**Supplementary Material**

**Study 1 – Positive reinforcement**

# Method

# Participants

Participants were individuals with high (HD) and low (LD) levels of depression symptoms. Three hundred and sixty-seven first-year undergraduate students from Tel Aviv University completed the Patient Health Questionnaire-9 (PHQ-9; Kroenke et al., 2001) and the Beck Depression Inventory (BDI-II; Beck et al., 1996) at the beginning of the academic year (i.e., during Week 2 of the semester). Only those with a PHQ-9 score ≥10, representing moderate depressive symptoms (Kroenke et al., 2001; Manea et al., 2012; Levis et al., 2019), coupled with a BDI-II score ≥14, representing mild depression (Beck et al., 1996; Smarr and Keefer, 2011), were deemed eligible to be part of the HD group. For the LD group, eligible participants were those who scored at the bottom of the PHQ-9 and BDI-II sampling pool, contingent on having a score <5 on both scales, and served as non-depressed control participants. Eligible participants were invited to participate in the study, which took place between a week to four weeks later (i.e., during Weeks 3-to-6 of the semester). All participants received course credit for participation, and provided written informed consent. We only invited individuals with normal or corrected-to-normal vision to participate in the study.

On the day of the study, participants completed several self-report questionnaires (see measures below), including the PHQ-9 for a second time[[1]](#footnote-1). HD participants who scored below the screening cutoff score of 10 were excluded to maintain a moderate level of depressive symptoms among HD participants (Kroenke et al., 2001; Manea et al., 2012). In total, four HD participants were excluded for this reason. An additional HD participant was excluded for not completing Day 2 of the experiment due to Covid-19 restrictions. LD participants were excluded if they scored above 9 on the PHQ-9, as a score of 10 is considered the cutoff score for moderate depressive symptoms on this scale (Kroenke et al., 2001)[[2]](#footnote-2). Only one LD participant was excluded for not meeting this requirement (i.e., scoring above 9), and additional two LD participants were excluded due to incompletion of Day 2 due to Covid-19 restrictions. The final sample included 28 HD participants (*mean* a*ge*=23.0+1.4, 22 [78.6%] females) and 30 LD participants (*age*=23.4+1.8, 21 [70.0%] females). Demographic and clinical characteristics by group are described in Table 1 (left panel).

Sample size was pre-determined following a power analysis using G\*Power 3.1.9.4 (Faul et al., 2009), and was based on a previous study using a similar gaze-contingent training task among depressed individuals (Shamai‐Leshem, Lazarov, Pine, & Bar‐Haim, 2021), which reported an effect size of *d*=.68 (*p*<.001) for the reduction in DT% from before to after the task. Hence, we used this effect size to power the current study to enable the detection of a corresponding reduction in DT%, reflecting online learning, among HD participants. The power analysis indicated that a group size of 25 would suffice to achieve a power of 0.95 (with *α*<0.05). However, as this was the first study to use this paradigm to examine selection history in depression we aimed at recruiting 30 participants per group.

**Measures**

***Depression levels*** at screening and day of participation were measured using the PHQ-9 (Kroenke et al., 2001), a 9-item self-report questionnaire evaluating symptoms of depression according to DSM-5 (American Psychiatric Association, 2013). Each PHQ-9 item corresponds to one of the nine symptoms of depression, rated in relation to the previous two weeks, with responses ranging from “Not at all” (0) to “Nearly every day” (3), for a total score of 0-to-27. PHQ-9 has good reliability (both internal consistency and test-retest reliability) and adequate validity, as does its Hebrew version (Geuolayov G, Jungerman T, Moses S, Friedman N, Miron R, 2009). Cronbach alpha in the present study was 0.91 at both screening and day of participation.

Depression levels at screening were also assessed using the BDI-II (Beck et al., 1996) – a widely-used 21-item self-report questionnaire evaluating symptoms of depression related to the past two weeks. The BDI-II has good test-retest reliability and internal consistency, as well as adequate convergent and discriminant validity (Beck et al., 1996; Segal, Coolidge, Cahill, & O’Riley, 2008; Sprinkle et al., 2002). Cronbach alpha of BDI-II in the present sample was 0.95.

***Trait anxiety*** was measured using the 20-item State-Trait Anxiety Inventory-Trait subscale (STAI-T; Spielberger et al*.*, 1970). Each item on the scale is a sentence that people usually use to describe themselves and respondents are asked to rate how well it describes themin general. Items are rated on a 5-point scale, yielding a total score ranging 20-80. STAI-T has good internal consistency, test-retest reliability, and validity (Speilberger and Vagg, 1984; Balsamo *et al.*, 2013). In the present study the validated Hebrew translation of STAI-T was used (Teichman and Melineck, 1979). Cronbach alpha in was 0.96.

***Anhedonia*** was measured by the Snaith–Hamilton Pleasure Scale (SHAPS; Snaith et *al.*, 1995). SHAPS is a brief 14-item self-report measure of hedonic tone (and its absence). Participants are asked to indicate how much they would be able to experience pleasure in different situations (i.e., “enjoy seeing other people's smiling faces” or “enjoy a cup of tea or coffee”). SHAPS was found to be highly reliable among MDD patients as well as non-clinical populations (Franken et al., 2007). SHAPS was translated from English to Hebrew for the purposes of the current study. Translation was validated with backward translation by bilingual speakers, and was compared to the original version. Cronbach alpha in the present study was 0.91.

***Musical anhedonia*** was measured using the Barcelona Music Reward Questionnaire (BMRQ; Mas-Herrero et al., 2012a). BMRQ consists of 20 self-report items assessing musical anhedonia, equally divided across five facets characterizing musical reward experiences – music seeking activities; emotion evocation; mood regulation; social rewarding experiences; and sensory-motor behavior. Participants indicate their level of agreement with each statement on a 5-point scale ranging from “fully disagree” (1) to “fully agree” (5). BMRQ demonstrated good internal consistency in previous studies (Mas-Herrero et al., 2012b, 2014). The translation to Hebrew was validated by backward translation by bilingual speakers, and compared to the original version. Cronbach alpha in the present study was 0.86.

**Experimental Tasks**

***Attention Allocation Assessment task.*** Attention allocation was assessed using an established eye-tracking-based free-viewing attention task (Lazarov et al., 2016, 2017b, 2018, 2001b, 2021a) adapted for the present study. During each of the 30 trials of the task, a 4X4 matrix comprising 16 different shapes was presented, with half of the shapes being rounded with no sharp angles (i.e., rounded shapes) and half having sharp angles (i.e., angular shapes; see Figure 1, right panel, for an example). For each matrix, the following parameters were followed: each single shape appeared randomly at any position within the matrix; each shape appeared only once in a given matrix; half the shapes were rounded and half were angular; and the four inner positions (i.e., the four positions located at the middle of each matrix, see Figure 1, right panel) were always comprised of two rounded and two angular shapes.

The task itself was preceded by a 5-point gaze calibration, followed by a 5-point validation procedure, ensuring the validity of gaze data. Calibration was repeated if visual deviation was >0.5 degrees on the X or Y axis, for any of the calibration points, and the task began only when these calibration parameters were achieved. Each trial started with the presentation of a fixation cross, shown until a fixation of 1,000ms was recorded, verifying that each trial began only when the participant’s gaze was located at the center of the matrix. Each matrix was then presented for 6,000ms followed by an inter-trial interval of 2,000ms until the next fixation cross appeared. Participants were instructed to look freely at each matrix in any way they chose until it disappeared. Internal consistency for attention allocation (i.e., percent dwell‐time (DT%) on rounded shapes; see below) was high, with Cronbach's α of .92, .93, .92, for the entire sample, HD participants, and LD participants, respectively, echoing previous attention research in depression using similar versions of this task (Lazarov, Ben-Zion, Shamai, Pine, & Bar-Haim, 2018; Shamai‐Leshem et al., 2021).

Gaze data were recorded and processed using Portable Due EyeLink (SR Research, Ltd., Ottawa, Ontario, Canada). Operating distance to the eye-tracking monitor was 70 cm. Stimuli were presented on a 22-inch Dell P2213 monitor (screen resolution 1680X1050). Sampling rate was 500 Hz.

***Gaze-Contingent Training Task.*** The training task was a modified version of the assessment task described above, designed to divert participants’ attention towards a specific shape type via music reward (Lazarov et al., 2017b; Dillon et al., 2021; Shamai‐Leshem et al., 2021; Umemoto et al., 2021; Zhu et al., 2022). Specifically, before each training block, participants selected a 12-minute music track to which they wanted to listen during the task. Music tracks were chosen from an extensive music menu, sorted by artists, that included the most popular musicians according to published rating charts (Each 12-min track comprised of several different songs of the chosen artist, with no repetitions of songs within or across tracks). After choosing the music, the calibration-validation procedure commenced, followed by the presentation of 30 successive shape matrices, each shown for 24 seconds, with no inter-trial intervals. Importantly, the music pre-selected by participants played (e.g., could be heard) only when fixating on one of the rounded shapes within the matrix. Conversely, fixating on one of the angular shapes stopped the music. Thus, learning the gaze-music contingency diverted one’s gaze toward the rounded shapes and away from the angular shapes. Rounded shapes were randomly chosen to serve as the target shape type[[3]](#footnote-3).

Gaze data were recorded and processed using the same apparatus described above for the assessment task.

**General procedure**

Participants completed the study in a quiet room at the university. They were told that they are going to participate in a 2-day study examining gaze patterns using an eye-tracker apparatus (see Figure 2). During Day 1, participants first completed the attention allocation assessment task (i.e., pre-training assessment), followed by two blocks of the training task (B1, B2). They then completed self-report questionnaires (see measures above). Day 2 began with two additional training blocks (B3, B4), followed by a post-training assessment task. Participants were then inquired as to their understanding of the gaze-music contingency (i.e., explicit rule learning). Specifically, participants were asked “*do you think there was a relationship between your eye movements and the playing of the music during the task*”. If participants answered that there was, they were then asked to specify this relationship. Only those who correctly identified the gaze-music contingency (e.g., “*the music played only when looking at one of the rounded shapes*” or “*looking at the pointed shapes stopped the music*”) were deemed as “explicit learners”. Explicit learning was treated as binary such that learning was coded as 1 while non-learning was coded as 0.

The procedure was delivered over 2 days to closely follow previous research that used a similar eye-tracking-based gaze-contingent music reward procedure in anxiety and depression (Lazarov, Pine, et al., 2017; Shamai‐Leshem et al., 2021), in which 2 sessions were delivered per week (excluding on two consecutive days). Hence, here too, the procedure was delivered over two non-consecutive weekdays, resulting in the two days being separated by 2-to-5 days. Two additional considerations were taken into account in deciding to deliver the procedure over two days. First, prior research on attentional learning shows that a between-session rest allows for a consolidation-related improvement in learning (e.g., Abend et al., 2014, 2013; Lazarov et al., 2017a). Second, as each session was approximately 60 minutes long, using a 2-day procedure enabled us to reduce participants’ fatigue, which might have lowered engagement with the task, possibly hindering learning.

**Study 2 – Negative reinforcement**

# Method

# Participants

Recruitment procedures were identical to Study 1, from a new pool of potential participants – 445 first-year undergraduate students from Tel Aviv University. Here, too, eligible participants for the HD group were those scoring ≥10 on the PHQ-9 and ≥14 on the BDI-II, and for the LD group those scoring <5 on both the PHQ-9 and BDI-II. Participants were included/excluded based on their PHQ-9 scores on the day of their participation using the same criteria used in Study 1. In Study 2, three HD participants were excluded for scoring below 10 on the PHQ-9. In the LD group, no participants were excluded due to scoring above 9 on the PHQ-9[[4]](#footnote-4), with one participant excluded after being unable to complete Day 2 due to COVID-19 restrictions. The final sample included 28 HD (*mean* a*ge*=23.2+2.9, 23 [82.1%] females) and 30 LD (*mean age*=24.3+3.4, 21 [70.0%] females) participants. Demographic and clinical characteristics of the two groups are described in Table 1 (right panel).

# Measures

Same measures of psychopathology were also administered in Study 2 (see Table 1), which demonstrated good (*α*=.87) to excellent (*α*=.96) internal consistency also in this study. Aiming to control for possible confounders related to coping with the aversive stimulus (as white noise was used in Study 2, rather than music), we included two additional self-report measures – one assessing resilience to adverse events and one noise annoyance (see below). Explicit rule leaning was assessed similar to Study 1, but here participants were asked “*do you think there was a relationship between your eye movements and the stopping of the noise during the task*”, and those responding positively were then asked to specify this relationship.

***Resilience*** ***to adverse events*** was measured using the 10-item version of the *Connor-Davidson Resilience scale* (CD-RISC; Campbell-Sills & Stein, 2007), a well-validated measure considered the ‘gold standard’ for measuring self-reported resilience. The CD-RISC was previously translated to Hebrew (Mosheva et al., 2020), showing good reliability (α=.88). The internal consistency in our sample was *α*=.92.

***Noise annoyance*** was measured using a single question developed and recommended by the International Commission on Biological Effects of Noise (ICBEN; Fields et al., 2001) to measure individual disturbance experienced due to aversive sounds, which was adopted for the context of the present study. Specifically, participants were asked to rate “how much the noise you heard throughout the experiment bothered, disturbed or annoyed you”. Rating was on a scale of 1-10.

**Procedure, tasks, and measures**

The procedure was identical to that described in Study 1, but with one crucial change – rather than music playing when fixating on one of the rounded shapes, here gazing at one of these shapes (the target AOI) stopped an aversive white noise that would otherwise be heard. Thus, in the present study the white noise served as a negative reinforcer aimed to divert gaze allocation to the rounded shapes and achieve an attention allocation pattern similar to that of Study 1. Due to ethical considerations and in line with extant studies using negative reinforcement procedures (Suarez-Jimenez et al., 2018, 2021), participants’ auditory threshold was set individually to a level deemed uncomfortable. Specifically, before Block 1 (Day 1) and Block 3 (Day 2), we adjusted individual thresholds by gradually increasing the volume until the participant reported the noise as being *unbearable*, and then decreased it slightly to a level deemed by the participant as *uncomfortable* (see Suarez-Jimenez et al., 2021, 2018 for a similar approach)*.*

**Integrated and exploratory analyses**

Codes for analyses are openly available in Open Science Foundation (OSF) at <https://osf.io/tseya/?view_only=c15b250d85b2414baf6e957a5f957e98>

**Integrated group-level analysis**

After witnessing a discrepancy in the group-by-time interaction effect of learning generalization (i.e., near-transfer effect) between the two studies, we explored whether this disparity is statistically significant using a unified model, consisted of all participants from both Studies (*N*=116). We conducted a 2x2x2 repeated-measures ANOVA for DT% on rounded shapes, with Group (HD/LD) and Reinforcer (music/white noise) as between-subject factors, and Time (pre/post) as a within-subject variable.

A main effect for time emerged, *F(1,112)*=18.5, *p*<.001, *η2p*=0.14, which was subsumed under a significant group-by-time-by-reinforcer interaction effect, *F(1,112)*=5.33, *p*=.02, *η2p*=0.05. There were no main effects for group or reinforcer, and no double interaction effects. The significant interaction was maintained after controlling for anxiety levels, *F(1,112)*=5.33, *p*=.023, *η2p*=0.05. The sensitivity analysis confirmed these results with the expected directionality, showing a significant positive effect for the post assessment, *unstandardized B*=0.07, *95% CI*=0.05, 0.09, *p*<.001, and a significant negative interaction effect for the HD group’s post assessment with the music reinforcer (group-by-time-by-reinforcer interaction), *B*=-0.14, *95% CI*=-0.17, -0.10, *p*<.001, with no other significant effects in the model (Table S5).

**Exploratory individual-level analysis**

To better understand the emergent learning processes, gaze data were also analysed at the individual level, taking a within-person approach. Using individual eye-tracking data, we defined and then compared groups on magnitude of learning, both online learning and generalization of learning (near-transfer). We then examined the associations between the three individual-based learning indices – explicit rule learning, online learning, and near-transfer of learning.

**Learning magnitude**

To measure ***online learning*** individually, we first computed a training baseline for each participant, defined as the average DT% on rounded shapes during the first 5 matrices of training (Block 1, matrices 1-5; see Lazarov et al. (2017b), and Shamai‐Leshem et al. (2021) for a similar approach). Next, we calculated for each participant the average DT% during the last 5 matrices of training Block 4 (matrices 116 to 120). We then computed standardized t-scores for the change from training beginning to end. Standard errors were calculated individually, using each participant’s personal standard deviation throughout training. The formula for standardized *online learning* scores was as follows:

To evaluate individual ***near-transfer learning effects***, we applied the same within-person approach only with DT% of the pre- and post-training assessments. The formula for calculation of near-transfer learning standardized scores was as follows:

Groups were then compared on the magnitude of learning, per learning type, using t-tests with individual standardized learning scores as the dependent variable. The association between online learning and near-transfer was computed with Pearson correlation, and the association of explicit rule learning (learners/non-learners; 1/0) with both online learning and near-transfer, was computed using point-biserial correlations.

Results replicated those of the group-level analyses. Specifically, groups did not differ on ***online learning*** when reinforced with music, *t(56)*=0.06, *p*=.95, or white noise, *t(56)*=0.04, *p*=.97 (see Figure 4 for descriptive individual trajectories of online learning; 4A for music and 4B for white noise). Examining ***near-transfer effects***, groups differed significantly when reinforced with music, *t(56)*=2.50, *p*=.016, with the LD group yielding higher standardized learning scores than the HD group (HD: *mean standardized score*=-0.60+4.18; LD: *mean standardized score*=2.81+6.00). When reinforced with white noise, there were no group differences in near-transfer effects, *t(56)*=-0.66, *p*=.51.

As depicted in Figure 5A, near-transfer effects and online learning were significantly associated under both reinforcers only in the LD group, *r* *of* .64 (music) and .73 (white noise), *p*<.001. In the HD group, this association emerged only when (negatively) reinforced with white noise, *r*=.64, *p*<.001, but not when reinforced with music, *r*=-.15, *p*=.46. A similar pattern emerged for near-transfer and explicit learning (Figure 5B) – among LD participants, a significant association emerged under both reinforcers, *r* of.67 (music) and .66 (white noise), *p*<.001, while among HD participants this association emerged only under white noise, *r*=.65, *p*<.001, but not when reinforced with music, *r*=-.27, *p*=.17. Conversely, online learning was highly associated with explicit rule learning in both groups, under both types of reinforcers (Figure 5C), *r’s* ranging between .63 and.87, *p*<.001.

**Predicting learning**

To explore whether specific changes in DT% between subsequent training steps could predict online learning and near-transfer effects, we grouped training matrices into assemblages of five (based on Lazarov et al. (2017b); Shamai‐Leshem et al. (2021)) and calculated the change in DT% between each two subsequent assemblages (for example: change in DT% from matrices 1-5 to matrices 6-10, from matrices 31-35 to 36-40, etc.[[5]](#footnote-5)). Next, Pearson correlation coefficients were computed between ΔDT% of each pair of subsequent steps and standardized scores of: (a) online learning; and (b) near-transfer effects. We conducted this analysis for each group under each reinforcer. Due to the exploratory nature of this analysis and reduced power[[6]](#footnote-6) we did not correct for multiple comparisons.

Results indicated that matrices 6-10 were the only assemblage that consistently predicted *online learning* in both groups under both reinforcers, *r* between.41-.72, *p*<.025. When exploring *near-transfer effects* this assemblage was predictive among LD participants under both the music, *r*=.48, *p*=.007, and white noise, *r*=.49, *p*=.007, reinforcers. Conversely, among HD participants, this assemblage predicted near-transfer effects under the white noise condition, albeit at a trend-level, *r*=.35, *p*=.066, while being non-significant under the music condition, *r*=.07, *p*=.71) (Table S6).

**Learning speed**

The results of the previous analysis suggested that online learning usually already occurs within the first ten training steps (i.e., matrices), as change in DT% from matrices 1-5 to 6-10 was found to be associated with online learning at training end. Zooming in on this ‘hot-spot’ phase, we explored whether HD and LD participants differed in learning speed.

To this end, we considered the DT% of each participant on each of these 10 matrices as separate observations, and controlled for within-person variance by modelling the participants as random factors in a multilevel model. Matrices were modelled as a continuous variable. We conducted a separate hierarchical 2-step linear regression model for each reinforcer. In the first step we introduced two interaction terms: matrix\*LD and matrix\*HD, without main effects, to examine each group independently. In the second step we introduced a main effect for matrix number and a matrix\*HD interaction term, to compare the LD group (which served as a reference group) and the HD group (that was contrasted against it) on learning speed. Thus, the interaction effect on step II enabled us to determine whether descriptive group differences in step I are statistically significant.

When reinforced with music, there was a significant increase in DT% in both the HD, *B*=0.010, *95% CI*=0.005, 0.016, *p*<.001, and LD, *B*=0.005, *95% CI*=0.000, 0.010, *p=*.04, groups, reflecting gradual learning during these first 10 matrices, with no group differences (as implied by the insignificant interaction effect in step II; *p*=.10). Conversely, when reinforced with white noise, a significant interaction effect emerged on step II, *p*=.01, implying group differences in learning speed during this initial phase of training. While HD participants showed a significant increase in DT% during the first 10 matrices, *B*=0.010, *95% CI*=0.004, 0.016, *p*<.001, LD participants did not, *B*=0.001, *95% CI*=-0.005, 0.006, *p=*.82.

**Learning patterns**

***Clustering.*** To explore potential different learning patterns throughout training, we clustered participants based on their gazing patterns using k-means clustering, introducing training matrices as input. We identified three distinct clusters (k=3[[7]](#footnote-7); see Figure 6) – Cluster 1 showed a steep increase in DT% at training beginning; Cluster 2 showed a more gradual increase in DT%; and Cluster 3 showed no change in DT% throughout training. We labelled theses clusters as quick-learners (n=38), slow-learners (n=23), and non-learners (n=55), respectively.

Next, to analyse learning trajectories we used logistic hierarchical generalized linear models (HGLM) which extend logistic regression to handle outcome data with a hierarchical (nested) structure. Where outcome variables range continuously between 0 and 1, such as the proportion of DT% on rounded shapes, logistic HGLM utilizes the beta distribution and logit link function to model non-linear relationships between predictors and the continuous outcome (Ene, Leighton, Blue, & Bell, 2015). We fitted separate models for each cluster, considering blocks (1-4) and matrix number within block (1-30) as predictors. Odds ratios (OR) indicate the increased likelihood of groups dwelling at rounded shapes during each block or matrix within it. Multiple comparisons were adjusted using FDR. Results showed that among the *quick-learners* cluster, HGLM indicated gradual increase in DT% as a function of matrix number during Block 1 (OR=1.09, 95% CI=1.07, 1.11, p<.001), with significant likelihood of dwelling on rounded shapes during Blocks 2-4 (OR between 21.2-29.5, p<.001), but without an additive effect for increase in matrix number within these blocks (Table S\_CA1). For slow learners, the likelihood of dwelling on rounded shapes increased for each matrix during Block 2 (OR=1.04, 95% CI=1.02, 1.06, p<.001), and was significant for Blocks 3 and 4 (OR between 4.89-10.7, p<.001) without additive effects for matrix number within these blocks (Table S\_CA2). Non-learners did not show significant effects for neither block nor matrix within blocks (Table S\_CA3). These results did not change when examined using a unified model including all three clusters (Table S\_CA4).

Next, to determine whether these three clusters differed significantly we fitted comparative HGLMs. In Comparison 1, the two learning clusters (i.e., quick and slow) were contrasted against the non-learning cluster which served as the reference group. In Comparison 2, quick-learners were contrasted against slow-learners, excluding non-learners from the model. The models showed significant differences in learning trajectories between quick and slow learners to non-learners (Table S\_CA5), and between quick learners and slow learners (Table S\_CA6).

***Cluster differences.*** A set of Chi-square tests were performed to explore cluster differences on reinforcer type, group, and explicit rule learning. Results showed that cluster distribution did not differ between *reinforcer types*, Χ2(2)=0.83, p=.66 (Table S\_CA7), which was also independent of *group* (HD, LD) under both the music (Χ2(2)=0.80, p=.67; Table S\_CA8) and white noise conditions (Χ2(2)=0.64, p=.73, Table S\_CA9). Cluster was associated with *explicit rule learning* for both music, Χ2(2)=33.8, p<.001, and white noise, Χ2(2)=50.5, p<.001 (Tables S\_CA10 and S\_CA11, respectively). This pattern was driven by low rates of explicit rule learning among non-learners (1.8% across groups and reinforcers) compared to the other two clusters (85.2%). Indeed, slow and quick learners did not differ in rule learning under either reinforcer.

Lastly, we also compared clusters on *near transfer t-scores* using mixed-effects linear models. Groups were modelled as random effects to account for their impact on near transfer. Contrasting slow and quick learners against non-learners showed that both learner-types were significantly higher on near transfer (unstandardized B between 4.42-6.34, *p* between <.001-.022) on both music (Table S\_CA12) and white noise (Table S\_CA14). When contrasting quick-learners against slow-learners, clusters did not differ on near transfer on either music (Table S\_CA13) or white noise (Table S\_CA15).

**References**

Abend, R., Karni, A., Sadeh, A., Fox, N. A., Pine, D. S., & Bar-Haim, Y. (2013). Learning to attend to threat accelerates and enhances memory consolidation. *PloS One*, *8*(4), e62501.

Abend, R., Pine, D. S., Fox, N. A., & Bar-Haim, Y. (2014). Learning and memory consolidation processes of attention-bias modification in anxious and nonanxious individuals. *Clinical Psychological Science*, *2*(5), 620–627.

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders (DSM-IV)*. Washington, DC: The American Psychiatric Association (APA). https://doi.org/https://doi.org/10.1016/j.cpr.2012.09.004

Balsamo, M., Romanelli, R., Innamorati, M., Ciccarese, G., Carlucci, L., & Saggino, A. (2013). The state-trait anxiety inventory: shadows and lights on its construct validity. *Journal of Psychopathology and Behavioral Assessment*, *35*(4), 475–486.

Beck, A. T., Steer, R. A., & Brown, G. K. (1996). *Beck depression inventory (BDI-II)* (Vol. 10). Pearson London, UK.

Campbell-Sills, L., & Stein, M. B. (2007). Psychometric analysis and refinement of the Connor-Davidson Resilience Scale (CD-RISC): Validation of a 10-item measure of resilience. *Journal of Traumatic Stress*. https://doi.org/10.1002/jts.20271

Dillon, D. G., Lazarov, A., Dolan, S., Bar-Haim, Y., Pizzagalli, D. A., & Schneier, F. R. (2021). Fast evidence accumulation in social anxiety disorder enhances decision making in a probabilistic reward task. *Emotion*.

Ene, M., Leighton, E. A., Blue, G. L., & Bell, B. A. (2015). Multilevel models for categorical data using SAS® PROC GLIMMIX: The basics. *SAS Global Forum*, 2015–3430.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G\* Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149–1160. https://doi.org/https://doi.org/10.3758/BRM.41.4.1149

Fields, J. M., De Jong, R. G., Gjestland, T., Flindell, I. H., Job, R. F. S., Kurra, S., … UNIVERSITY, R. T. A. T. R. (2001). Standardized general-purpose noise reaction questions for community noise surveys: Research and a recommendation. *Journal of Sound and Vibration*, *242*(4), 641–679.

Franken, I. H. A., Rassin, E., & Muris, P. (2007). The assessment of anhedonia in clinical and non-clinical populations: further validation of the Snaith–Hamilton Pleasure Scale (SHAPS). *Journal of Affective Disorders*, *99*(1–3), 83–89.

Geuolayov G, Jungerman T, Moses S, Friedman N, Miron R, G. R. (2009). Validation of the Hebrew version of the PHQ-9, a screening instrument for depression in primary care. *Isr J Psychiatry*, *46*(1), 36.

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ‐9: validity of a brief depression severity measure. *Journal of General Internal Medicine*, *16*(9), 606–613. https://doi.org/https://doi.org/10.1046/j.1525-1497.2001.016009606.x

Lazarov, A., Abend, R., Seidner, S., Pine, D. S., & Bar-Haim, Y. (2017). The effects of training contingency awareness during attention bias modification on learning and stress reactivity. *Behavior Therapy*, *48*(5), 638–650.

Lazarov, A., Basel, D., Dolan, S., Dillon, D. G., Pizzagalli, D. A., & Schneier, F. R. (2021). Increased attention allocation to socially threatening faces in social anxiety disorder: A replication study. *Journal of Affective Disorders*, *290*, 169–177. https://doi.org/10.1016/j.jad.2021.04.063

Lazarov, A., Ben-Zion, Z., Shamai, D., Pine, D. S., & Bar-Haim, Y. (2018). Free viewing of sad and happy faces in depression: A potential target for attention bias modification. *Journal of Affective Disorders*, *238*(February), 94–100. https://doi.org/10.1016/j.jad.2018.05.047

Lazarov, A., Pine, D. S., & Bar-Haim, Y. (2017). Gaze-contingent music reward therapy for social anxiety disorder: a randomized controlled trial. *American Journal of Psychiatry*, *174*(7), 649–656. https://doi.org/10.1176/appi.ajp.2016.16080894

Lazarov, A., Suarez-Jimenez, B., Zhu, X., Pine, D. S., Bar-Haim, Y., & Neria, Y. (2021). Attention allocation in posttraumatic stress disorder: an eye-tracking study. *Psychological Medicine*, *52*(15), 1–10. https://doi.org/10.1017/S0033291721000581

Levis, B., Benedetti, A., & Thombs, B. D. (2019). Accuracy of Patient Health Questionnaire-9 (PHQ-9) for screening to detect major depression: individual participant data meta-analysis. *BMJ*, *365*, l1476. https://doi.org/10.1136/bmj.l1476

Manea, L., Gilbody, S., & McMillan, D. (2012). Optimal cut-off score for diagnosing depression with the Patient Health Questionnaire (PHQ-9): A meta-analysis. *CMAJ*, *184*(3), E191–E196. https://doi.org/10.1503/cmaj.110829

Mas-Herrero, E., Marco-Pallares, J., Lorenzo-Seva, U., Zatorre, R. J., & Rodriguez-Fornells, A. (2012a). Barcelona Music Reward Questionnaire. *Music Perception*.

Mas-Herrero, E., Marco-Pallares, J., Lorenzo-Seva, U., Zatorre, R. J., & Rodriguez-Fornells, A. (2012b). Individual differences in music reward experiences. *Music Perception: An Interdisciplinary Journal*, *31*(2), 118–138.

Mas-Herrero, E., Zatorre, R. J., Rodriguez-Fornells, A., & Marco-Pallarés, J. (2014). Dissociation between musical and monetary reward responses in specific musical anhedonia. *Current Biology*, *24*(6), 699–704.

Mosheva, M., Hertz-Palmor, N., Dorman Ilan, S., Matalon, N., Pessach, I. M., Afek, A., … Gothelf, D. (2020). Anxiety, pandemic-related stress and resilience among physicians during the COVID-19 pandemic. *Depression and Anxiety*, *37*(10), 965–971. https://doi.org/10.1002/da.23085

Segal, D. L., Coolidge, F. L., Cahill, B. S., & O’Riley, A. A. (2008). Psychometric properties of the Beck Depression Inventory—II (BDI-II) among community-dwelling older adults. *Behavior Modification*, *32*(1), 3–20.

Shamai‐Leshem, D., Lazarov, A., Pine, D. S., & Bar‐Haim, Y. (2021). A randomized controlled trial of gaze‐contingent music reward therapy for major depressive disorder. *Depression and Anxiety*, *38*(2), 134–145.

Smarr, K. L., & Keefer, A. L. (2011). Measures of depression and depressive symptoms: Beck depression Inventory‐II (BDI‐II), center for epidemiologic studies depression scale (CES‐D), geriatric depression scale (GDS), hospital anxiety and depression scale (HADS), and patient health Questionna. *Arthritis Care & Research*, *63*(S11), S454–S466.

Snaith, R. P., Hamilton, M., Morley, S., Humayan, A., Hargreaves, D., & Trigwell, P. (1995). A scale for the assessment of hedonic tone the Snaith–Hamilton Pleasure Scale. *The British Journal of Psychiatry*, *167*(1), 99–103.

Speilberger, C. D., & Vagg, P. R. (1984). Psychometric properties of the STAI: a reply to Ramanaiah, Franzen, and Schill. *Journal of Personality Assessment*, *48*(1), 95–97.

Spielberger, C. D., Gorsuch, R. L., & Lushene, R. E. (1970). State-trait anxiety inventory manual. *Mind Garden, Inc*.

Sprinkle, S. D., Lurie, D., Insko, S. L., Atkinson, G., Jones, G. L., Logan, A. R., & Bissada, N. N. (2002). Criterion validity, severity cut scores, and test-retest reliability of the Beck Depression Inventory-II in a university counseling center sample. *Journal of Counseling Psychology*, *49*(3), 381.

Suarez-Jimenez, B., Balderston, N. L., Bisby, J. A., Leshin, J., Hsiung, A., King, J. A., … Ernst, M. (2021). Location-dependent threat and associated neural abnormalities in clinical anxiety. *Communications Biology*, *4*(1), 1–12.

Suarez-Jimenez, B., Bisby, J. A., Horner, A. J., King, J. A., Pine, D. S., & Burgess, N. (2018). Linked networks for learning and expressing location-specific threat. *Proceedings of the National Academy of Sciences*, *115*(5), E1032–E1040.

Teichman, Y., & Melineck, H. (1979). Hebrew translation of the State Trait Anxiety Inventory. *Tel Aviv: Tel Aviv University Press (in Hebrew)*.

Umemoto, A., Cole, S. L., Allison, G. O., Dolan, S., Lazarov, A., Auerbach, R. P., & Schneier, F. (2021). Neurophysiological predictors of gaze-contingent music reward therapy among adults with social anxiety disorder. *Journal of Psychiatric Research*, *143*, 155–162.

Zhu, X., Lazarov, A., Dolan, S., Bar-Haim, Y., Dillon, D. G., Pizzagalli, D. A., & Schneier, F. R. (2022). Resting state connectivity predictors of symptom change during gaze-contingent music reward therapy of social anxiety disorder. *Psychological Medicine*.

1. To minimize the burden put on participants (each session was approximately 60 minutes long) we decided to only administer the PHQ-9 on the day of participation, as it is considerably shorter than the BDI-II (9 items vs 21 items, respectively), therefor taking less time to complete. [↑](#footnote-ref-1)
2. Of the eligible LD participants at screening, one participant scored 9 on the PHQ-9 on the day of participation, three scored 7, three scored 6, and three scored 5. [↑](#footnote-ref-2)
3. All participants were trained toward the rounded shapes. Training toward rounded shapes was chosen randomly by the investigators prior to the study (i.e., when designing the experiment). [↑](#footnote-ref-3)
4. Of eligible LD participants at screening, three participant scored 9 on the PHQ-9 on the day of participation, one scored 8, one scored 6, and one scored 5. [↑](#footnote-ref-4)
5. Training matrices 1-5 were contrasted against the last five matrices (26-30) of the pre-training assessment task. [↑](#footnote-ref-5)
6. An a-posteriori power analysis using G\*Power implied that our power was approximately *1-β*~.75, given that our lowest significant correlation had a coefficient of *r*=.40 [↑](#footnote-ref-6)
7. Within-Cluster Sum of Squares Elbow Plots (for k>2) indicated 3 clusters as the optimal k [↑](#footnote-ref-7)