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Statistical learning as a predictor of attention bias modification outcome: A preliminary study among socially anxious patients

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ABSTRACT

Attention bias modification (ABM) is a novel therapy designed to modulate attentional biases towards threat typically observed among anxious individuals. Bias modification is allegedly achieved via extraction of a statistical regularity embedded within the treatment task. However, no prior study examined prediction of ABM therapeutic response in relation to patients' capacity to extract statistical properties from the environment, a capacity known as "statistical learning". Here, 30 treatment-seeking patients with social anxiety disorder completed a gold-standard statistical learning task at baseline and then received six sessions of ABM therapy. Results indicate that baseline statistical learning capacity predicts treatment outcome: the better patients' statistical learning capacity, the greater their reduction in clinician-rated and self-reported social anxiety symptoms. Restricted capacities for statistical learning could account for the moderate effect sizes of ABM therapy in clinical trials. Poor response may occur in patients who fail to extract the underlying contingency embedded in ABM.

1. Introduction

Attention bias modification (ABM), a novel therapy for anxiety disorders, attempts to modulate attentional biases towards threat (Bar-Haim, Lamy, Pergamin, Bakermans-Kranenburg, & Van Ijzendoorn, 2007; Fox, Russo, Bowles, & Dutton, 2001; Mogg & Bradley, 1998). Randomized controlled trials suggest that systematically training patients to attend away from threat, as compared to control conditions, reduces levels of anxiety symptoms, with small-to-medium effect sizes (Cisler & Koster, 2010; Hakamata et al., 2010; Linetzky, Pergamin-Hight, Pine, & Bar-Haim, 2015; Price et al., 2016; Van Bockstaele et al., 2014). Small effects in ABM might arise at least partly from some patients' limited ability to cognitively engage the treatment's target (Bar-Haim, 2010; Clarke, Notebaert, & MacLeod, 2014). The current study introduces a new measure of target engagement capacity in ABM and examines its relation to clinical outcome.

Theory suggests that successful ABM therapy teaches patients to extract an embedded contingency as a vehicle for bias modification (Bar-Haim, 2010; Grafton, Mackintosh, Vujic, & MacLeod, 2014). For instance, in dot-probe-based ABM protocols two stimuli, one threat-related and one neutral, appear simultaneously followed by a target probe that appears more frequently at the location previously occupied by the neutral rather than the threat stimulus. Patients are expected to extract this statistical contingency during hundreds of training repetitions, so that implicit rule extraction leads to modification of attention. However, patients may differ at baseline in their capacities to learn these contingencies, and these individual differences may moderate the degree to which the intended ABM serves to attenuate attentional bias to threat, which in turn may influence ABM therapy outcome.

Statistical learning is the capacity to extract regularities from the environment (for reviews see Erickson & Thiessen, 2015; Thiessen, Kronstein, & Hufnagle, 2013). Much early research on statistical learning examines language and speech segmentation (e.g., Saffran, Aslin, & Newport, 1996), and more recent work examines more general capacities of cognitive systems in other contexts and various modalities such as vision (e.g., Kirkham, Slemmer, & Johnson, 2002; Newport & Aslin, 2004) and touch (e.g., Conway & Christiansen, 2005). Across these areas, studies most frequently quantify people's ability to extract the probability that one stimulus follows another amidst a continuous stream of stimuli.

One common paradigm (e.g., Frost, Siegelman, Narkiss, & Afek, 2013; Glicksohn & Cohen, 2013) presents a stream of shapes. Unbeknownst to participants, the stream contains several successively-appearing triplets of shapes. Participants receive a surprise recognition

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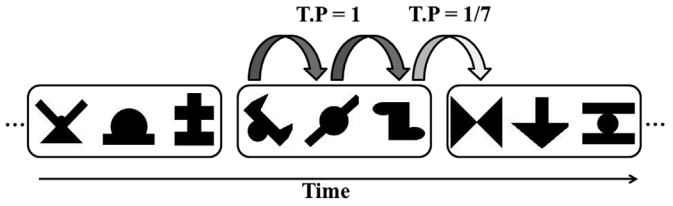

Fig. 1. In the statistical learning task participants were exposed to a continuous visual stream of single shapes comprised of eight triplets of black shapes (indicated by black rectangles in the figure above). The triplets were randomly mixed with the constraint that the same triplet could not repeat itself in an immediate succession. Thus, the transitional probability (T.P) within the same triplet was 1 (the shapes of each triplet always appeared in succession) and the T.P between triplets was 1/7 (each triplet could be presented after each of the other seven triplets in an equal probability).

test after viewing this triplet-embedded stream, to assess statistical learning, which manifests as participants' capacity to identify the previously-viewed embedded triplets at a rate greater than chance. Performance on this task predicts functioning in other domains such as the ability to acquire literacy in a first (Arciuli & Simpson, 2012) or second language (Frost et al., 2013). We applied this procedure to quantify patients' baseline capacity to extract rules similar to those embedded in ABM training regimens.

Both classic statistical learning tasks and ABM involve similar learning processes: (1) both present a stream of stimuli with differential temporal probabilities, which participants are required to extract (see Figs. 1 and 2); (2) both induce learning gradually, over numerous repetitions (Bar-Haim, 2010; Saffran et al., 1996); and (3) both are assumed to be implicit (Bar-Haim, 2010; Kim, Seitz, Feenstra, & Shams, 2009). Therefore, the aim of the current study was to explore whether performance on a gold-standard statistical learning task at baseline predicts ABM outcome, expressed as a symptom reduction among patients with social anxiety disorder. We expected that better statistical learning capacity at baseline would predict better treatment outcome, expressed as a greater reduction in symptoms.

2. Method

2.1. Participants

Thirty treatment-seeking patients with social anxiety disorder (16 females; M = 30.33 years, SD = 8.51, range = 21–59) participated in the study. Inclusion criteria were a primary diagnosis of social anxiety disorder and an age of 18–65 years. Exclusion criteria were: (1) any history or present diagnosis of psychosis; (2) high risk for harm to self or others; (3) concurrent posttraumatic stress disorder, eating disorder, or bipolar disorder; (4) epilepsy or brain injury; (5) drug or alcohol misuse; (6) a pharmacological treatment that is not stabilized in the past three months; and (7) any concurrent psychotherapy.

Social anxiety disorder was evaluated using the Mini International Neuropsychiatric Interview (MINI; Sheehan et al., 1998) and the Liebowitz Social Anxiety Scale clinical interview (LSAS; Liebowitz, 1987), with an LSAS cutoff score ≥50 as an additional inclusion criterion. This LSAS cutoff score represents a good balance between specificity and sensitivity for diagnosis of social anxiety disorder (Mennin et al., 2002). The study was approved by the local ethics committee and participants provided written informed consent prior to participation.

2.2. Clinical measures

To obtain comprehensive information on clinical outcome, social anxiety symptoms were assessed using both clinician-rated and self-reported instruments serving as primary and secondary outcomes, respectively.

The Liebowitz Social Anxiety Scale (LSAS; Liebowitz, 1987) is a clinician-rated inventory consisting of 24 items describing socially relevant situations. Each situation is rated in relation to the past week on two sub-scales ranging 0–3: level of fear and level of avoidance experienced in response to these situations. Item scores are summed to a total score ranging 0–144. The LSAS has strong psychometric properties (Fresco et al., 2001). Cronbach's alphas for this sample were 0.83 and 0.92 at pre- and post-treatment, respectively.

The Social Phobia Inventory (SPIN; Connor et al., 2000) is a self-reported questionnaire comprised of 17 items on a 5-point scale depicting social worries and problems. Participants rate to what extent these situations have bothered them in the past week. Item scores are summed to a total score ranging 0–68. The SPIN has strong psychometric properties (Connor et al., 2000). Cronbach's alphas for this sample were 0.78 and 0.88 at pre and post-treatment, respectively.

2.3. Statistical learning task

Fig. 1 depicts the visual stream of stimuli presented in the familiarization phase of this task.

Familiarization phase. A frequently used task of visual statistical learning was applied (e.g., Frost et al., 2013) in which a sequence of shapes appeared in the center of the screen one shape at a time ("*the familiarization phase*"). The stream of stimuli was comprised of 24 black shapes divided into eight triplets. The shapes appertaining to the same triplet were always presented successively. The order of presentation of the triplets was pseudo-randomized with a rule that the same triplet

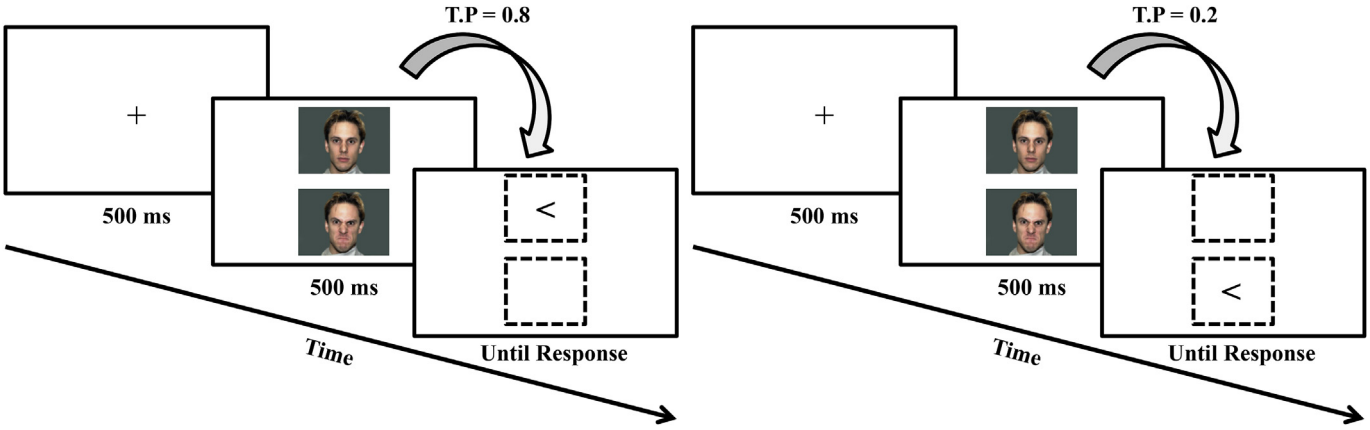

Fig. 2. In the current study, on 80% of the dot-probe trials (left-handed illustration) probes replaced neutral faces and on 20% of the trials (right-handed illustration) probes replaced angry faces. This generated differential T.Ps between the location of the neutral or the angry faces and the location of the probe, with a greater T.P for neutral face-probe (0.8) than angry face-probe (0.2).

could not repeat twice in a row. Twelve of the shapes were adapted from Fiser and Aslin (2002), and 12 shapes were taken from Turk-Browne, Jungé, and Scholl (2005). All stimuli appeared at a stimulus onset asynchrony (SOA) of 1000 ms, with an inter-stimulus interval (ISI) of 200 ms. The familiarization phase consisted of 24 cycles of repetition; in every cycle each of the 8 triplets was presented once. After 16 cycles a break slide appeared, allowing participants to take a rest until they decided to proceed to the remaining of the familiarization phase by pressing a key. The familiarization phase lasted approximately 10 min.

Test phase. A surprise two-forced-choice recognition test was administered to assess the acquisition of the statistical structure of the triplets. In each test item, participants were presented with two triplets each consisting of three shapes presented in succession: one triplet appeared 24 times in the familiarization phase; the other triplet was a foil triplet that never appeared successively in the familiarization phase. Each foil triplet was constructed from shapes taken from 3 different real triplets, with the constraint that each element in the foil triplet remained in the same position as in the original triplet (e.g., the second element in the foil triplet was in the second position in its original triplet). Thus, all the stimuli in the test phase were presented for an equal number of times in the familiarization phase, so that the only information available for distinguishing between the two test triplets was their statistical properties. Each test triplet was presented with the same exposure parameters of the familiarization phase (i.e., SOA = 1000 ms, ISI = 200 ms). In each test trial, the first triplet was presented, followed by an asterisk presented in the middle of the screen for 1000 ms, and then the second triplet appeared. After the two triplets had been presented, participants were asked to choose the triplet which they were more familiar with. The choice was made by pressing one of two keys with no time limitation; no feedback was provided regarding the correctness of the response. The order of the two test triplets was counterbalanced across test trials. Each of the 8 triplets was tested against 4 foil triplets (out of a pool of 8 foil triplets) with the constraint that the same shape could not appear in both test triplets. That is, there were 32 test trials in total (8 triplets-by-4 foil triplets paired to each triplet). To assess the statistical learning capacity for each participant, a statistical learning score was calculated as the percent of correct answers in the test phase.

2.4. Attention bias modification (ABM)

Fig. 2 presents the two variations of trials on the dot-probe-based ABM task. The ABM task used here is a slightly modified version of the TAU-NIMH ABM initiative protocol (Abend, Pine, & Bar-Haim, 2014). The task included face stimuli from 10 actors (5 women) taken from the NimStim face set (Tottenham et al., 2009). Each actor contributed two facial expressions: angry and neutral. In each therapy session, the patients were presented with 200 training trials. In each trial, a fixation cross appeared for 500 ms, followed by a pair of chromatic faces of the same actor showing an angry and a neutral expression appearing for 500 ms. Immediately following the faces, a probe (“ < ” or “ > ”) appeared in the location of one of the faces. To induce learning to attend away from threat, in 160 trials (80% of all trials) the probe appeared in the location of the neutral face, and in the other 40 trials (20% of all trials), the probe appeared in the location of the angry face. Participants were instructed to indicate the orientation of the arrowhead by clicking the left or right mouse button using their dominant hand. The probe remained on-screen until participants responded, and then the next trial began. Angry face location, probe type, and actor were fully counterbalanced in presentation. In the current study, ABM was delivered in six bi-weekly sessions over a period of three weeks, with a total of 1200 trials. This dose represents the middle of the range of number of trials in ABM studies with similar populations (Price et al., 2017). Twice-a-week sessions are common in ABM research, reflecting a concerted brief effort that is acceptable to patients and helps reduce dropout (e.g., Amir et al., 2009; Naim, Kivity, Bar-Haim, & Huppert, 2018).

2.5. Procedure

Participants contacted our lab in response to an advertisement for a computerized treatment of social anxiety. Following a brief telephone screening, those who appeared eligible were invited to an in-person clinical assessment. Participants who met inclusion criteria and did not meet any exclusion criteria were offered participation in the study. Consenting participants completed the statistical learning task and then began ABM therapy, which consisted of 6 twice-weekly sessions over 3 weeks. Post-treatment clinical evaluation was conducted 1–2 weeks after the last session.

2.6. Data analysis

To examine prediction of change in social anxiety symptoms by baseline statistical learning capacity separate analyses were performed on clinician-rated LSAS scores and self-reported SPIN scores. In each of the two separate models, we regressed post-treatment social anxiety levels (LSAS or SPIN) on baseline statistical learning capacity and on the corresponding baseline social anxiety measure. For illustrative purposes, we also plotted changes in social anxiety scores (the difference between pre- and post-treatment scores in LSAS and SPIN) as a function of statistical learning capacity. Pearson correlation coefficients for these plots are also provided.

2.7. Power analysis

Power analyses were conducted using G*Power3.1.9.2 software (Faul, Erdfelder, Lang, & Buchner, 2007). Given that we had no previous data to gauge the magnitude of the effect of statistical learning capacity on social anxiety symptoms following ABM treatment, we wanted to allow detection of a medium effect size of 0.50, at 0.80 power and $\alpha = 0.05$, two-tailed, which would have required 26 participants. In addition, to estimate the desired sample size for the within-group effect of social anxiety reduction following ABM therapy, we conducted a meta-analysis on the four randomized controlled trials most closely resembling the current study (Amir et al., 2009; Bunnell, Beidel, & Mesa, 2013; Heeren, Reese, McNally, & Philippot, 2012; Schmidt, Richey, Buckner, & Timpano, 2009). These studies applied multiple sessions of ABM to treatment-seeking adults with clinically diagnosed social anxiety disorder in the lab. The combined effect size for clinician-rated measures was $d = 0.90$ (ranging 0.58–1.70 in individual studies), and $d = 1.27$ (ranging 0.66–1.92 in individual studies) for self-reported measures. Taking a conservative approach, to achieve a power of 0.80 with $\alpha = 0.05$, two-tailed, for the smallest effect obtained in these previous trials ($d = 0.58$, Schmidt et al., 2009), again a sample size of 26 was indicated. We therefore decided to slightly increase power by enrolling 30 participants.

3. Results

Social anxiety symptoms were reduced post-treatment compared to pre-treatment on both the LSAS and SPIN scales, $ts(29) = 3.52$ and 4.30, $ps = 0.001$, $ds = 0.64$ and 0.78, respectively. Regularity within the statistical learning task was detected at the group level (i.e., above chance level of 50%), mean score = 56.15%, $t(29) = 2.32$, $p = 0.028$, $d = 0.42$. Statistical learning at baseline did not correlate with pre-treatment social anxiety symptoms as assessed by both LSAS, $r(29) = -0.15$, $p = 0.44$, and SPIN, $r(29) = 0.02$, $p = 0.91$.

Table 1 presents estimated coefficients for the regression models predicting the effects of statistical learning capacity and pre-treatment social anxiety symptoms (LSAS or SPIN) on post-treatment social anxiety symptoms. The overall model accounted for 56.2% of the variance in post-treatment LSAS scores and 41% of the variance in post-

Table 1
Regression predictors on post-treatment social anxiety levels.

Dependent Variable	Predictors	*B*	*SE*	95% CI	*t*	*P*
Post-treatment LSAS	Pre-treatment LSAS	0.82	0.16	.48 to 1.15	4.97	< .001
	Statistical Learning	−38.4	16.08	−71.4 to −5.42	−2.39	.024
Post-treatment SPIN	Pre-treatment SPIN	0.67	0.19	.29 to 1.05	3.64	.001
	Statistical Learning	−25.9	10.66	−47.7 to −4.01	−2.43	.022

Note. The table presents regression predictors on post-treatment LSAS scores (top rows) and SPIN scores (bottom rows). Estimated coefficients (*B*), standard errors (*SE*), confidence intervals (CI), t-scores (*t*) and significant values (*P*) are presented for these predictors. LSAS = Liebowitz Social Anxiety Scale; SPIN = Social Phobia Inventory.

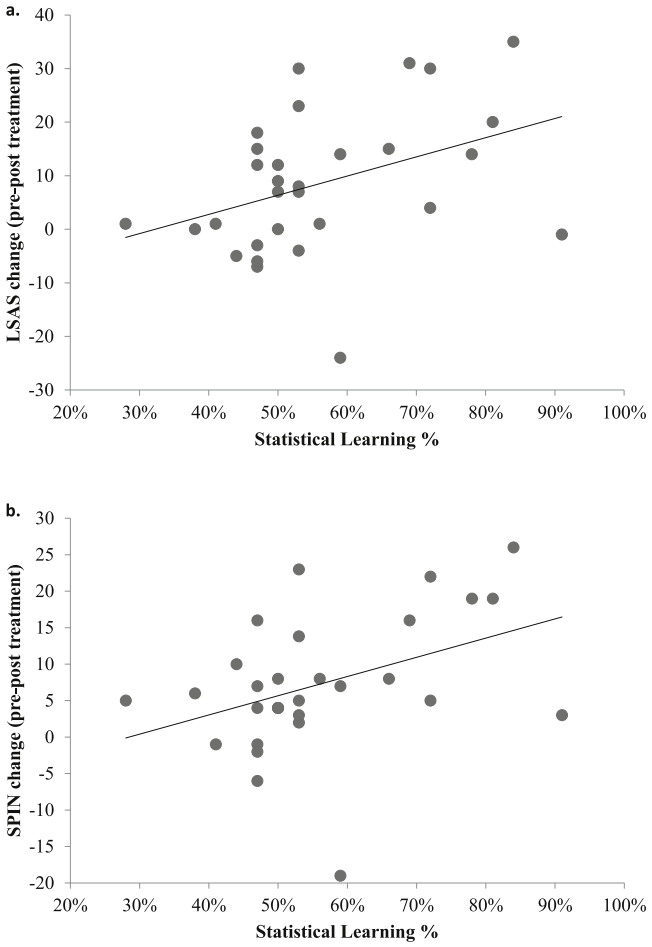

Fig. 3. Scatter plots a and b depict the correlation between statistical learning scores (x-axis) and change in symptoms (y-axis) calculated as the difference between pre- and post-treatment scores. The dependent variable in plot a is the LSAS difference score, and in the plot b is the SPIN difference score. Linear regression lines are drawn in black.

treatment SPIN scores. Statistical learning uniquely accounted for additional 9.3% of the variance in post-treatment LSAS scores, $F(1,27) = 5.71$, $p = 0.024$, and 12.9% of the variance in post-treatment SPIN scores, $F(1,27) = 5.89$, $p = 0.022$. To illustrate these associations we plotted change in social anxiety scores as a function of statistical learning capacity for clinician-rated LSAS (Fig. 3a, $r(29) = 0.39$, $p = 0.033$), and self-reported SPIN (Fig. 3b, $r(29) = 0.41$, $p = 0.024$).

4. Discussion

The present study suggests that individual differences in patients' basic ability to extract statistical regularity predict clinical outcome in ABM for social anxiety disorder. The higher patients' statistical learning capacity, the greater their clinical improvement. These results suggest a promising predictor for ABM treatment outcome that could potentially inform about mechanisms underlying ABM and its clinical application. Successful statistical learning may be one factor supporting successful ABM. If a patient's ability for statistical learning is limited, his or her ability to benefit from ABM may also be limited. A reliable tool for quantifying statistical learning capacity could help guide the tailoring of ABM to patients most likely to benefit. Similarly, for patients with poor learning capacity, ABM could be adapted through more explicit instruction, or longer training, to increase treatment response (Grafton et al., 2014; Lazarov, Abend, Seidner, Pine, & Bar-Haim, 2017).

Despite their clear pattern, the results of the current study should be considered in light of important limitations and a need for further research. First, the current study design cannot unequivocally confirm that statistical learning plays a mechanistic role in ABM. One can argue that patients who scored higher on baseline statistical learning are also generally better in any kind of learning or other cognitive tasks, and therefore may benefit more from any treatment irrespective of its specific underpinning mechanisms. Alternatively, in the absence of a no-contingency control group the effect of statistical learning on the observed reduction in social anxiety symptoms might be attributed to less enduring social anxiety symptoms among those who display higher statistical learning capacities. It is therefore advisable for future studies to include a control group with no embedded contingency, and possibly also a learning task that is irrelevant to ABM in order to further validate the mechanistic role of statistical learning in ABM.

Second, attentional bias to threat was not assessed in this study. Bias measurement before and after ABM could have permitted a more direct assessment of the assumption that poor statistical learners fail to extract the training contingency, and therefore ABM exerts lower impact on their attentional bias and consequently reduces therapeutic impact. Future studies are encouraged to include measurements of attentional bias to further elucidate the mechanistic role of statistical learning in ABM.

Third, performance on the statistical learning task uniquely accounted for only 9%–12% of the variance in social anxiety symptoms post-treatment. One might expect a higher percent if statistical extraction is a prerequisite condition for successful ABM. It is notable in this respect that statistical learning capacity was assessed through a basic task that is fairly remote from the dot-probe training task in its parameters. Specifically, statistical learning was assessed in a neutral emotional context while the specific regularity to extract from the dot-probe-based ABM task occurs in an emotional context. Another significant difference between the two tasks is that while the statistical learning task assesses the capacity to extract temporal contingencies (i.e., what temporally follows what), the contingency embedded within the dot-probe ABM task is also of a spatial nature (i.e., what follows in the spatial location of what). Future attempts to assess statistical learning within emotional and spatial contexts, and specifically in the context of dot-probe-based ABM, may enhance the predictive power of statistical learning capacity on treatment outcome. For instance, to predict more accurately the degree to which the regularity is extracted from the dot-probe task, it is possible to use statistical learning tasks applying emotional stimuli similar to those presented in the dot-probe task and/or with spatial regularity.

Fourth, although the results appear quite robust, they reflect a first demonstration of statistical learning as a predictor of ABM outcome with only 30 patients and a specific anxiety disorder. Thus, replicating this effect with larger samples, preferably by independent research groups, and extending the current findings to other disorders is critical for clinical considerations and for establishing the boundary conditions of the phenomenon both in social anxiety disorder and in other conditions applying ABM (e.g., other anxiety disorders, depression, addiction, eating disorders). In addition, the current design permitted to investigate the therapeutic response to ABM merely 1–2 weeks after therapy ended. Given that the statistical learning capacity measured here at baseline is a trait-like capacity, our focus in the current study was on whether it might influence training-intake and thus treatment outcome. Future studies could extend the current findings by adding follow-up assessments with longer intervals. Future research could also strive to determine a viable and reliable patient-level statistical learning capacity cutoff. Such cutoff could assist in determining the likelihood that a specific patient would benefit from ABM.

Finally, this first demonstration of statistical learning capacity as a relevant ingredient in successful ABM outcome still does not reveal the unfolding dynamics of contingency learning within dot-probe-based ABM. Specifically, it is not yet clear when rule extraction occurs during the course of multiple therapy sessions. That is, whether learning is incremental or perhaps stable once it shows. Future studies could explore these learning processes, which could eventually allow to generally or even individually optimize ABM parameters such as number of trials per session and number of therapy sessions.

In conclusion, this study reveals a promising predictor of ABM treatment outcome that could potentially account for the moderate effect sizes of ABM therapy at the group level (Hakamata et al., 2010; Linetzky et al., 2015), as well as the large variability in treatment outcome at the individual level (Bar-Haim, 2010). The practical implication of this finding is that patients who are limited in their capacity to extract statistical contingencies are less likely to benefit from the effects targeted by ABM. Future attempts to establish general statistical learning capacity and statistical learning capacity in emotional and spatial contexts as reliable predictors of treatment outcome may advance the field of ABM toward a more effective personalized treatment approach.

Declaration of conflicting interests

The authors declare no conflicts of interest.

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