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A trait-based network perspective on the validation of the French Short Boredom Proneness Scale

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Abstract

The Short Boredom Proneness Scale (SBPS) has recently been developed. Using a standard confirmatory factor analysis, we report on the structural validation of the French SBPS, which provided support for the original construct. A network analysis (n = 490) revealed the structure of the relationships of the SBPS and of the two facets of the Curiosity and Exploration Inventory-II (CEI-II). The analysis revealed positive connections between the boredom and curiosity items, whereas the connections between the boredom and exploration items were negative. To evaluate measurement invariance, we compared the French-speaking sample (n = 490) with an English-speaking sample (n = 364). Full configural, metric, and scalar invariance was established; thus, we provide a valid French translation of a widely used measure of boredom that may advantage future research.

Keywords: boredom, exploration, curiosity, French version, measurement invariance

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We are all familiar with the sensation of boredom that arises despite our wish for a life filled with excitement, adventure, and opportunities to grow and to learn. Boredom is indeed a universal experience that has been attracting increased interest in psychological research. Boredom has been defined as the "aversive experience of wanting, but being unable, to engage in satisfying activity" (Eastwood et al., 2012, p. 482), and researchers have been highlighting both its cognitive and emotional components.

The sensation of boredom arises when there is a mismatch between the individual cognitive resources available and the demands of the ongoing task (Eastwood et al., 2012; Westgate & Wilson, 2018; Tam et al., 2021) and/or when there is a mismatch between the individual goals and the value of the ongoing task (Pekrun et al., 2010; van Tilburg & Igou, 2012; Westgate & Wilson, 2018). Recent models (e.g., Wolff & Martarelli, 2020) based on previous empirical and theoretical work (Bench & Lench, 2013, 2019; Danckert, 2019; Elpidorou, 2014, 2018a; Gomez-Ramirez & Costa, 2017; Kurzban et al., 2013) highlight the adaptive function of boredom, insofar as it leads us to explore behavioral alternatives that might lead to greater reward in the future. The current increased interest in the adaptive function of boredom in terms of exploration behavior mainly reflects boredom on a *state* level. In this study, we aim to characterize the link between boredom and exploration on a *trait* level. Specifically, we investigate how boredom proneness emerges in a trait-based network that further considers curiosity and exploration.

Indeed, the concept of exploration has long been investigated in the context of *curiosity*. Curiosity is referred to as the desire for information, interest in learning new things, and openness toward whatever is attended (Kidd & Hayden, 2015; Litman & Spielberger, 2003), but it also includes people's tendency to explore new opportunities (Kashdan & Silvia, 2009; Loewenstein, 1994). For example, Kashdan et al. (2009) define curiosity as “recognizing, embracing, and seeking out knowledge and new experiences” (p. 988), where “seeking out” represents the explorative component of curiosity. In line with this definition, Kashdan et al. (2009) developed and validated the Curiosity and Exploration Inventory-II (CEI-II), a two-factorial measure including the dimensions Curiosity (i.e., people’s tendency to embrace new ideas and experiences) and Exploration (i.e., people’s tendency to actively seek opportunities for new ideas and experiences). The authors refer to the curiosity dimension in terms of embracing, and to the exploration dimension in terms of stretching. In this paper, we will exclusively use the terms curiosity and exploration to refer to these two dimensions.

Notable recent exceptions notwithstanding (Danckert et al., 2018; Elpidorou, 2018a, 2018b; Mugon et al., 2018; Tam et al., 2021), most theories of boredom focus on state boredom and theorizing on trait boredom has been largely overlooked so far. This is contrasting with the extensive empirical evidence of negative trait-like boredom proneness-associated consequences (e.g., Sommers & Vodanovich, 2000). This has prompted researchers to emphasize the need for a strong theoretical framework of boredom proneness, which in turn should lead to a refinement of its operationalization (Gana et al., 2018). Current theories define boredom proneness (i.e., the tendency to experience boredom more frequently and more intensely, Farmer & Sundberg, 1986) as a dysfunction of self-regulatory processes making that individuals repeatedly fail to attain satisfactory engagement (Danckert et al., 2018; Elpidorou, 2018a, 2018b; Mugon et al., 2018; Tam et al., 2021). Tam and colleagues refine this view in their model, by pointing out that boredom proneness might be characterized by not knowing what to do with one’s own life, or knowing, but being unable to engage with it. Hunter et al. (2016) found that boredom proneness, after controlling for an overall personality taxonomy (HEXACO), positively predicted deprivation-type epistemic curiosity and exploration, but not interest-type epistemic curiosity, absorption, or creativity. Epistemic curiosity is defined as the desire to find new knowledge in order to reduce informational *deprivation* (i.e., deprivation-type epistemic curiosity) or in order to stimulate intellectual *interest* (i.e., interest-type epistemic curiosity) (Litman, 2005). The authors advanced an interpretation of boredom proneness in terms of being curious but unable to bring curiosity to fruition.

To advance research on boredom proneness, the present paper aims to 1) provide a French translation of a widely used boredom proneness scale and 2) investigate the boredom-curiosity-exploration trait-based network. Because of the increased interest in boredom proneness, we believe that a French version of this scale would be a valuable addition to the current scales.

The first objective of our study was to validate the French SBPS. Numerous scales have been developed to assess boredom (for an overview, see Vodanovich & Watt, 2016). More recently, Struk et al. (2017) assessed the factor structure and validity of the Boredom Proneness Scale (BPS) and the Boredom Proneness Scale–Short Form (BPS-SR) and found that inconsistencies in the results of previous factor analyses of the scales can be explained by the use of reverse-coded items in the Internal Stimulation subscale. They showed that by rewording these items, and by omitting items with poor discriminatory value, the two-factorial solution disappeared, and so they proposed and validated the SBPS, which is a one-factorial measure of eight consistently worded items.

In the light of the need for *short* measures that reliably assess trait boredom, we translated the SBPS into French. We chose the SBPS of Struk and colleagues (2017), as it has been shown to be a reliable and valid measure of boredom proneness. Several studies in different areas have successfully used the SBPS, for example, in relation with problematic phone usage (Elhai et al., 2018; Yang et al., 2020) or in the context of the COVID-19 pandemic (Boylan et al., 2020; Wolff, Martarelli, et al., 2020). Boredom proneness, as measured by the SBPS, has been shown to positively correlate with constructs such as aggression (Isacescu et al., 2017), sadism (Pfattheicher et al., 2020), depression, anxiety, and stress (Lee & Zelman, 2019), risk-taking (Kılıç et al., 2020), noisy decision-making (Yakobi & Danckert, 2021), and to negatively correlate with constructs such as self-control (Isacescu & Danckert, 2018). The SBPS has also been successfully translated into other languages, notably German (Martarelli et al., 2020) and Chinese (Peng et al., 2020), thus supporting the cross-cultural robustness of the one-factorial solution. As for the construct's latent structure, we expected to replicate a one-factorial model for the SBPS. For validation we measured the Openness scale of the Big Five Inventory. We expected to find a negative relation between boredom and openness to experience (Culp, 2006; Martarelli et al., 2020). Further, we used measurement invariance to examine if the SBPS has a uniform factor structure for French and English-speaking participants.

The second objective of our study was to explore the proposed relationship between boredom, curiosity, and exploration (Hunter et al., 2016). To assess the relationships between these three dimensions, we estimated a Gaussian graphical model (GGM) with the Extended Bayesian Information Criterion Graphical Least Absolute Shrinkage and Selection Operator (EBICglasso) algorithm (Epskamp & Fried, 2018), a method from the field of network psychometrics (Fried & Cramer, 2017; Golino & Epskamp, 2017) that has recently been employed with personality trait questionnaires (e.g., Christensen et al., 2019; 2020; Martarelli et al., 2020; Schwaba et al., 2020). Simulation studies have shown that Exploratory Graph Analysis (EGA) is equivalent and in some cases outperforms Exploratory Factor Analysis (EFA) (Golino et al., 2020). In the context of the validation of the French SBPS, this approach can reveal whether the boredom items remain located in the boredom dimension when placed in a multidimensional context of related concepts. Further, by providing insight into the connections between all items that include the SBPS and the CEI-II, this approach fits perfectly with the second objective of this study. We aim to reveal the network structure of the SBPS and CEI-II. Based on recent theorizing on boredom proneness (Danckert et al., 2018; Elpidorou, 2018a, 2018b; Mugon et al., 2018; Tam et al., 2021), we expected negative associations between boredom and exploration items and positive associations between boredom and curiosity items, when controlling for all other items in the network.

Method

Participants

As reported in the preregistration on the Open Science Framework (OSF; https://osf.io/rdhnu/), we aimed to test 490 participants. Kretzschmar and Gignac (2019) showed that latent variable correlations stabilize at $N = 490$ in typical research scenarios (population correlation of 0.20 and composite score reliability of 0.70).

French-speaking convenience sample. The sample was collected online via social media. 572 participants completed the questionnaire without receiving a specific incentive. Of these participants, 82 (14.3%) did not answer at least one of the two validity items correctly and were excluded from further analyses. The remaining sample (we had no missing values) consisted of 490 participants (73% female) with an average age of 33.87 years ($SD = 11.49$). Their occupations were classified as student (33%), academic (14%), social services (13%), technician (9%), health sector (8%), service sector (5%), and other (28%).

English-speaking MTurk sample. To evaluate measurement invariance, we analyzed data obtained from the study by Martarelli et al. (2020) using the original version of the SBPS. The sample consisted of 364 participants (45.33% female). Respective information on this sample can be found in Martarelli et al. (2020).

Measures

Short Boredom Proneness Scale (SBPS; Struk et al., 2017). We administered the SBPS, which is a short questionnaire used to investigate trait boredom (8 items, e.g., "I find it hard to entertain myself"). The eight items all consist of 7-point Likert scales ranging from strongly disagree to strongly agree.

Curiosity and Exploration Inventory-II (CEI-II; Kashdan et al., 2009). We used the CEI-II, which was recently translated into French by Audrin et al. (2021). It is a short questionnaire used to investigate the facets of Exploration (5 items, e.g., "I actively seek as much information as I can in new situations") and Curiosity (5 items, e.g., "I prefer jobs that are excitingly unpredictable"). The 10 items all consist of 7-point Likert scales ranging from strongly disagree to strongly agree.

Openness Scale (John et al., 2008; Plaisant et al., 2010). We also administered the Openness Scale. It consists of 10 items (e.g., "Has an active imagination") rated on 5-point Likert scales ranging from strongly disagree to strongly agree.

Validity items (Oppenheimer et al., 2009). Two validity items (e.g., "It is very important that you are focused while filling out this survey. Please check Option 7 (strongly agree)") were included to detect participants that failed to follow instructions.

Procedure

The SBPS was translated into French through a forward- and back-translation procedure. The questionnaire was translated by two independent translators and discrepancies were then discussed by the two translators and the authors of this paper. Next, the French version was translated back into English by an independent translator (bilingual) and the discrepancies were again discussed by the translators and the authors of this paper. The translated items can be found at https://osf.io/thaum/.

Participants completed the questionnaires online using LimeSurvey (www.limesurvey.org). After providing informed consent, the participants reported their age, gender, and employment status. To detect participants that failed to follow instructions we included two validity items: one in the SBPS, and one in the CEI-II. The SBPS, CEI-II, and the Openness Scale were presented in counterbalanced order. The items within the questionnaires were presented in randomized order. The local ethics committee approved the study, which was conducted in accordance with the Declaration of Helsinki.

Analytical approach

To assess the trait-based network of boredom, curiosity, and exploration on an item level, we estimated a GGM with the EBICglasso algorithm (Chen & Chen, 2008; Epskamp & Fried, 2018; Foygel & Drton, 2010; Friedman et al., 2008). This part of the analysis was conducted in *R* (R Core Team, 2020) using the *EGAnet* (Golino & Christensen, 2019) and the *qgraph* packages (Epskamp et al., 2012, 2018). EGA uses the Walktrap algorithm (Pons & Latapy, 2006) to estimate the number of dimensions. We used the default four steps of random walk suggested by Golino and Epskamp (2017). The R code to reproduce the main analyses, the dataset, and the questionnaires are available on OSF (https://osf.io/thaum/).

To assess the structural validity of the French SBPS, we used a standard confirmatory approach, including a confirmatory factor analysis (CFA) and measurement invariance analyses. This part of the analysis was conducted in *jamovi* (The Jamovi Project, 2021) and *R* (R Core Team, 2020) using the *lavaan* (Rosseel, 2018) and *psych* packages (Revelle, 2019). We constrained factor variances to one and employed maximum likelihood estimates. To assess model fit, we used the following measures: comparative fit index (CFI) above .95 for a good fit, standardized root square mean residual (SRMR) below .08 for a good fit, root mean square error of approximation (RMSEA) below .05 for a good fit, and Tucker-Lewis Index (TLI) above .90 for an acceptable fit and above .95 for a good fit. To assess measurement invariance, we tested configural, metric, and scalar invariance. We used a cutoff value of .01 for changes in the CFI and of .015 for changes in the RMSEA to indicate non-invariance (Chen, 2007).

Results

Descriptive summary of measures is reported in Table 1. Skewness and kurtosis were low, and the scales showed high internal consistency.

Table 1

Descriptive summary of measures

Measure	Mean (SD)	Skewness	Kurtosis	Alpha	Omega
SBPS	2.47 (1.10)	0.96	0.59	0.858	0.863
CEI-II-C	4.14 (1.17)	-0.17	-0.19	0.722	0.728
CEI-II-E	5.16 (1.00)	-0.42	0.42	0.747	0.749
Openness	3.71 (0.63)	-0.39	0.14	0.808	0.821

Note. SBPS = Short Boredom Proneness Scale; CE-I-II-C = Curiosity and Exploration Inventory-II Curiosity; CEI-II-E = Curiosity and Exploration Inventory-II Exploration.

Network analysis

In a network analysis, the closer the items, the more likely they belong to the same dimension. The regularized partial correlations (edges) colors connecting the items illustrate the direction of the relationship (blue representing positive and red representing negative), and the thickness of an edge shows the strength of the relationship. Edges represented in the network are all relevant given that small values are shrunk to zero (Epskamp & Fried, 2018). The identified trait-based network is illustrated in Figure 1.

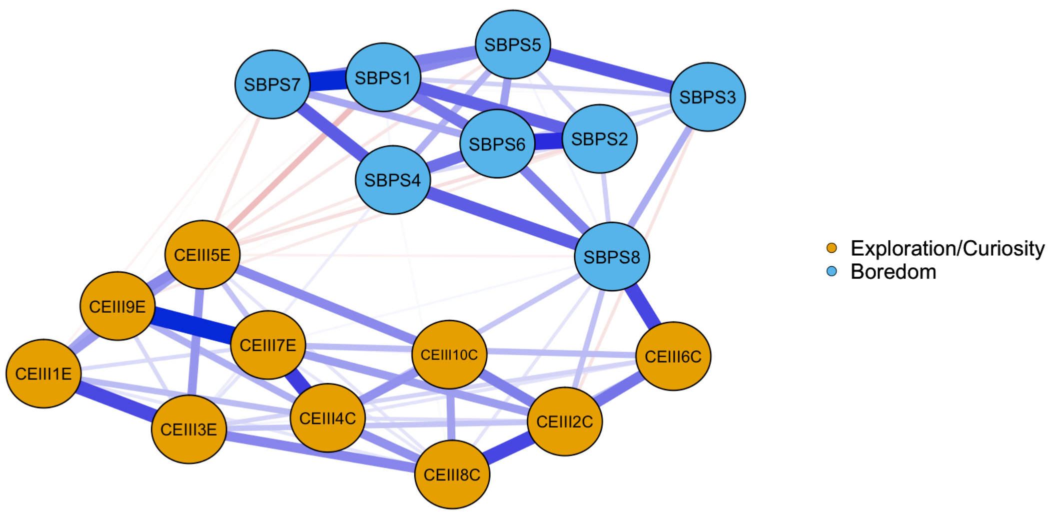

Figure 1. Network analysis showing the relationships between the 18 items of the SBPS and CEI-II based on EBICglasso. The Walktrap algorithm identified two dimensions (i.e., the exploration/curiosity and the boredom subnetworks). Items are reported in Table 2.

Table 2

Code	Item
SBPS1	I often find myself at “loose ends,” not knowing what to do
SBPS2	I find it hard to entertain myself
SBPS3	Many things I have to do are repetitive and monotonous
SBPS4	It takes more stimulation to get me going than most people
SBPS5	I don’t feel motivated by most things that I do
SBPS6	In most situations, it is hard for me to find something to do or see to keep me interested
SBPS7	Much of the time, I just sit around doing nothing
SBPS8	Unless I am doing something exciting, even dangerous, I feel half-dead and dull
CEIII1E	I actively seek as much information as I can in new situations
CEIII3E	I am at my best when doing something that is complex or challenging
CEIII5E	I view challenging situations as an opportunity to grow and learn
CEIII7E	I am always looking for experiences that challenge how I think about myself and the world
CEIII9E	I frequently seek out opportunities to challenge myself and grow as a person
CEIII2C	I am the type of person who really enjoys the uncertainty of everyday life
CEIII4C	Everywhere I go, I am out looking for new things or experiences
CEIII6C	I like to do things that are a little frightening
CEIII8C	I prefer jobs that are excitingly unpredictable
CEIII10C	I am the kind of person who embraces unfamiliar people, events, and places

Note. Items represented in Figure 1.

Contrary to our expectations, the Walktrap algorithm detected a two and not a three-dimensional structure (i.e., the exploration/curiosity and the boredom subnetworks were identified). The proportion of times each item replicated within the defined dimension was above 0.91 and the average dimension stability was above 0.97 for the two dimensions (based on bootstrapping method, 1000 iterations). Thus, item and dimension stability were very high. In the network, the SBPS items were identified as one dimension as well as the curiosity/exploration items. It is important to note, that the boredom subnetwork was clearly identified, which is relevant for the main aim of this study (validation of the French SBPS). Figure 1 helps to inspect grouping of items, since the items with higher relations are plotted together. This visual inspection revealed positive connections between boredom and curiosity items, especially between the SBPS8 item “Unless I am doing something exciting, even dangerous, I feel half-dead and dull” and the CEI-II6C item “I like to do things that are a little frightening.” The connections between the boredom and exploration items were negative, particularly between the SBPS1 item “I often find myself at ‘loose ends,’ not knowing what to do” and the CEI-II5E item “I view challenging situations as an opportunity to grow and learn.”

To better understand the resulted network, we worked with a standard approach (analysis suggested in the review process and thus not pre-registered). We computed an exploratory factor analysis using the maximum likelihood method, no rotation, and forcing a three-factor structure. The results were largely similar to the network approach and are reported in Table 3. First of all, and important for the validation part of our study, this analysis supported the internal structure of the SBPS to a large degree. Only the SBPS8 item appears to tap the curiosity/exploration network. Further, we see that the internal structure of the CEI-II is problematic. As already revealed by the network analysis one dimension is sufficient for representing the CEI-II. Interestingly, the items CEII-I5E and CEII-I6C were also tapping the boredom dimension. These results are highly consistent with the network analysis presented above.

Table 3

Factor loadings	Boredom	Exploration	Curiosity
SBPS1	**0.75**	−0.09	0.08
SBPS2	**0.66**	−0.07	0.09
SBPS3	**0.48**	−0.07	0.08
SBPS4	**0.70**	0.12	0.01
SBPS5	**0.68**	−0.07	0.07
SBPS6	**0.79**	−0.01	0.07
SBPS7	**0.72**	−0.08	−0.01
SBPS8	**0.51**	**0.27**	**−0.21**
CEIII1E	−0.06	**0.48**	**0.24**
CEIII3E	0.01	**0.56**	0.03
CEIII5E	**−0.27**	**0.51**	0.17
CEIII7E	0.03	**0.71**	0.17
CEIII9E	−0.11	**0.60**	**0.37**
CEIII2C	0.09	**0.63**	**−0.34**
CEIII4C	0.07	**0.66**	0.06
CEIII6C	**0.21**	**0.48**	**−0.32**
CEIII8C	0.09	**0.63**	−0.19
CEIII10C	−0.00	**0.49**	−0.10

Note. Maximum likelihood extraction method was used. Shaded cells correspond to the intended factor where the main loading should be present. Bold values correspond to loadings over |.20|. RMSEA = 0.049 [90% CI = 0.041 – 0.058], TLI = 0.935.

One-factorial model of boredom

CFA in the French-speaking sample. All factor loadings were significant (see Table 4). The fit indices ranged from acceptable to good ($\chi2(20) = 90.15$, $p < .001$; CFI = .952, TLI = .933, SRMR = 0.037, RMSEA = .085 [90% CI = .067 – 0.103]).

Table 4

Factor loadings in the French-speaking sample

Factor	Indicator	Estimate	SE	95% Confidence Interval Lower	95% Confidence Interval Upper	Z	p	Stand. Estimate
SBPS	SBPS1	1.18	0.06	1.06	1.31	18.74	< .001	0.76
	SBPS2	0.97	0.06	0.85	1.09	15.78	< .001	0.67
	SBPS3	0.77	0.07	0.63	0.91	10.68	< .001	0.48
	SBPS4	1.18	0.07	1.04	1.32	16.52	< .001	0.69
	SBPS5	1.04	0.06	0.91	1.16	16.40	< .001	0.69
	SBPS6	1.13	0.06	1.02	1.24	20.05	< .001	0.79
	SBPS7	1.13	0.06	1.01	1.26	17.66	< .001	0.73
	SBPS8	0.73	0.07	0.59	0.86	10.42	< .001	0.47

Measurement invariance. To evaluate measurement invariance across samples speaking different languages, we compared the data of the French-speaking sample, with an English-speaking sample (CFA in the English-speaking sample can be found in Martarelli et al., 2020). Differences in the CFI and the RMSEA are reported in Table 5 and support an invariant factor structure, invariant factor loadings, and invariant item intercepts. We conclude that the estimated factors are measuring the same underlying latent construct within each sample.

Table 5

Measurement invariance analysis

Model	df	AIC	BIC	Chisq	Chisq diff	CFI	CFI diff	RMSEA	RMSEA diff
Configural	40	27024	27259	165.26		0.972		0.080	
Loadings	47	27037	27238	192.36	27.098***	0.968	0.004	0.079	0.000
Intercepts	54	27046	27212	215.33	22.968**	0.964	0.004	0.078	0.001

Note. *** Difference is significant at the 0.001 level (two-tailed). ** Difference is significant at the 0.01 level (two-tailed). Cutoff value of .01 for changes in the CFI and of .015 for changes in the RMSEA were used to indicate non-invariance.

Evidence of construct validity

We analyzed the associations between boredom and curiosity, exploration, openness (descriptive summary of measures is reported in Table 1). Boredom and curiosity were weakly positively correlated ($r = 0.122$, $p = 0.007$), whereas the negative association between boredom and exploration did not reach statistical significance ($r = -0.085$, $p = 0.060$). Contrary to our expectations, boredom was not associated with openness ($r = -0.016$, $p = 0.719$). We conclude that evidence of construct validity is rather low.

Discussion

Concerning the validation of the French SBPS, the CFA confirmed the one-factorial structure of the scale. Furthermore, configural, metric, and scalar invariances were given, thus suggesting that the same construct (metric invariance) was assessed in the same way (scalar invariance) in the French-speaking and English-speaking samples. Contrary to previous findings (Culp, 2006; Martarelli et al., 2020), we could not replicate the negative relationship between boredom proneness and the openness to experience personality dimension in this sample. However, in previous research, other scales were used to measure the constructs, and the effects were small ($r = -.16$ in Culp, 2006 and $r = -.20$ in Martarelli et al., 2020). Taken together, our findings speak for the validity of the newly translated scale. Moreover, we found that the French SBPS is not only unidimensional and internally consistent—as shown by the confirmatory factor analysis and reliability analysis—but also that it remains homogeneous when placed in the context of related dimensions, as shown by the network analysis.

Current theoretical and empirical work on boredom highlights its powerful function of promoting exploration behavior to achieve higher rewards in the future (Bieleke & Wolff, 2021). On a conceptual level, boredom and curiosity can be regarded as complementary, with boredom signaling the decreasing value of the current task, and curiosity signaling the increasing value of other tasks (Agrawal et al., 2020). While both are reward-oriented, boredom is a disengagement-related process and curiosity an engagement-related process, in that they motivate attentional disengagement vs. engagement, respectively. Although boredom and curiosity can be thought of as cognitive-affective *states*, here we investigated the relationships among *trait*-like individual differences in boredom, curiosity, and exploration.

The trait-based network analysis revealed positive relationships among the boredom and curiosity items and negative relationships among the boredom and exploration items. It seems that boredom-prone individuals are disposed to embrace new ideas and experiences; however, they will not *actively* explore new opportunities. These findings fit well with a self-regulatory approach of boredom (e.g., Danckert et al., 2018, Mugon et al., 2018). Danckert and colleagues have proposed that boredom is an experience that interrupts the current focus of attention and motivates action, first to stop the aversive experience of boredom, and then to find new opportunities to increase reward. It is conceivable that individuals using the signal of boredom in an adaptive manner might only rarely feel bored, while boredom-prone individuals might experience boredom more often and more intensely because they fail to adaptively respond to the signal of boredom (Danckert et al., 2018). To complicate matters further, our results suggest that boredom-prone individuals are motivated to engage in other more rewarding activities (indicated by positive relationships with the curiosity items); however, they fail in doing so (indicated by negative relationships with the exploration items). These findings suggest that the functional signal of boredom that motivates the search for more rewarding activities is at work in boredom-prone individuals, but it is not *enacted*. In other words, boredom-prone individuals fail to act and remain trapped in the aversive experience of boredom.

Limitations and future directions

Boredom proneness was relatively low in our sample (*mean* = 2.47, *SD* = 1.10). Though being in a comparable range as in other studies, this might be problematic because it has been suggested that high boredom prone individuals might be characterized by distinct self-regulatory profiles (Mugon et al., 2018). Other samples including high boredom prone individuals should be tested, especially because the measurement of boredom proneness has clinical relevance. Moreover, we worked with an admittedly small set of scales, and several other variables are known to correlate with the variables under investigation here. Notably, Hunter et al. (2016) found that boredom proneness, after controlling for an overall personality taxonomy (HEXACO), positively predicted deprivation-type epistemic curiosity and exploration. They explained their findings in terms of the inhibited part of personality that is partialled out from boredom proneness and concluded that it is not curiosity itself that poses a challenge to the boredom-prone person but finding a way for this curiosity. A further potential variable that might interact with the boredom-curiosity-exploration network is self-control, which is central in balancing exploration-exploitation trade-offs (Bieleke et al., 2021). Future research would benefit from using other methodologies, such as experience sampling methods, to examine a possible state-trait interaction. To conclude, our findings indicate that the French SBPS is an accurate instrument of boredom that may advantage future research.

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