Seva, 95 Timmerman, & Kiers, 2011) suggested a five-factor solution. As a result, we 96 tested both five factor and six factor solutions.

The initial five-factor solution with all 48 items showed the presence of 98 cross-loading items (item 42, 16, & 1) and poor factor loading (<.30) items 99 (item 20,3,15, 17, 40, 4, 11, 39, 18, 45, 29, 25, 8, & 46). At first we discarded 100 the items with poor factor loading and ran another EFA on the remaining 34 101 items. This iteration of EFA also appeared as a misfit in terms of poor 102 factor-loading (Item 12, 22, 38, 6) and cross-loading (Items 23, 31, 37, 48). 103 Another two rounds of EFA were conducted with gradually identifying problematic items and discarding them from the model. Finally, a five-factor 105 EFA solution with 23 items was accepted with low RMSR = 0.04, no loading 106 smaller than .30 and no cross-loading greater than .30. The obtained latent 107

construct was also confirmed by using minimum residual extraction method 108 (see the supplementary). Table?? displays the factor loadin (structural 109 coefficients) and commonality of the items. The absolute value of the 110 factor-loading ranged from .47 to .99 indicating strong coefficients. The 111 commonalities ranged between .10 to .99. However, the histogram of the 112 absolute values of non-redundant residual-correlations (Fig4 showed 26.09% 113 correlations greater than the absolute value of .05, indicating under-factoring. 114 (C. D. Desjardins, 2018). Subsequently, we fitted a six-factor solution. However, 115 in the six factor solution a factor emerged with only two salient variable 116 loading thus disqualifying the six-factor solution. 117

Confirmatory Factor Analysis

119 Discussion

118

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Table 1

Descriptive Statistics

	Mean	SD	Skew	Kurtosis	Shapiro-Wilk Statistics	Item-Total Correlation
ltem1	1.12	0.49	5.02	27.80	0.25*	.16
Item2	2.16	1.19	0.71	-0.54	0.84*	.14
Item3	4.14	0.99	-1.23	1.14	0.79*	.19
Item4	2.87	1.59	0.08	-1.60	0.83*	.19
Item5	1.76	1.23	1.35	0.44	0.66*	.38
Item6	2.73	1.46	0.20	-1.36	0.87*	.33
Item7	3.86	1.67	-0.99	-0.85	0.65*	.23
Item8	3.76	1.14	-0.68	-0.45	0.86*	.00
Item9	3.42	1.83	-0.45	-1.69	0.69*	.33
Item10	2.74	1.04	0.09	-0.74	0.91*	.28
ltem11	2.60	1.25	0.29	-0.86	0.89*	.35
Item12	2.11	1.17	0.77	-0.39	0.83*	.32
Item13	2.94	1.03	-0.12	-0.40	0.91*	.10
Item14	3.62	1.64	-0.68	-1.25	0.74*	.32
Item15	1.64	1.18	1.79	2.02	0.60*	.15
Item16	3.51	1.30	-0.70	-0.59	0.85*	.39
Item17	1.96	0.98	1.02	0.69	0.82*	.05
Item18	2.44	1.31	0.38	-1.14	0.86*	.11
Item19	3.80	1.29	-0.87	-0.42	0.82*	.17
Item20	4.01	1.40	-1.22	0.07	0.70*	.13
Item21	1.33	0.91	3.03	8.43	0.41*	.01
Item22	2.59	1.41	0.27	-1.27	0.86*	.19
Item23	1.31	0.81	2.75	6.92	0.43*	.21

Table 1 continued

	Mean	SD	Skew	Kurtosis	Shapiro-Wilk Statistics	Item-Total Correlation
Item24	1.47	1.18	2.38	4.00	0.43*	.28
Item25	2.56	1.27	0.33	-1.00	0.89*	.11
Item26	1.54	1.25	2.13	2.86	0.46*	.36
Item27	4.30	1.08	-1.79	2.53	0.67*	.22
Item28	2.27	1.39	0.74	-0.81	0.81*	.25
Item29	3.26	1.09	-0.26	-0.45	0.91*	.14
Item30	2.22	1.48	0.71	-1.02	0.76*	.30
Item31	1.05	0.36	7.23	52.98	0.13*	.18
Item32	1.54	1.21	2.07	2.75	0.49*	.31
Item33	1.04	0.33	8.99	85.28	0.10*	.16
Item34	3.36	1.38	-0.48	-1.03	0.87*	.16
Item35	2.26	1.25	0.70	-0.60	0.85*	.19
Item36	2.36	1.22	0.59	-0.62	0.87*	.25
Item37	1.14	0.59	4.79	24.05	0.25*	.16
Item38	2.25	1.27	0.69	-0.64	0.84*	.18
Item39	3.93	1.48	-1.06	-0.44	0.71*	.18
Item40	3.57	1.07	-0.65	-0.17	0.88*	.21
Item41	3.55	1.65	-0.60	-1.34	0.76*	.43
Item42	3.00	1.62	-0.08	-1.61	0.83*	.44
Item43	1.56	1.23	2.00	2.45	0.50*	.32
Item44	2.97	1.20	-0.06	-0.94	0.91*	10
Item45	2.79	1.55	0.19	-1.48	0.85*	.20
Item46	2.14	1.31	0.77	-0.78	0.80*	.26
Item47	2.18	0.90	0.60	0.12	0.86*	.26

Table 1 continued

	Mean	SD	Skew	Kurtosis	Shapiro-Wilk Statistics	Item-Total Correlation
Item48	1.48	1.11	2.18	3.35	0.48*	.24

Note. *p<.001

Table 2

	F1	F2	F3	F4	F5	Communalities
item1	0.06	-0.03	0.01	0.03	0.35	0.13
item2	0.12	-0.10	-0.11	0.69	-0.03	0.51
item5	0.01	0.16	0.09	0.01	0.69	0.52
item7	0.06	-0.09	0.66	-0.01	-0.03	0.45
item10	-0.01	0.82	0.07	0.02	0.02	0.68
item13	-0.06	0.34	-0.03	0.10	0.00	0.13
item14	0.00	0.05	0.89	-0.08	-0.08	0.81
item16	0.10	0.05	0.29	-0.11	0.31	0.21
item19	0.02	-0.06	0.00	0.80	0.03	0.64
item21	-0.05	-0.02	-0.34	0.03	-0.06	0.12
item24	-0.03	0.10	0.10	0.11	0.54	0.33
item26	0.93	0.00	0.13	-0.01	0.13	0.90
item27	-0.01	0.07	0.38	-0.12	0.21	0.21
item28	0.02	0.00	-0.05	0.01	0.31	0.10
item30	0.06	0.01	0.11	-0.04	0.52	0.29
item32	0.80	0.00	0.05	0.13	0.10	0.67
item34	-0.01	-0.14	0.02	0.84	0.12	0.74
item35	-0.04	0.46	0.04	-0.17	0.04	0.25
item36	0.09	0.63	0.10	-0.15	0.11	0.45
item41	0.05	0.07	0.70	0.30	0.14	0.60
item43	0.99	0.00	0.06	0.01	0.03	0.99
item44	-0.03	-0.47	-0.01	0.10	0.01	0.24
item47	0.02	0.82	-0.05	-0.06	0.16	0.70

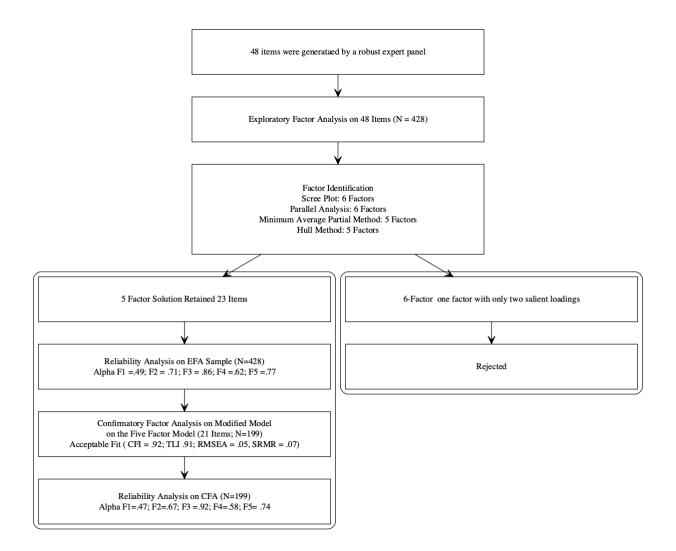


Figure 1. ABC

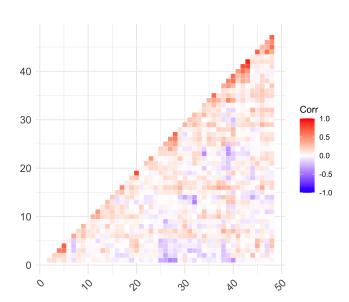


Figure 2. Iter-correlation of the items

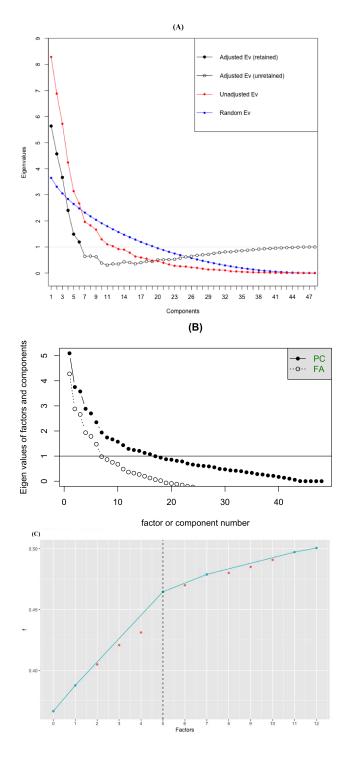


Figure 3. Factor Identification (A) Parallel analysis (B) Scree Plot, (C) Hull method

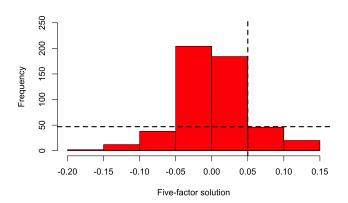


Figure 4. Histogram of residulas: five-factor solution