Methodological approaches to boredom and its measurement

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Abstract

The goal of this chapter is to review the methodologies used to assess boredom. The most widely used methods are self-report measures in the context of experimental research and cross-sectional surveys. We expand upon previous reviews of dispositional and situational self-report measures of boredom by presenting the established as well as recently developed psychometric scales, which are used to assess trait and state boredom in general and in domain-specific contexts, such as education, work, or sports. Next to retrospective state scales, probe-caught methods are used in experimental boredom research. In these experiments, participants are tasked to report their levels of boredom when a probe interrupts their current task. The subjective nature of self-reported boredom has motivated researchers to combine these measures with behavioral, physiological, and neurological markers. In the last part of this chapter, we will review this work, which reports promising results and encourages further research to identify the measures that are sensitive to boredom. In this last part of the chapter, we will also explore objective methodologies for studying boredom that are mainly based on human–computer interaction research.

Methodological approaches to boredom and its measurement

Most of us are familiar with the experience of boredom; however, when it comes to conceptualizing the experience, it is difficult to give a clear definition in lay terms. This might be because boredom is a multifaceted experience that includes different phenomenological aspects, such as unpleasantness, low arousal (but also high arousal), lack of engagement, lack of control, and lack of meaning, to mention only a few characteristics (see chapter XX of this book). A growing number of studies have investigated the construct of boredom in terms of its antecedents and consequences, but also more broadly in terms of its affective, behavioral, cognitive, and neurophysiological correlates (see chapter XX of this book). Furthermore, differences within and between the tendency to get bored have been observed. For example, the experience of boredom seems to peak during adolescence and diminish with age (e.g., Spaeth et al., 2015). As another example, individuals suffering from traumatic brain injury have been shown to score higher on boredom proneness when compared to healthy controls (Goldberg & Danckert, 2013). Also, boredom has been shown to share variance with attention deficit hyperactivity disorder (Malkovsky et al., 2012). In a related vein, researchers have highlighted factors that depend on personality (i.e., internal factors) as well as those contingent upon the situation (i.e., external factors) to explain the experience of boredom. In sum, the past few years have seen a surge of empirical research and theoretical accounts of boredom in a wide range of domains, especially in psychology.

Given the diversity, vagueness, and subjectivity of the experience of boredom, it is not surprising that methodological approaches to its measurement have sometimes been criticized as lacking a sound theoretical background (Gana et al., 2019). Recently, researchers have highlighted the challenges of measuring boredom given its complexity and temporal instability (Mills & Christoff, 2018) and suggested placing emphasis on psychoneurophysiological approaches to systematically monitor fluctuations of boredom over time (Wolff & Martarelli, 2020). Is it possible to measure a construct such as boredom? What is the reliability and validity of existing methods? Some very good reviews of the existing measurements of boredom have been published in the past (e.g., Sharp et al., 2018; Vodanovich, 2003; Vodanovich & Watt, 2016; Vogel-Walcutt et al., 2012). The purpose of this chapter is to provide an updated review of boredom assessments, with a focus on more recent developments.

There are broadly two methodologies for assessing boredom: subjective and objective methods. Subjective methods refer to self-reporting methods (i.e., methods that are introspective in nature). This category includes questionnaires about trait and state boredom, as well as probe-caught methods to assess self-reported boredom. Subjective methods are the most frequently used methods to investigating boredom. Objective measures include behavioral (e.g., performance, reaction times, or eye movements), physiological (e.g., pupil size, heart rate, or skin conductance), and neurological measures (e.g., fMRI or EEG). Moderate associations between subjective and objective measurements of boredom have been reported (Merrifield & Danckert, 2014), thus endorsing the use of subjective methodologies in this field of research. In the first part of this chapter, we will focus on subjective methods, and we will review the current state of research using objective methods in the second part of this chapter.

Subjective methods for investigating boredom

In their 2016 publication, Vodanovich and Watt reviewed the psychometric measures of boredom in extensive detail. They reported on *16 boredom scales*, including *two domain-general trait measures*, which consisted of the Boredom Proneness Scale (BPS; Farmer & Sundberg, 1986) and the Zuckerman Boredom Susceptibility Scale (ZBS; Zuckerman, 1979). To this list were added the *five domain-specific trait measures* of the Boredom Coping Scale (BCS; Hamilton et al., 1984), the Leisure Boredom Scale (LBS; Iso-Ahola & Weissinger, 1990), the Free Time Boredom Scale (FTBS; Ragheb & Merydith, 2001), the Sexual Boredom Scale (SBS; Watt & Ewing, 1996), and the Relational Boredom Scale (RBS; Harasymchuk & Fehr, 2012); the *three domain-general state measures* of the Multidimensional State Boredom Scale (MSBS, Fahlman et al., 2013), the State Boredom Measure (SBM; Todman, 2013), and the Boredom Experience Scale (BES; Tilburg & Igou, 2012); and *six domain-specific state measures*, which included Lee's Job Boredom Scale (LJBS; Lee, 1986), the Dutch Boredom Scale (DUBS; Reijseger et al., 2013), the Boredom Coping Scale (BCS-A; Nett et al., 2010), the boredom subscale of the Achievement Emotions Questionnaire (AEQ; Pekrun et al., 2002), the Academic Boredom Scale (ABS-10; Acee et al., 2010), and the Precursors to Boredom Scale (PBS; Daschmann et al., 2011). We will not review these scales in detail in the present chapter and refer the interested reader instead to Vodanovich and Watt's (2016) paper for more details on these assessment methods.

Since 2016, research on boredom has been growing steadily. When it comes to the psychometric measurement of boredom, these past few years have seen the development of short forms of existing questionnaires; see, for example, the Short Boredom Proneness Scale (SBPS; Struk et al., 2017) or the Multidimensional State Boredom Scale Short-Form (MSBS-SF; Hunter et al., 2016), which we present below. New scales that better represent the theoretical scope and complexity of boredom have also been developed (Bieleke, Ripper, et al., 2021; O'Dea et al., 2022; Tam et al., 2022). Furthermore, new domain-specific scales have been developed, such as the Bored of Sports Scale (BOSS; Wolff, Bieleke, Stähler, et al., 2021), which is to be used in a sporting context. Finally, in recent years, many validations of translated versions of these scales (e.g., Martarelli, Bertrams, et al., 2021; Peng et al., 2020), as well as adapted versions (e.g., Spoto et al., 2021), have been published. In the paragraphs below, we review these recent developments. See Table 1 for a summary of the scales.

Boredom proneness. Boredom proneness is the most common conceptualization of trait boredom and it has shown relevant associations with a host of variables, mainly in terms of negative emotions and behavior (despite boredom being a powerful motivator for both positive and negative behaviors alike; Bench & Lench, 2019). For example, boredom proneness has been found to relate to negative constructs, such as anger (Dahlen et al., 2004), anxiety (Sommers & Vodanovich, 2000), and lack of control (Wolff, Bieleke, Englert, et al., 2022). Despite the large amount of research correlating boredom proneness with other constructs—especially those with negative connotations—most theories focus on state boredom rather than trait boredom. However, some researchers have theorized of boredom as a trait-like construct (Elpidorou, 2018; Mugon et al., 2018; Tam, Tilburg, Chan, et al., 2021). On a phenomenological level, high boredom-prone individuals seem to experience boredom more frequently and more intensely (Farmer & Sundberg, 1986), and it appears that they may not know what they really want to do with their lives (Tam, Tilburg, & Chan, 2021). Danckert et al. (see e.g., Danckert, Mugon, et al., 2018; Mugon et al., 2018) propose that boredom-prone individuals might fail to adaptively respond to the signal of boredom, which is a trigger to action, to stop the experience of boredom and find novel opportunities to increase reward. This proposition is further supported by the results of a recent study (Martarelli, Baillifard, et al., 2022), where it was shown that while boredom-prone individuals are motivated to engage in other activities, they fail in doing so. There is a large amount of empirical work on behaviors associated with boredom proneness, paired with rather underdeveloped theorizing on the concept, which has prompted researchers to call for more careful definitions of the boredom proneness construct (Mercer-Lynn et al., 2014; Tam, Tilburg, & Chan, 2021) and further investigation into the existence of trait boredom, as well as determining whether the existing questionnaires fully capture the construct (Gana et al., 2019). Given its high clinical and psychological relevance, further research, such as assessing whether trait-like boredom can be measured by current boredom proneness measures, is needed. For deeper theorizing on boredom proneness, we refer the interested reader to the chapter XX of this book.

The most widely used boredom proneness questionnaire, already reviewed by Vodanovich and Watt (2016), is the BPS (Farmer & Sundberg, 1986). This questionnaire consists of 28 items composed in a true-false format, with questions in the form of statements, such as, "Time always seems to be passing slowly." Other studies have used a seven-point Likert format, with responses ranging from "highly disagree" to "highly agree" (e.g., Mercer-Lynn et al., 2014). The BPS (both formats) has shown good internal consistency, with Cronbach's alphas ranging from .75 to .91. However, its factor structure has been found to be unstable, with a number of identified factors varying between two to five (Vodanovich & Watt, 2016). The BPS was later shortened to the Boredom Proneness Scale – Short Form (BPS-SF) by Vodanovich et al. (2005). The BPS-SF, a 12-item questionnaire using seven-point Likert scale responses, is a two-factorial measure of boredom, with an internal stimulation subscale assessing an individual's inability to self-generate engagement and an external stimulation subscale assessing an individual's inability to engage in nourishing activities (Sung et al., 2021; Vodanovich et al., 2005). Cronbach's alphas were .86 for the internal stimulation subscale and .89 for the external stimulation subscale in the original validation study of Vodanovich et al. (2005). More recently, Struk et al. (2017) proposed and validated the SBPS. By rewording reverse-coded items of the BPS and excluding items with poor discriminatory value, they found a one-factorial measure of eight consistently worded items. This scale showed very good internal consistency on its own (e.g., .93 in Bieleke et al., 2021) and also in its translated versions (e.g., .86 in Martarelli, Baillifard et al., 2022).

Van Tilburg et al. (2019) were concerned by the fact that the SBPS includes items that not directly tag boredom (e.g., "I find it hard to entertain myself") they thus created the Harthouse Boredom Proclivity Scale (HBP; item examples "How prone are you to feeling bored?" or "How often do you experience boredom"), a four-item scale to be answered with a seven-point Likert format with responses ranging from "not at all/never" to "very much/all the time". The scale showed a one-factorial structure and very high internal consistency (Cronbach's alpha of .94). The authors suggest using this scale in combination with the SBPS to create a boredom proneness index (see also O'Dea et al., 2022).

In a recent study, Bieleke, Ripper, et al. (2021) developed new domain-general trait boredom scales that consider the urge to avoid and escape boredom, as well as the ways (maladaptive vs. adaptive) in which individuals deal with boredom. These authors developed the four-item Boredom Avoidance and Escape Scale (BAE; item example: "When I feel bored, I must do something about it immediately") and the six-item Dealing with Boredom Scale (DWB; item example: "I try to be productive" or "I do things that are generally known to be bad") to be answered with a seven-point Likert format, with responses ranging from "highly disagree" to "highly agree." The BAE is a one-factorial measure with very good internal consistency (Cronbach's alpha = .92), whereas the DWB is a two-factorial measure with satisfactory internal consistency (Cronbach's alpha = .74).

Tam et al. (2022) developed the Boredom Beliefs Scale, with the subscales Boredom Dislike and Boredom Normalcy. The three items of the Boredom Dislike Scale (item example: "I am afraid of being bored") measure the extent to which one dislikes boredom, and the three-item Boredom Normalcy Scale (item example: "Boredom is a natural emotional response") measures the extent to which one normalizes the experience of boredom. The scales are to be answered with a seven-point Likert format, with responses ranging from "strongly disagree" to "strongly agree." The authors validated the two-factors structure of the scale and internal consistency was found to be satisfactory (Cronbach's alpha of .74 for the Boredom Dislike Scale and Cronbach's alpha of .59 for the Boredom Normalcy Scale).

Domain-specific trait boredom. It is reasonable to assume that there are differences between domains and, at the same time, that boredom-prone individuals might report having experienced boredom more intensely and more frequently across domains (see also the notion of a "holistic perception of life being boring," described by Tam, Tilburg, & Chan, 2021). Several studies show associations between boredom proneness (e.g., measured with the BPS) and the assessment of boredom in the academic context (Farmer & Sundberg, 1986), the sporting context (Martarelli et al., 2023), or the work context (Baratta & Spence, 2018). To our knowledge, no study has compared the answers to different domain-specific scales and domain-general scales to give a precise estimation of the variance explained by a domain-general factor and that which is domain-specific. Modeling the different sources of variance could be an interesting approach for future research.

Vodanovich and Watt (2016) reviewed five important domain-specific trait scales that are still used today (see list above). After 2016, other domain-specific trait scales were developed. For example, in the sporting domain, Wolff, Bieleke, Stähler, et al. (2021) developed the BOSS to assess individual differences in boredom proneness in a sporting context, with items such as "Exercising is dull and monotonous" or "I find my mind wandering while I exercise." The BOSS has shown very good internal consistency, with a Cronbach's alpha of .97 in the original paper presenting the scale. Wolff, Bieleke, Martarelli, et al. (2021) have called for further development of sport-specific questionnaires to measure boredom in specific settings (e.g., individual vs. collective activities or competition vs. exercise).

In addition, researchers have started to develop questionnaires that simultaneously assess both trait and state boredom in domain-specific contexts. An example is the AEQ, developed by Pekrun et al. (2002, 2011), which measures a number of achievement emotions, including boredom, experienced in academic settings. This modular questionnaire has to be answered on five-point Likert scales ranging from "strongly disagree" to "strongly agree." Bieleke et al. (2021) have recently developed and validated a short version of the AEQ referred to as the AEQ-S. The AEQ-S includes eight boredom items (item examples: "I get restless because I can't wait for the class to end" and "studying for my courses bores me"), with Cronbach's alphas for the boredom scales ranging from .80 to .88. Confirmatory factor analysis provides evidence that the boredom items belong to one factor (Bieleke et al., 2021). Another example is the Academic Boredom Survey Instrument (ABSI) of Sharp et al. (2021) for the assessment of trait and state boredom in higher education academic contexts. In this case, the authors identified three second-order factors of academic boredom

(boredom proneness, class-related boredom, and study-related boredom), which were divided into seven subscales (time, tedium, and stimulation for boredom proneness; concentration and confinement for class-related boredom; and disinterest and distraction for study-related boredom). The ABSI has shown good internal consistency, with Cronbach's alphas ranging from .85 to .90 for the three second-order factors (Sharp et al., 2021).

State boredom. Is there a link between boredom proneness (viewed in terms of personal characteristics) and state boredom (viewed in terms of situational characteristics)? Despite their different origins (person vs. situation), the concepts have shown a moderate overlap, in the sense that boredom-prone individuals are more likely to experience boredom in a given moment (Mercer-Lynn et al., 2014). Furthermore, correlates between state boredom and negative behavioral consequences, such as drug consumption, have been observed (e.g., Woodall, 2012), reflecting the relevant associations of trait boredom with many negative emotions and behaviors. Frequently used scales to investigate state boredom are the State Boredom Measure (SBM; Todman, 2013) and the MSBS (Fahlman et al., 2013). While the SBM focuses on the past two weeks, the MSBS assesses the actual experience of boredom at a given moment. The SBM is a short questionnaire of eight items to be answered on seven-point Likert scales (item example: "What is the longest period of time that you have been able to tolerate being bored before trying to do something about it?"). The items are usually not averaged into a single score; however, good internal consistency has been shown for a single score (Cronbach's alpha of .81; Todman, 2013). The MSBS comprises five factors—disengagement, high arousal, inattention, low arousal, and time perception—consisting of 29 items to be answered on seven-point Likert scales ranging from "strongly disagree" to "strongly agree." The internal consistency was good, with Cronbach's alphas ranging from .80 to .92 for the subscales and of .95 for the overall boredom factor (Fahlman et al., 2013). This questionnaire was adapted for adolescents (Spoto et al., 2021) and translated into Spanish (Alda et al., 2015), among other changes.

In 2015, Baratta and Spence proposed the MSBS 15-Item Version (MSBS-15). To select the 15 items, they relied on item response theory, which allows for the identification of items that are more precise and thus provides more information. Three items came from the original time perception factor (item example: "Time is dragging on"), five were associated with the low arousal factor (item example: “I feel empty”), two came from the inattention factor (item example: “It is difficult to focus my attention”), three were derived from the high arousal factor (item example: “I feel agitated”), and two came from the disengagement factor (item example: “I want something to happen, but I am not sure what”). This short version of the MSBS maintains the five-dimensional structure of the original scale. In 2016, Hunter et al. proposed another short form of eight items, referred to as the Multidimensional State Boredom Scale Short-Form (MSBS-SF). Five of the eight items came from the original disengagement factor, two were obtained from the inattention factor, and the last came from the time perception factor. The MSBS-SF is a one-factorial measure with high reliability in its original version as well as in its translations (Donati et al., 2019; Dursun & Tezer, 2013).

Psychometric analyses of the different versions of the MSBS have been established, and the reliability of these scales has been found to be adequate (e.g., Mercer-Lynn et al., 2013; Oxtoby et al., 2018). For example, Oxtoby et al. (2018) assessed the psychometric properties of these three versions (full scale, MSBS-15, and MSBS-SF), as well as the construct validity and test–retest reliability. They found Cronbach’s alphas ranging from .91 to .98 for the full scale and its short forms, and alphas ranging from .90 to .94 for the second-order factors of the MSBS and MSBS-15. Moreover, they found moderate correlations between the MSBS and the SBM (Todman, 2013), depression, anxiety, and stress, as measured by the Depression Anxiety Stress Scales (DASS; Lovibond & Lovibond, 1995). They replicated these correlations with the short forms of the MSBS.

State boredom has also been assessed at the end of an activity with questions such as, “How bored do you feel at the moment?”, “How boring would you consider the tasks you just completed?”, and “Do you experience boredom right now?” (Chan et al., 2018; O’Dea et al., 2022; van Tilburg & Igou, 2013). Further, researchers have adopted *probe-caught methods* by stopping participants throughout a task and asking them to indicate how bored they are at that particular moment (e.g., Blondé et al., 2021; Merrifield & Danckert, 2014). *Experience-sampling methods*, where participants are probed about their feelings of boredom within their natural environment, have also been used successfully (e.g., Chin et al., 2017). Next to probe-caught and experience-sampling methods, one could envisage *self-caught methods*. Instead of interrupting the participants throughout a task, it would be the participants who voluntarily indicate, at any moment in a given task, whether they are bored. To our knowledge, self-caught methods have not yet been used in boredom research. There might be good reasons for this, as participants must be aware that they are bored without any prompting. We propose that future research could benefit from this methodology to also address the awareness of state boredom.

Domain-specific state boredom. Baratta and Spence (2018) developed and validated the State Boredom Inventory (SBI), an 11-item measure to be answered on seven-point Likert scales ranging from "strongly disagree" to "strongly agree," which assesses state boredom in the work context. This questionnaire comprised three factors (disengagement, e.g., "I wish there was something for me to do," low arousal, e.g., "I feel lethargic," and inattention, e.g., "I am having trouble concentrating") and showed very good internal consistency (average Cronbach's alpha of .91 for the three factors). Even though the authors presented their scale as a measure to be used in the work context, this questionnaire can easily be applied to other contexts.

Another example of a domain-specific state boredom measurement is the Epistemically-Related Emotion Scales (EES) of Pekrun et al. (2017). In this case, participants must evaluate different emotions (i.e., the extent to which they felt a particular way during a given academic activity), including their experience of boredom. These scales are well-validated and can be used in contexts other than the academic environment. For example, Martarelli, Wolff, et al. (2021) used the three adjectives of the boredom subscale (bored, dull, and monotonous; Cronbach's alphas for this scale in different contexts > .81) in a study investigating the experience of boredom during the COVID-19 pandemic. The AEQ (Pekrun et al., 2002) and AEQ-S (Bieleke et al., 2021) previously mentioned are generally used as a trait measure, however they can also be used to assess emotions in a specific situation (i.e., as a state).

Table 1

Overview of boredom measures.

Stability	Domain	Specific domain	Name	Items	Reliability	Factors	Reference
Trait	General		Boredom Avoidance and Escape Scale (BAE)	4	.92	1	Bieleke, Ripper, et al. (2021)
Trait	General		Boredom Beliefs Scale (BBS)	6	.59-.74	2	Tam et al. (2022)
Trait	General		Boredom Proneness Scale (BPS)*	28	.75-.91	2-5	Farmer & Sundberg (1986)
Trait	General		Boredom Proneness Scale – Short Form (BPS-SF)	12	.86-.89	2	Vodanovich et al. (2005)
Trait	General		Dealing With Boredom Scale (DWB)	6	.75 - .89	2	Bieleke, Ripper, et al. (2021)
Trait	General		Harthouse Boredom Proclivity Scale (HBP)	4	.94	-	Van Tilburg et al. (2019)
Trait	General		Short Boredom Proneness Scale (SBPS)	8	.86-.93	1	Struk et al. (2017)
Trait	General		Zuckerman Boredom Susceptibility Scale (ZBS)*	10	.52 - .65	-	Zuckerman (1979)
Trait	Specific	Academic	Academic Boredom Survey Instrument (ABSI)	10	.85-.9	3	Sharp et al. (2021)
Trait	Specific	Academic	Achievement Emotions Questionnaire (AEQ)*	11	.88 -.93	1	Pekrun et al. (2002, 2011)
Trait	Specific	Academic	Achievement Emotions Questionnaire Short (AEQ-S)	8	.8 - .88	1	Bieleke et al. (2021)
Trait	Specific	Introspection	Boredom Coping Scale (BCS)*	10	.64 - .8	-	Hamilton et al. (1984)
Trait	Specific	Sport	Bored of Sports Scale (BOSS)	11	.97	-	Wolff, Bieleke, Stähler, et al. (2021)
Trait	Specific	Leisure	Free Time Boredom Scale (FTBS)*	33	.78 - .92	-	Ragheb & Merydith (2001)
Trait	Specific	Leisure	Leisure Boredom Scale (LBS)*	16	.76 - .91	2	Iso-Ahola & Weissinger (1990)
Trait	Specific	Relationships	Relational Boredom Scale (RBS)*	15	.91 - .92	-	Harasymchuk & Fehr (2012)
Trait	Specific	Sex	Sexual Boredom Scale (SBS)*	18	.81 - .95	-	Watt & Ewing (1996)
State	General		Multidimensional State Boredom Scale (MSBS)*	29	.8-.98	5	Fahlman et al. (2013)
State	General		Multidimensional State Boredom Scale 15-Item Version (MSBS-15)	15	.96	5	Baratta & Spence (2015)
State	General		Multidimensional State Boredom Scale Short-Form (MSBS-SF)	8	.91	1	Hunter et al. (2016)
State	General		State Boredom Measure (SBM)*	8	.81	-	Todman (2013)
State	General		Boredom Experience Scale (BES)*	7	.87	-	Tilburg & Igou (2012)
State	Specific	Academic	Academic Boredom Scale (ABS-10)*	10	.78 - .91	1-2	Acee et al. (2010)
State	Specific	Academic	Boredom Coping Scale (BCS-A)	20	.83 - .92	4	Nett et al. (2010)
State	Specific	Academic	Epistemically-Related Emotion Scales (EES)	21	.76 - .88	7	Pekrun et al. (2017)
State	Specific	Academic	Precursors to Boredom Scale (PBS)*	22	.69 - .94	8	Daschmann et al. (2011)
State	Specific	Workplace	Dutch Boredom Scale (DUBS)*	6	.8 - .87	1	Reijseger et al. (2013)
State	Specific	Workplace	Lee's Job Boredom Scale (LJBS)*	17	.94 - .95	-	Lee (1986)
State	Specific	Workplace	State Boredom Inventory (SBI)	11	.91	3	Baratta & Spence (2018)

Note. Scales denoted by an asterisk were reviewed in Vodanovich and Watt (2016). Scales are ordered by stability, domain specificity group and alphabetically. The number of factors were only included if there was satisfactory confirmatory evidence for the respective factor structure.

Objective methods for investigating boredom

Compared to the large number of subjective methods used to investigate boredom, the identification of objective measures of boredom has received little attention, and consensus about such measures that are sensitive to boredom has yet to be reached. Can, for example, eye measures (e.g., eye fixation, blinks, or pupil dilation) be used as an objective method to distinguish between bored and non-bored states? The advantage of measuring phenomena like eye movement or pupil dilation, both being detectable with non-invasive methods, is that they provide online and continuous independent measures of specific mechanisms. Complementing existing subjective methods with objective methods is especially important in the field of boredom research, given that social desirability may play a role in self-reported boredom. For instance, there may be certain groups (e.g., older people) who want to present themselves in a more positive fashion and thus systematically report lower levels of boredom. Furthermore, subjective measures rely on the ability to reflect on one's own inner state, which might vary among individuals. Thus, more work is needed to test the convergent validity between objective and subjective measures of boredom.

Eye (and body) movements to investigate boredom. So far, eye correlates of boredom have received surprisingly little attention. In one particular study, Danckert et al. (2018) found a positive relationship between trait boredom proneness and blink rate. This result is intriguing, given that state boredom showed no association with blink rates in the same study. These results thus deserve further research; eye movements (i.e., fixations, saccades, fixational eye movements, blinks, and ocular vergence) and pupillary responses are measures of attention, insofar as they disclose where attention is deployed (fixations; Duc et al., 2008), sustained attention (blinks; Smilek et al., 2010), cognitive load (pupil dilation; Wel & Steenbergen, 2018), and arousal (pupil dilation; Unsworth & McMillan, 2013), to mention just a few of these indications. Given that boredom is linked to attention and effort (e.g., Eastwood et al., 2012) eye-tracking might be a promising tool in boredom research.

Empirical work has revealed an association between pupil dilation and the locus coeruleus, as Laeng et al. (2012) have shown in their discussion of the value of pupillometry in understanding mental activity. In this work, the authors put forward pupillometry (phasic and tonic pupillary changes) as a measure of the two modes (phasic and tonic) of the locus coeruleus, which directly links to different patterns of attention ("focused exploitation" vs. "diffuse exploration"; see Laeng et al., 2012). There is a lot of evidence of time-locked phasic pupillary changes when one is engaged in a task (Wel & Steenbergen, 2018). Tonic pupillary changes are especially evident in situations of fatigue, when pupil dilation variability augments and its size diminishes steadily (Karatekin et al., 2007). Pupil size, which is difficult to control voluntarily, may be a valuable method to investigate bored vs. non-bored states, as well as to understand the intricate interconnection of complex constructs, such as boredom, attention, and self-control (Wolff & Martarelli, 2020).

Eye-tracking can be used not only as a research tool, but also in educational settings, to improve learning. D'Mello et al. (2012) used real-time eye-tracking to detect and to decrease boredom, to promote engagement and learning. More specifically, they developed an eye gaze reactive tutor, and showed that gaze reactivity was efficient to reorient attention in students, and thus had a positive impact on learning. In the same vein D'Mello et al. (2007) investigated posture as predictor of engagement in a learning setting and found that boredom was related to an increase in the pressure exerted on the back as well as with a change in seat pressure. These two postures associated with boredom might relate to laying back and restlessness respectively. The researchers used the seat pressure, the back pressure, and the seat pressure change with a machine learning approach (three algorithms, i.e., a Bayesian model, a neural network, and a simple nearest neighbor classifier) to predict engagement / disengagement states and found that the three algorithms were able to discriminate boredom from flow above chance level.

Electroencephalography and neuroimaging to investigate boredom. Some studies have investigated the neural signature of boredom with EEG; for example, Perone et al. (2019) found that low levels of trait boredom were associated with a leftward shift in frontal activity during boredom induction. The authors interpret this finding as evidence of active regulatory processes that emerge in low boredom-prone individuals during a boring task. Yakobi et al. (2021) extended this work and used EEG to investigate boredom by including the study of event-related potentials (ERPs), specifically the stimulus-locked P300 and the response-locked error-related negativity (ERN), as indexes of attention. Indeed, they found an association between higher levels of experienced boredom and reduced amplitudes in P300 and ERN, thus confirming diminished attentional control as a core aspect of boredom.

Recent studies have also investigated the neural signature of boredom with neuroimaging, which has mainly revealed higher activation in the default mode network (including the prefrontal regions, cingulate cortex, and hippocampal areas, among others) during the experience of boredom (Danckert and Merrifield, 2018). It remains an open question whether the implication of the default mode network is directly linked to boredom, or whether it is mediated by the failure to engage attention, which is a core dimension of the experience of boredom (Eastwood et al., 2012). Indeed, a large amount of research has shown the implications of the default mode network in disengaged states (e.g., mind wandering; Mason et al., 2007). By taking a different approach, Dal Mas and Wittmann (2017) studied the neural correlates of boredom in an approach/avoidance context. More specifically, they tasked their participants with choosing between carrying out a boring task (i.e., deciding whether the frame of the *same* landscape is blurred over approximately five minutes) and paying to listen to music (among other control choices). The authors showed an association between the willingness of participants to pay higher prices (when the other option was a boring task) and enhanced activity in the caudate nucleus. In sum, this study revealed that the caudate nucleus is implicated in decisions to relieve boredom. For further developments in EEG and fMRI findings on boredom, we refer the reader to the chapter by XX in this book.

Galvanic skin response and biopotentials to investigate boredom. Some earlier work in the context of human–computer interaction reported on the use of physiological measures to model affective states. For example, Mandryk and Atkins (2007) used galvanic skin response, electrocardiography, electromyography, and heart rate to infer arousal and valence during a computer game experience (five-minute period of hockey), which were in turn used to infer the experiences of boredom, challenge, excitement, frustration, and fun. The authors used fuzzy logic to model their data. However, the modeling seemed to work best with fun and excitement, whereas the correlations between objective and subjective boredom were non-significant. This lack of consistency can be explained by the fact that the experience of boredom was low in general, which is to be expected, since a computer game situation is mainly characterized by experiences of fun and excitement.

In the same vein, Jang et al. (2015) analyzed several physiological signals to identify boredom, pain, and surprise. In this case, the authors used various stimuli to induce the emotions (e.g., presentation of a "+" symbol on the screen combined with a repetitive sound of numbers from 1 to 10 for 3 min to induce boredom) and collected 27 physiological parameters. Using a data-driven approach, they identified six physiological measures (heart rate, skin conductance level, skin conductance response, mean skin temperature, blood volume pulse, and pulse transit time) to distinguish among the three affective states.

With a theory-driven approach, Merrifield and Danckert (2014) showed increased heart rate and reduced skin conductance levels associated with boredom when compared to sadness, both of which were induced with a video (e.g., two men hanging laundry to induce boredom). These results suggest that boredom might be related to increased arousal and attentional disengagement, thus keeping the discussion open on whether bored individuals feel aroused (agitated) or not (apathic).

Keystroke analysis to detect boredom. Keystroke analysis is concerned with the time points of keypresses and releases while writing a text on a computer. It was originally and still is primarily used in user authentication (see Sullivan & Lindgren, 2021, for an overview), whereby algorithms typically create a profile of the users typing rhythm by evaluating training data, which is then used for password-free authentication. Early work in the field (Shepherd, 1995) showed that rollover patterns (e.g., overlapping keypresses as a record of a keypress while the previous has not been fully released) are distinct and therefore useful for identification purposes. However, there is not only inter- but also intra-individual variability in keystroke patterns. Vizer et al. (2009) used a decision tree to detect changes in the typing patterns of people experiencing cognitive and physical stress compared to a control group. They found some of the most important differences to be average pause length, time per keystroke, and backspace key rate. In a related vein, Khanna and Sasikumar (2010) tried to infer positive, negative, or neutral emotional states from keystroke patterns. By using various classification algorithms, they correctly identified up to 89% of both positive vs. neutral and negative vs. neutral classifications.

Bixler and D'Mello (2013) used a similar technique; however, they tried to classify affect more specifically by creating models that differentiated between the affective states of engagement, neutrality, and boredom while also considering task appraisals and trait measures. The authors showed that their model could classify the affective states about 17% more accurately than chance level. Notably, the best model was a combination of keystroke dynamics, task appraisals, and trait measures, since keystroke dynamics alone were not as predictive. More specifically, individual differences at the trait level were necessary for a good model fit. Considering this finding, it makes sense to take individual differences into account when analyzing keystroke dynamics. Note that the authors did not have any previous keystroke data about the participants. However, it would be interesting to evaluate whether these individual differences could also be accounted for by generating keystroke profiles based on (perhaps individual) training data.

Natural language processing to detect boredom. Natural language processing (NLP) uses machine-learning algorithms to analyze natural language data (i.e., to comprehend natural text and extract meaning from it; Nadkarni et al., 2011). There are a multitude of different applications for NLP algorithms. For example, they are widely used in the field of translation, human–computer interactions with smart assistants or customer service chatbots. NLP-based analyses are as diverse as their fields of application. *Sentiment analysis* is a special case of applying NLP with the goal of recognizing affective states. Sentiment analyses assess textual polarity (i.e., differentiating between negative, neutral, and positive text). Recently, Slater et al. (2017) applied more advanced models to detect different affective states, such as confusion, engaged concentration, frustration, and boredom, as experienced by middle-schoolers through an investigation of the linguistic properties of an online mathematics tutor. One of the predictors of boredom was how common the combination of words in the mathematical problems was, and students were less bored when exposed to word sequences that were more common in academic contexts. Note that in this study, the linguistic properties were analyzed to predict boredom, whereby a different approach may concentrate on the semantics of the words and their combinations. Additionally, more advanced models could combine keystroke analysis and NLP models to detect boredom (e.g., by analyzing text in the process of writing). Furthermore, since NLP is based on machine-learning methods, the models predicting boredom could be highly customized to groups of people (e.g., high school classes) or even to individuals by training the model on the respective data.

Even though the subject area is still in its infancy, the study by Slater et al. (2017) seems to be particularly promising, as the field of sentiment analysis is rapidly evolving, and we can expect more complex and differentiated NLP models in the future. Such developments may allow us to reliably predict more complex emotions like boredom, especially when combined with keystroke analysis and with consideration of the high customizability of the respective models.

Outlook

In the present chapter we reviewed subjective and objective methods to assess boredom, with a focus on recent developments. Over the last years, great progress has been made in the conceptualization and measurement of boredom. There has been an uptick in boredom research, including the validation of existing questionnaires, the development of new questionnaires, as well as triangulation of methods, including self-report, behavioral, and neurological measures.

Despite the significant advancements, there is a need for future boredom research. For example, studies testing the construct validity of different measurement approaches are needed. Do we obtain the same results when using different measurement methods? Do we obtain the same results when testing in a laboratory or in an online setting? What is the predictive validity of current boredom measurements? Self-report methods are characterized by poor measurement (Flake & Fried, 2020), it is thus primordial to consider different related aspects, such as whether asking about boredom influences the experience of boredom, whether different measurement methods bias the responses, whether it is possible to study both the appearance of boredom and its duration (how long does a boredom episode last?) to mention a few. To conclude, all measurements (subjective and objective) are important to study boredom; the choice of measurement method largely depends on the research question. We believe that combining methods will advance boredom measurement, as well as exchange and adversarial collaborations (in the sense of Daniel Kahneman) if boredom researchers with opposing views work together.

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