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Research paper

Altered emotion regulation at the earliest stage of visual perception in adolescents with non-suicidal self-injury

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ABSTRACT

Background: Deviating emotion perception affects the interpretation of emotional stimuli and is linked to maladaptive emotion regulation. In adolescents with non-suicidal self-injury (NSSI), it remains unclear whether emotion regulation is altered from the earliest stage of visual emotion perception. The early visual system decomposes visual scenes into various spatial frequencies, processes these components individually, and then integrates them to form perception. Altered processing of these frequencies impacts the decoding of emotional stimuli, influencing emotion regulation from the onset of perception.
Methods: This study explored emotion perception in 42 adolescent patients with NSSI and 43 healthy controls. Participants judged images of faces for emotional or neutral expressions across sessions featuring happy and sad valence. Gaussian apertures at random locations unveiled different facial areas at distinct spatial frequencies in each trial for emotion classification. Images from correct emotion classification were used to train an image classifier distinguishing emotional from neutral facial expressions in >33,000 trials per group and valence.
Results: Cross-validation demonstrated deviating performances between the NSSI and control models in classifying sad facial expressions, with the NSSI model more frequently misclassifying sad expressions as neutral. Layer-wise relevance propagation identified the underutilization of key facial features as contributors to the lower accuracy in the NSSI model. Further analyses revealed components of emotional competence as predictors of the utilization of specific facial regions for the classification of sad expressions.
Conclusion: The disparity in identifying sad emotions suggests the utilization of different spatial frequency information as an emotion-specific avoidance strategy among adolescents with NSSI.

1. Introduction

Non-suicidal self-injury (NSSI) is defined as the deliberate infliction of direct physical harm on one's own body without suicidal intent (Regier et al., 2013). NSSI affects approximately 18 % of adolescents globally (Moloney et al., 2024). Despite its high prevalence, numerous aspects of NSSI remain poorly understood. Recognizing the growing significance of NSSI as a subject of clinical research, the American Psychiatric Association included NSSI as a behavior requiring further investigation in the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders in 2013 (American Psychiatric Association and American Psychiatric Association, 2013). A crucial factor in understanding NSSI is emotion regulation. NSSI is often conceptualized as a maladaptive strategy for managing emotions (Erol and Inozu, 2024; Plener et al., 2009), providing short-term relief by reducing negative affect and increasing positive affect (Bruckbauer-Schwed et al., 2023; Claes et al., 2010; Jenkins and Schmitz, 2012). However, in which phase of the emotion regulation process this maladaptive coping strategy arises in patients with NSSI remains unclear. Within the process model of emotion regulation, accurate emotion perception is considered a crucial prerequisite for adaptive emotion regulation (Gross, 2014, 2015), whereas a deficiency in the ability to correctly recognize emotional

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facial expressions impairs the regulatory process and leads to an incongruent interpretation of social situations (In-Albon et al., 2013; Lane, 2000; Mayer, 2001; Yoo et al., 2006). This discrepancy between the actual social situation that is presented and subjective perception can cause distress and potentially foster maladaptive coping strategies (Izard et al., 2001).

Although emotion dysregulation is central to NSSI, there is a lack of consensus regarding emotion perception alterations in adolescents with NSSI, with studies yielding conflicting results. The discrepancies in emotion perception research can be categorized into four main areas. First, some studies suggest that individuals with NSSI exhibit increased sensitivity to specific emotions, demonstrating an enhanced ability to recognize and respond to emotional cues more accurately or rapidly than their peers (Lynch et al., 2006; Wagner and Linehan, 1999; Ziebell et al., 2017). Conversely, other research indicates decreased sensitivity, where patients with NSSI are more prone to errors, frequently misidentifying or confusing various emotional expressions (Robin et al., 2012; Seymour et al., 2016; Ziebell et al., 2020). Additionally, several studies have reported no significant differences in emotion perception between individuals with NSSI and healthy control groups or other patient populations, implying that their ability to recognize emotions may be comparable across these groups (In-Albon et al., 2015). Another line of research has identified a negative bias in NSSI patients, where neutral or ambiguous facial expressions are often misclassified as negative, suggesting a tendency towards a more pessimistic perception of emotional expressions (Daros et al., 2013). Lastly, a more recent study has highlighted altered cognitive activation in areas associated with inhibitory control during the processing of negative emotional facial expressions, suggesting that even when emotion recognition is intact, there may be disruptions in emotional regulation (Zhao et al., 2023). The discrepancies in methodology, sample size, and comorbidities across these studies could account for the conflicting results. The variations in methodology (i.e., presentation of either static or dynamic, grayscale or colored images, in isolation or with prosodic information, as subtle emotional expressions or strongly pronounced emotions, and the measurement of response time or accuracy) (In-Albon et al., 2015; Lynch et al., 2006; Minzenberg et al., 2006; Robin et al., 2012; Seymour et al., 2016; Wagner and Linehan, 1999; Ziebell et al., 2017, 2020) inevitably lead to different processing mechanisms influencing the response behavior of patients with NSSI. Therefore, it is essential to adopt an approach that begins at the earliest possible stage in the emotion perception process.

The early visual system decomposes images into spatial frequency channels, with low frequencies conveying global object shapes and high frequencies capturing detailed features, such as edges (Blakemore and Campbell, 1969; Perfetto et al., 2020). Spatial frequency information plays a key role in perceiving emotional facial expressions, and individuals vary in their ability to identify emotions based on this information (Becker et al., 2012; Cesarei and Codispoti, 2013; Kumar and Srinivasan, 2011). Although the impact of altered emotion perception in individuals with NSSI is debated, no study has investigated whether adolescent patients utilize spatial frequency information differently for categorizing emotions. By leveraging machine learning inspired by neural processing in the visual system (Rawat and Wang, 2017), an image classifier can be trained to recognize emotions from facial expressions using spatial frequency data. Convolutional neural networks excel at identifying subtle patterns (Al-Saffar et al., 2017; Rawat and Wang, 2017), potentially making them more suitable than traditional methods for identifying differences in emotion perception between groups, such as adolescents with NSSI and healthy controls.

Therefore, in this study, participants underwent an experiment to determine the spatial frequency information required for accurate classification of emotional facial expressions. By training an image classifier on the respective group datasets, we anticipate varying model accuracies in emotion classification between the NSSI and control models. By isolating the key facial features influencing the model accuracy, we aimed to identify the factors impacting emotion perception, including comorbidities, emotional competence, emotion regulation, and emotional reactivity.

2. Materials and methods

2.1. Participant recruitment

Patients engaging in NSSI behavior based on the DSM-5 criteria for an NSSI diagnosis on five or more occasions within the last year were recruited from the Clinic of Child and Adolescent Psychiatry, Psychosomatics and Psychotherapy of the University Regensburg, Germany (American Psychiatric Association and American Psychiatric Association, 2013). Exclusion criteria were specific comorbid disorders, such as autism, acute psychotic disorders, bipolar disorder, attention deficit hyperactivity disorder, or brain-organic diseases, an intelligence quotient (IQ) < 80, and other acute psychiatric conditions that could affect a patient's ability to consent. The healthy control group did not report any mental illness and had not received any outpatient, inpatient, day-care psychiatric, or psychotherapeutic treatment. We obtained written informed consent from all participants and their legal guardians. The Freiburg Visual Acuity Test (Bach, 2006) was performed to ensure adequate vision. All participants received compensation in the form of a voucher worth 25 euros. The University of Regensburg's Ethics Committee approved the study (ID: 21–2177-101), and the study was registered in the German Clinical Trials Register (DRKS; ID: DRKS00026252).

2.2. Psychological measurements

Sociodemographic information and clinical characterizations were obtained from all participants. The psychiatric diagnoses were determined using the German Version of the Mini-International Neuropsychiatric Interview for Children and Adolescents (M.I.N.I. KID 6.0, D. Sheehan et al., 2003; D. V. Sheehan et al., 1998) and cross-validated by experienced clinicians. Common comorbidities in NSSI were analyzed using the German version of the Structured Clinical Interview for DSM-IV, Axis II (SCID II, First and Gibbon, 2004; Wittchen et al., 1997), subsection BPD, the German version of the Beck Depression Inventory II (BDI-II, Beck, 1961; Kühner et al., 2007), and the German version of the Adolescent Dissociative Experiences Scale (A-DES, Armstrong et al., 1997; Brunner et al., 1999). In addition, the German Version of the Alexithymia Questionnaire for Children (AQC) with subscales assessing difficulty identifying feelings, describing feelings, and externally oriented thinking was administered (Jarvers et al., 2022; Rieffe et al., 2006). Suicidal and NSSI behavior were queried using the German version of the Self-Injurious Thoughts and Behavior Interview (SITBI-G, Fischer et al., 2014; Nock et al., 2007). Participants' intelligence scores were obtained from recent inpatient, outpatient, or day-care clinic assessments, or approximations were determined using the Culture Fair Intelligence Test, part A (CFT-20-R, Weiß, 2006). Emotional competence was determined using the Emotional Competencies Inventory (EKF-S & EKF-S+), which includes subscales measuring the ability to recognize one's own emotions, the ability to recognize emotions in others (EA subscale), the regulation and control of one's own feelings (RC subscale), emotional expressiveness, the regulation and handling of others' feelings, and the attitude towards emotions in general (EU subscale, Rindermann, 2009). Difficulties in emotion regulation were assessed using the German version of the Difficulties in Emotion Regulation Scale (DERS, Gratz and Roemer, 2004; Gutzweiler and In-Albon, 2018), which includes subscales measuring lack of emotional clarity, lack of emotional awareness, impulse control difficulties, non-acceptance of emotional responses, difficulties engaging in goal-directed behavior, and limited access to emotion regulation strategies. Lastly, emotional reactivity was assessed using the German version of the Emotion Reactivity Scale (ERS, Lüönd et al., 2023; Nock et al., 2008), which encompasses subscales measuring sensitivity, intensity, and persistence of perceived emotions.

2.3. Bubble technique

The bubble technique is a procedure designed to isolate crucial visual information from presented images (Gosselin and Schyns, 2001). The presented stimuli were overlaid with two-dimensional medium-gray masks and punctuated by randomly positioned Gaussian windows, referred to as bubbles. These bubbles selectively revealed specific regions of the face, corresponding to different spatial frequency information: larger bubbles exposed lower spatial frequencies, emphasizing broader facial features, while smaller bubbles revealed higher spatial frequencies, highlighting finer details. This method ensured that only specific portions of the facial expressions were visible at any given time, enabling a nuanced assessment of how spatial frequency content influences emotional perception. Participants were thus presented with a randomly assembled subset of spatial frequency information, effectively limiting the data available for their decision-making processes.

2.3.1. Stimuli

Stimuli for the experiment were sourced from the "Karolinska Directed Emotional Faces" database (Lundqvist et al., 1998). Individual frames were extracted to obtain static images, including neutral expressions and happy and sad expressions with reduced emotional expressivity to ensure comparability across stimuli. These stimuli underwent further processing, including conversion to grayscale, elliptic cut-outs, and matching of luminance and contrast. The resulting pictures were decomposed into a six-level Laplacian image pyramid (Simoncelli, 2015) to present the image content within non-overlapping spatial frequency scales. Next, opaque bubbles were superimposed on the images to reveal underlying facial features. The size of the bubbles was determined by the spatial frequencies, with lower frequency scales featuring larger bubbles and higher frequency scales featuring smaller bubbles (Fig. 1). Finally, the scales containing bubbles were merged to create a unified image for stimulus presentation. The density of the bubbles was adjusted using an adaptive threshold estimation procedure targeting a 75 % performance threshold (Watson and Pelli, 1983). For a detailed description of stimulus generation, see the supplementary material A.

As a result of this threshold estimation, customized stimuli were generated for each participant, incorporating the essential facial information necessary for accurate emotion classification, which were later utilized in a machine learning approach.

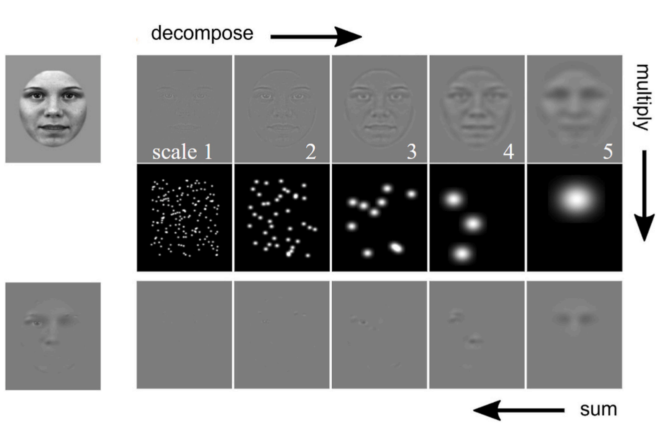


Fig. 1. Depiction of stimulus generation. Face images were decomposed into five subscales with non-overlapping spatial frequency bands from 3.13 to 106 cycles per face (cpf; top row). Gaussian apertures were placed at random locations, each subtending two cycles of the center spatial frequency of the scale ('bubbles', middle row). Face and bubble images were combined by element-wise multiplication and summed across scales (bottom row).

2.4. Procedure

Participants completed two conditions (happy: happy vs. neutral, sad: sad vs. neutral) in random order over 1–2 days. The average time between experimental sessions was 5.78 days, with a maximum interval of 50 days. A chin rest maintained a consistent viewing distance of 60 cm, and participants used their index fingers to respond. Participants indicated whether the displayed face showed an emotional or neutral expression by pressing labeled keys. Response keys were consistent within conditions but randomized between participants to control for effects of handedness.

2.5. Psychometric measures

Parametric and non-parametric tests were utilized to analyze group differences and equivalence. Independent sample *t*-tests and Welch's t-test were used for parametric analyses, whereas the Mann-Whitney *U* test was used for non-parametric analyses. A TOST test was used to assess group equivalence, and an exact Fisher's test compared categorical variables between groups. The effect size for parametric tests was determined using Hedge's g. Pearson's r was calculated for effect size in the Mann-Whitney U test. All results with multiple comparisons underwent correction using the false discovery rate (Benjamini and Hochberg, 1995), and the *p*-values correspond to this correction. The missing completely at random (MCAR) test (Thabtah et al., 2005) indicated random missing values for most questionnaires, which were addressed using the expectation-maximization (EM) algorithm (Moon, 1996). No MCAR values were detected for the EKF-S+ questionnaire, so no replacement method was applied, and group comparisons were carried out according to manual guidelines. As the A-DES was included in the study at a later stage due to an independent research question, six participants did not complete the questionnaire. These missing values were not imputed using the EM algorithm.

2.6. Residual network for 50 layers (ResNet50)

The ResNet50 image classifier (He et al., 2016) is a deep learning architecture designed for image classification tasks. In this study it was tailored for a binary classification (sad vs. neutral and happy vs. neutral) with no fixed layers except the classification layer. Input images were 224 × 224 pixels. The training configuration comprised an Adam optimizer (*PyTorch 2.0*, Kingma and Ba, 2017) with default beta values ($\beta1 = 0.9$, $\beta2 = 0.99$) and epsilon (10^{-8}), a learning rate of 0.001, no L2 regularization, a batch size of 64, and 100 epochs utilizing the cross-entropy loss function. Data augmentation techniques, including random affine transformations and horizontal flipping, were employed to enhance the diversity of the training dataset by applying transformations to the original image. The dataset was divided into training and testing sets using a split-half approach, in which each participant's data was equally allocated — half of the dataset for each condition went into the testing set, while the other half was used for the training set. The training datasets consisted of only stimuli that resulted in correct response reactions and were divided based on conditions and groups. Groups did not differ in their utilization of spatial frequencies for correct classification. The test dataset included stimuli from both groups under one condition. Model accuracy was evaluated per condition and group. Multivariate ANOVAs were carried out to analyze the effects of independent variables on model accuracy, including model (NSSI vs. control model), emotion (happy vs. sad), valence (emotional vs. neutral), and group dataset (control vs. patient dataset). Effect size was measured using generalized eta squared (η^2G, Bakeman, 2005).

2.7. Layer-wise relevance propagation

Layer-wise relevance propagation (LRP) is a method used to analyze the decision-making process of neural networks by identifying the diagnostic features of stimuli that contribute to the predictions (Montavon et al., 2019). In this study, LRP was utilized to determine the specific facial information that influenced the model's decision regarding whether an image represented an emotional or neutral expression.

LRP was carried out using Zennit (version 0.5.1) with default settings. Epsilon-plus-flat rule with an epsilon value of 10^{-6} was applied for relevance calculations. LRP images for binary classification (sad vs. neutral) were generated using both the NSSI and control model. Individual LRP images underwent smoothing by a 9×9 pixel Gaussian filter with a standard deviation of 3 pixels. The relevance proportion for accurately classifying sad emotions was computed for each participant, model, and pixel. Dependent *t*-tests were performed to ascertain differences in means between models for each pixel, participant, and model. Bonferroni correction (Sedgwick, 2012) was applied to the resulting t-values. Cluster correction was also performed using a permutation test, taking into account the number of neighboring significant pixels to identify reliable clusters of significant differences. Identified clusters of relevant facial regions were used for further analysis.

2.8. Individual LRP

For regression analysis, participant-specific LRP analyses were performed with split half datasets (training and testing of each participant individually) to obtain the participant-specific mean relevance portions per cluster. This method allowed for the exploration of how individual differences in comorbidity and emotional processing abilities influence the relevance of each cluster for the correct classification of emotional expressions.

On average, participant-specific datasets contained 399 ± 93 images. We hypothesized that clusters contributing more to the accurate classification of sad faces by the control model, as opposed to the NSSI model, would exhibit weaker associations with the level of comorbidities, difficulties in emotion regulation, and emotional reactivity while presenting stronger associations with higher emotional competence. Conversely, clusters predominantly utilized by the NSSI model for classification were expected to demonstrate stronger associations with higher levels of comorbidity, difficulties in emotion regulation, and emotional reactivity, as well as lower emotional competence.

2.9. Linear mixed model (LMM)

The LMMs were estimated via the restricted maximum likelihood (REML) method utilizing the “lme4” package in R (Bates et al., 2015). Individual differences were accounted for by including each participant as a random effect, resulting in a random intercept per person. Fixed effects included comorbid conditions, group membership, emotion processing questionnaires, age, school type, and the within-subject variable “cluster type” (C1, C2, C3), along with their interactions with questionnaire scores. Multiple emotion processing questionnaires were incorporated into the mixed linear model to assess various aspects of the emotion regulation process, including both perception and generation. This methodology enhances the ability to pinpoint specific emotion processing stages that contribute to the observed differences in emotion perception between the patient and control groups. The category “other” was removed from the variable “school type” to convert the variable into an ordinal scale, thereby resulting in the exclusion of one participant from the analysis. Due to a lack of convergence for the random slope coefficient of the variable “cluster type”, an intercept-only model was utilized with the significance level set at $\alpha = 0.05$. Categorical predictors were defined using C1 as the reference category, and continuous predictors were z-standardized and centered to address multicollinearity. Assumptions of LMMs were met. To aid in interpretability, the values of dependent variable (DV) “relevance proportion” were multiplied by scaling each individual's relevance proportion of clusters C1, C2, and C3 by a factor of 100,000. Model optimization involved identifying and excluding minimal predictor contributions to explain the variance. Final model comparisons utilized the Log-likelihood Fit Index (LLFI) and Akaike Information Criterion (AIC), supplemented by a χ^2 test to evaluate differences between the models.

3. Results

A total of 98 participants participated in this study. After exclusions due to failure to complete both experimental sessions ($n = 5$), withdrawal of consent ($n = 1$), later diagnosed exclusion criteria ($n = 1$), and performance issues ($n = 6$) which prevented threshold analysis, the final sample consisted of 85 participants aged 12 to 19 years. Sociodemographic details are presented in Table 1. The patient and control groups did not significantly differ in age ($U = 809.00$, $p = 0.409$, $r = 0.09$) but failed to establish equivalence at $\alpha = 0.05$ ($t(74.18) = 3.56$, $p < 0.001$). Fisher's exact test revealed a significant association between group membership and school type ($p < 0.001$), whereas no significant association was found between group membership and handedness ($p = 0.607$). Therefore, school type and age were included as predictors in the LMM. Given the significant group difference in school type, group differences in IQ were examined. No significant group difference was found ($t(77) = -0.26$, $p = 0.799$). In addition, there was no significant difference between groups in terms of visual acuity ($p = 0.061$). Group differences in questionnaires related to comorbidities and emotion processing are presented in Table 2.

Table 1
Demographic and clinical characteristics.

Demographic and clinical characteristics.				
Group	NSSI		Healthy Controls	
	N (%)	*M (SD)*	*N*	*M (SD)*
Biological sex				
female	42 (100)		43 (100)	
male	0 (0)		0 (0)	
Gender identity				
female	41 (97.6)		43 (100)	
male	1 (2.4)		0 (0)	
Age	42 (100)	15.84 (1.60)	43 (100)	16.41 (2.35)
School type				
Mittelschule	5 (11.9)		0 (0)	
Realschule	16 (38.1)		9 (20.9)	
Gymnasium	17 (40.5)		18 (41.9)	
FOS/BOS	1 (2.4)		3 (7.0)	
Apprenticeship	1 (2.4)		0 (0)	
University	1 (2.4)		13 (30.2)	
others	1 (2.4)		0 (0)	
Handedness				
right-handed	36 (85.7)		39 (90.7)	
left-handed	5 (11.9)		4 (9.3)	
ambidextrous	1 (2.4)		0 (0)	
ICD-10 psychiatric diagnoses				
F1	1 (2.4)		0 (0)	
F3	30 (71.4)		0 (0)	
F4	3 (7.1)		0 (0)	
F5	2 (4.8)		0 (0)	
F6	5 (11.9)		0 (0)	
F9	1 (2.4)		0 (0)	

Note. NSSI = non-suicidal self-injury. School type = After four years of elementary school, the Germany's education system branches into three tiers based on academic performance. The Mittelschule prepares for a variate of apprenticeships, the Realschule awards a general certificate of secondary education, and the Gymnasium and FOS/BOS provide a pathway to a university entrance qualification. ICD-10 diagnoses correspond to primary diagnoses. F1 = Mental and behavioral disorders due to psychoactive substance use. F3 = Mood (affective) disorders. F4 = Neurotic, stress-related and somatoform disorders. F5 = Behavioral syndromes associated with psychological disturbances and physical factors. F6 = Disorders of adult personality and behavior. F9 = Behavioral and emotional disorders with onset in childhood and adolescent.

Table 2
Group differences in psychometric measures.

	NSSI		Healthy Controls				
	n	*M (SD)*	*n*	*M (SD)*	*test statistic*	*p*	*effect size*
ERS	41	50.78 (18.63)	43	24.10 (14.60)	−7.34[1]	**< 0.001*****	1.60[3]
Sensitivity		24.83 (8.79)		12.31 (7.77)	−6.92[1]	**< 0.001*****	1.51[3]
Intensity		16.18 (7.19)		7.49 (5.20)	−6.32[1]	**< 0.001*****	2.60[3]
Persistence		9.78 (3.71)		4.26 (3.21)	−7.31[1]	**< 0.001*****	1.59[3]
DERS	41	129.33 (19.65)	43	68.96 (20.73)	46.00[2]	**< 0.001*****	0.82[4]
Clarity		18.68 (4.73)		9.65 (3.63)	142.50[2]	**< 0.001*****	0.72[4]
Awareness		20.59 (4.13)		13.60 (4.67)	244.00[2]	**< 0.001*****	0.62[4]
Impulse		19.00 (6.02)		9.26 (2.91)	131.50[2]	**< 0.001*****	0.73[4]
Non-acceptance		20.63 (5.98)		10.09 (3.93)	13900[2]	**< 0.001*****	0.73[4]
Goals		19.71 (3.76)		12.00 (4.72)	195.00[2]	**< 0.001*****	0.67[4]
Strategies		30.73 (6.08)		14.35 (6.60)	100.50[2]	**< 0.001*****	0.69[4]
AQC	42	1.19 (0.28)	43	0.53 (0.32)	137.00[2]	**< 0.001*****	0.74[4]
DIF		1.35 (0.46)		0.43 (0.44)	185.00[2]	**< 0.001*****	0.69[4]
DDF		1.62 (0.39)		0.55 (0.50)	117.50[2]	**< 0.001*****	0.76[4]
EOT		0.78 (0.31)		0.59 (0.34)	−2.67[1]	**0.009****	0.58[3]
EKF-S	41	2.63 (0.38)	43	3.68 (0.56)	131.00[2]	**< 0.001*****	0.73[4]
EE		2.29 (0.55)		3.85 (0.71)	95.50[2]	**< 0.001*****	0.77[4]
EA		3.63 (0.68)		3.93 (0.67)	2.06[1]	**0.043***	1.93[3]
RC		2.66 (0.55)		3.62 (0.59)	7.74[1]	**< 0.001*****	1.68[3]
EX		1.94 (0.34)		3.34 (0.85)	8.49[1]	**< 0.001*****	2.14[3]
EKF-S+	40	3.38 (0.51)	43	3.84 (0.51)	4.09[1]	**< 0.0001*****	0.90[3]
RA		3.28 (0.64)		3.62 (0.50)	2.70[1]	**0.009****	0.59[3]
EU		3.48 (0.59)		4.09 (0.60)	367.50[2]	**< 0.001*****	0.49[4]
BDI-II	42	35.69 (10.92)	43	4.93 (5.61)	18.00[2]	**< 0.001*****	0.84[4]
SCID II	42	10.25 (4.62)	43	0.33 (0.64)	0.00[2]	**< 0.001*****	0.89[4]
A-DES	38	4.41 (2.62)	41	0.97 (1.00)	95.50[2]	**< 0.001*****	0.75[4]

Note. [1] t-test, [2] Mann-Whitney-U test, [3] Hedge's *g*, [4] Person's *r*, ERS = Emotion Reactivity Scale, DERS = Difficulties in Emotion Regulation Scale, Clarity = Lack of emotional clarity, Awareness = Lack of emotional awareness, Impulse = Impulse control difficulties, Non-acceptance = Non-acceptance of emotional responses, Goals = Difficulty engaging in goal-directed behavior, Strategies = Limited access to emotion regulation strategies, AQC = Alexithymia Questionnaire for Children, DIF = difficulty identifying feelings, DDF = difficulty describing feelings, EOT = externally oriented thinking, EKF-S & EKF-S+ = Emotional Competencies Inventory, EE = Recognizing own emotions, EA = Recognizing emotions in others, RC = Regulation and control of own feelings, EX = Emotional expressiveness, RA = Regulation and handling of feelings in others, EU = Attitudes towards emotions. BDI-II = Beck Depression Inventory II, SCID II = Structured Clinical Interview for DSM-IV, Axis II, subsection BPD, A-DES = Adolescent Dissociative Experiences Scale. An FDR correction was applied. ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

3.1. ResNet50

Participants completed an average of 19.29 trials within the bubble experiment, with no significant differences between the experimental and control groups (sad condition: $t(83) = 0.83$, $p = 0.411$; happy condition: $t(83) = 1.74$, $p = 0.086$). Each trial included 60 bivariate decisions for emotion classification. >33,000 trials with correctly classified images per group and binary classification (sad vs. neutral and happy vs. neutral) were included in the model training. Significant effects were found for model ($F(1,41) = 7.95$, $p = 0.007$, $\eta^2G = 0.004$) and emotion ($F(1,41) = 312.65$, $p < 0.001$, $\eta^2G = 0.347$) on model accuracy, but not for valence ($F(1,41) = 0.00$, $p = 0.979$, $\eta^2G = 0.000$). Interaction effects were observed between model and emotion ($F(1,41) = 23.25$, $p < 0.001$, $\eta^2G = 0.015$), indicating that the NSSI model was less accurate than the control model in identifying sad emotions. A significant interaction effect was also found between model and valence ($F(1,41) = 704.87$, $p < 0.001$, $\eta^2G = 0.536$), with the NSSI model showing higher accuracy than the control model in classifying neutral facial expressions. Furthermore, an interaction effect was observed between emotion and valence ($F(1,41) = 206.00$, $p < 0.001$, $\eta^2G = 0.526$), indicating that neutral facial expressions were generally identified more accurately when presented with sad expressions and less accurately when presented with happy expressions. No significant effect was found for group dataset ($F(1.41) = 0.77$, $p = 0.387$, $\eta^2G = 0.003$), and no interaction effects were observed between group dataset and model, valence, or emotion (model: $F(1,41) = 0.07$, $p = 0.795$, $\eta^2G < 0.001$; valence: $F(1,41) = 0.21$, $p = 0.650$, $\eta^2G = 0.002$; emotion: $F(1,41) = 0.82$, $p = 0.371$, $\eta^2G = 0.001$). Triple interactions were observed exclusively between model, emotion, and valence ($F(1,41) = 213.12$, $p < 0.001$, $\eta^2G = 0.295$), indicating that the NSSI model performed worse than the control model in identifying sad emotions when presented alongside neutral facial expressions (Fig. 2). No four-way interaction was identified.

3.2. Layer-wise relevance propagation

We further addressed which facial information was utilized by the respective group models in regard to their differing accuracy for sad emotions. LRP images were generated for both models, identifying relevant pixels for correct emotion classification of sad facial expressions. Fig. 3 (A) displays the relevance of each pixel for correctly classifying sad facial expressions across both the NSSI and control models, demonstrating the comparability of pixel relevance for precise classification between the two models. Permutation tests identified three significant clusters (C1, C2, C3) in which the relevance for correct classification of sad facial expressions differed between the NSSI and control models. A difference map and t-value plot of dependent *t*-tests were generated to visualize differences between the NSSI and control

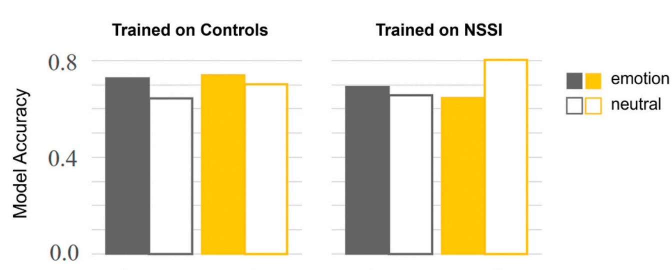


Fig. 2. Comparison of model accuracy for emotion perception between NSSI and control models. “Happy” and “sad” correspond to the conditions (happy vs. neutral, sad vs. neutral); emotion in the happy condition corresponds to happy, emotion in the sad condition corresponds to sad.

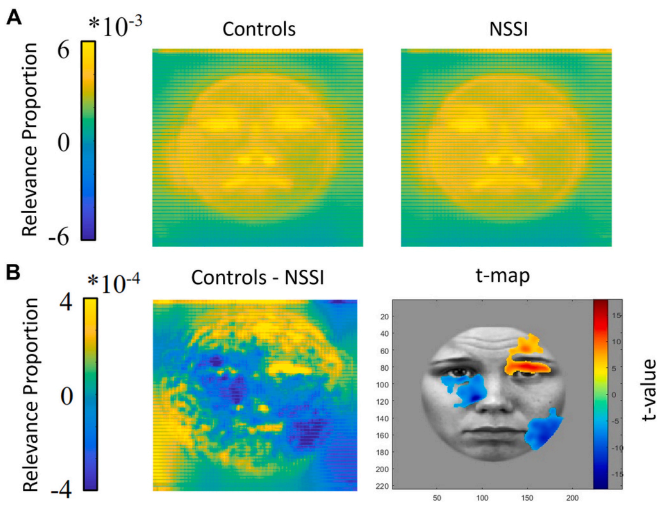


Fig. 3. Relevance of each pixel for accurate emotion classification and cluster generation. A: The relevance scores were averaged across participants. Yellow pixels indicate higher relevance scores for classifying sad facial expressions, whereas green and bluish pixels have lower relevance for identifying sadness. B: Results of the dependent *t*-tests per pixel, $p < 0.05$, Bonferroni-corrected. Each pixel represents the difference in relevance between the corresponding pixels of the two models. Positive values indicate that the pixel is more relevant for the control model, whereas negative values suggest greater relevance for the NSSI model in classifying sad expressions. Three clusters of differentiating relevance proportions were identified between the NSSI and control models: Cluster C1 comprised 1167 positive pixels in the left forehead and eye area ($p = 0.009$). Cluster C2 included 1110 negative pixels in the right lower eyelid and nasalis muscle ($p = 0.037$). Cluster C3 contained 1090 negative pixels in the left depressor anguli oris muscle ($p = 0.044$). As the control model demonstrated higher accuracy in classifying sad expressions compared to the NSSI model, increasing the utilization of C1 relative to C2 and C3 enhanced the likelihood of accurate recognition of sad facial expressions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

models in the relevance proportions for classifying sad facial expressions to provide insights into the distinctive features utilized by each model for emotion classification (Fig. 3, B).

3.3. Linear mixed model

Lastly, we hypothesized that the influence of comorbidities and emotion processing on the relevance of facial regions for emotion classification varies depending on the cluster type (C1, C2, C3) used for emotion recognition. Therefore, person-specific relevance proportions were generated for each identified cluster, and an LMM was created using C1 as the reference category. Initially, a full model was obtained including all predictors (group, AQC, SCID II, BDI-II, A-DES, EKF-S, EKF-S+, DERS, ERS, age, and school type) (Supplemental section B, Table B.1). Subsequently, significant effects of EKF-S and EKF-S+ were observed, leading to the creation of more refined models including subscales of the Emotional Competencies Inventory and optimized predictors (Supplemental section B, Tables B.2-B.4). All models exhibited comparable AIC and LLFI values and did not significantly differ from each other. Due to higher parsimony, the rEKF-S/S+ model was chosen for interpretation (Table 3).

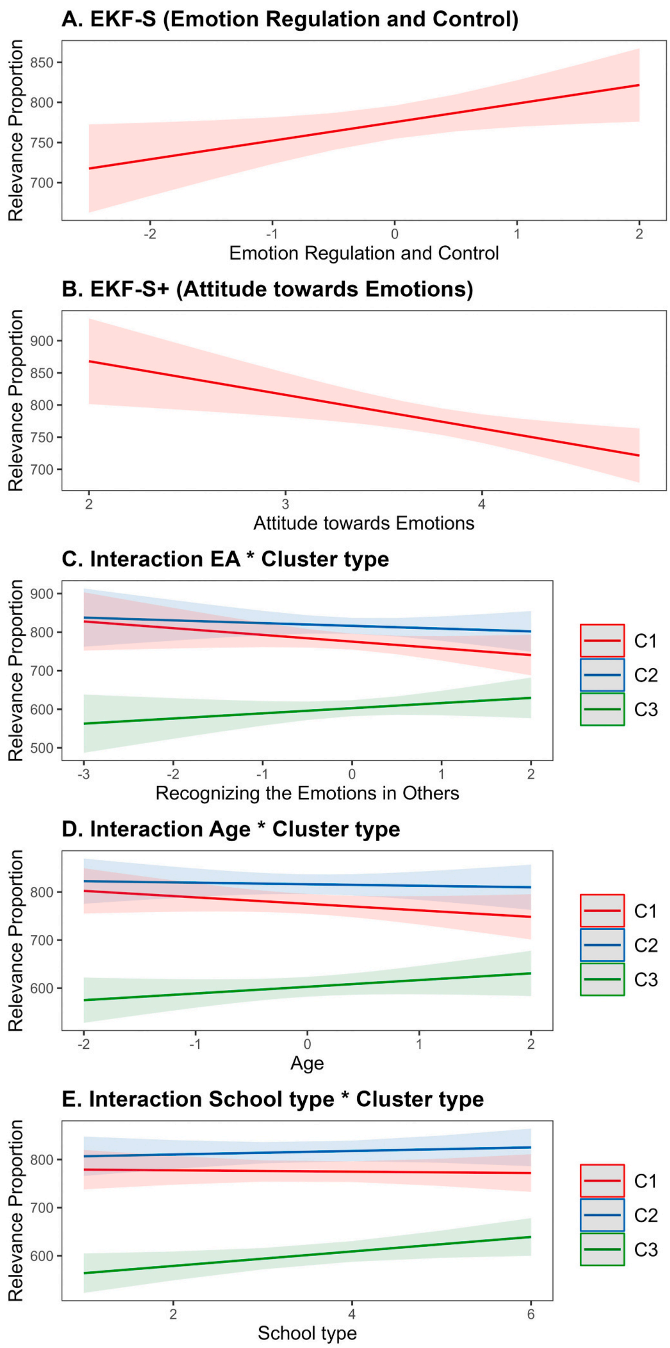
Some data points were missing for A-DES and school type. After including only complete cases, the analysis included 76 participants. The model explained 55 % of the variance with fixed factors (R^2*marginal*) and 79 % with the entire model (R^2*conditional*). Approximately 54 % of the total variance in the DV was attributed to individual differences among participants. To facilitate interpretation, cluster relevance scores were scaled by a factor of 100,000. The estimated residual variance ($\sigma^2 = 0.003$) before scaling indicated acceptable remaining uncertainty. The results from the LMM analysis revealed significant effects of components of emotional competence (EKF-S & additional scales EKF-S+) on the relevance of clusters for correct emotion classification (Table 3).

First, regardless of which facial regions were particularly suitable for classifying sad emotions, the relevance of all clusters for emotion recognition increased as the subjective ability to control and regulate one's own emotional states improved (RC subscale). Second, a heightened attitude towards emotions led to reduced utilization of all clusters for emotion recognition (EU subscale). An additional interaction effect was observed between the EKF-S (EA subscale) and cluster type C3, with the relevance of C3 increasing with higher subjective perception of the ability to recognize emotions in others. Simultaneously, the relevance of C1 and C2 decreased. Both age and school type showed significant effects on the relevance proportion, with C3 gaining relevance with increasing age and higher school type. Finally, the relevance of all clusters varied in classifying sad expressions, with the eye and forehead region having greater importance for correct classification compared to the mouth region. A comprehensive depiction of all effects can be found in Fig. 4.

Table 3
Influence of emotional competence, age, and school affiliation on emotion perception of sad facial expressions in the rEKF-S/S+ model.

	Relevance Proportion					
Predictors	*Estimates*	*std. Error*	*CI*	*Statistic*	*p*	*df*
(Intercept)	775.40	10.45	754.73–796.08	74.17	**< 0.001*****	133.56
EKF-S (EA)	−17.44	12.29	−41.78–6.90	−1.42	0.158	113.30
EKF-S (RC)	23.14	10.33	2.52–43.75	2.24	**0.028***	70.00
EKF-S+ (EU)	−34.82	12.06	−58.88 to −10.77	−2.89	**0.005****	70.00
Age	−13.51	10.75	−34.77–7.75	−1.26	0.211	131.38
School type	−2.15	10.56	−23.04–18.74	−0.20	0.839	132.66
C2	40.85	10.06	20.96–60.74	4.06	**< 0.001*****	144.00
C3	−172.60	10.06	−192.49 to −152.71	−17.15	**< 0.001*****	144.00
EKF-S (EA) × C2	10.30	10.22	−9.90–30.50	1.01	0.315	144.00
EKF-S (EA) × C3	30.80	10.22	10.60–50.99	3.01	**0.003****	144.00
Age × C2	10.34	10.21	−9.84–30.52	1.01	0.313	144.00
Age × C3	27.46	10.21	7.28–47.64	2.69	**0.008****	144.00
School type × C2	7.74	10.11	−12.25–27.73	0.77	0.445	144.00
School type × C3	25.00	10.11	5.01–44.98	2.47	**0.015***	144.00

Note. The relevance proportions (DV) are scaled by a factor of 100,000. C1 corresponds to the reference cluster. If no significant interaction effect is observed between a predictor and C2 or C3, this implies that the relationship between the reference category C1 and the predictor also applies to C2 and C3. CI corresponds to the 95 % confidence interval. EKF-S & EKF-S+ = Emotional Competencies Inventory, EA = Recognizing emotions in others, RC = Regulation and control of own feelings, EU = Attitude towards emotions. An FDR correction was applied. ***p < 0.001; **p < 0.01; *p < 0.05.



(caption on next column)

Fig. 4. Factors influencing emotion perception between the NSSI and control models. The x-axis represents each significant predictor, centered around the mean. Each unit step on this scale corresponds to 1 standard deviation away from the average score of the predictor. The y-axis displays the mean relevance proportion of pixels in clusters (C1, C2, C3) for correctly classifying a sad facial expression by the image classifier, relative to the entirety of all pixels. If the interaction between the relevance proportions of clusters C2 and C3 with the predictor does not significantly differ from the interaction of reference cluster C1 with the predictor, then the associations are presented jointly. This implies that the association between reference category C1 and the predictor also extends to C2 and C3. If the association between the predictor and C2 or C3 differs from the association with C1, interactions between predictors and clusters are presented individually. A: Emotion regulation and control = Ability to regulate and control one's own feelings; Emotional Competencies Inventory (EKF-S) Subscale. B: Attitude towards Emotions: According to the manual, higher scores on the Emotional Competencies Inventory additional scales (EKF-S+) “Attitude towards Emotions” indicate that participants perceive emotions as particularly significant and prefer a positive approach to emotional states with a desire to participate in the emotional experiences of others. C: EA = the ability to recognize the emotions in others. D: Age = age in years and month. E: School type is displayed in hierarchical order (Mittelschule, Realschule, Apprenticeship, FOS/BOS, Gymnasium, University). Category “others” was excluded from the analysis.

4. Discussion

This study investigated altered emotion perception in female adolescents with NSSI, with a focus on exploring differences in the utilization of spatial frequency information between groups. We also sought to identify key facial features for emotion recognition among both groups and to examine how comorbid conditions and emotion processing influence alterations in emotion perception.

The machine learning results showed that patients utilized visual spatial frequency information for sad emotions differently than the control group. The model trained on patient data tended to misclassify sad facial expressions as neutral, indicating a tendency of the patient group to interpret sad emotions as less emotional. One potential interpretation of the results suggests that patients employ an avoidance strategy, particularly towards sad or unpleasant emotions. Individuals with NSSI often struggle with emotion regulation, finding it difficult to cope with distressing emotional states (Nock et al., 2008; You et al., 2018). This can lead to a more intense reaction to emotional stimuli (Kandsperger et al., 2022; Mayo et al., 2021) and to the individual utilizing less effective or less frequently chosen adaptive emotion regulation strategies (Giordano et al., 2023; You et al., 2018). Consequently, situations that may trigger aversive emotions become risk factors for distress and NSSI.

Furthermore, evidence links adverse childhood experiences with both NSSI (Serafini et al., 2017) and altered emotion perception (Bérubé et al., 2023). Adolescents with NSSI often report high rates of childhood maltreatment, such as emotional, physical, or sexual abuse, as well as neglect (Calvo et al., 2024). Avoidance strategies, which reduce exposure to distressing stimuli — such as unresolved childhood trauma or emotionally charged interpersonal conflicts — could serve as a protective mechanism to prevent unsuccessful or maladaptive emotion regulation as in NSSI. Avoiding distressing stimuli during perception may help patients reduce the likelihood of unsuccessful emotion regulation by leaving the distressing situation early enough. This interpretation aligns with Chapman and colleagues' experiential avoidance model (Chapman et al., 2006), which suggests that individuals with NSSI tend to actively avoid unpleasant experiences instead of accepting and processing them appropriately. However, this avoidance strategy may ultimately lead to difficulties regulating emotion, promoting NSSI in the long term (Chapman et al., 2006). Thus, the avoidance strategy demonstrated by patients in this study can be seen as a maladaptive emotion regulation strategy.

We further examined which facial features were utilized by the groups in perceiving emotions. Both the control and NSSI models considered regions around the eyes, nose, and mouth as crucial for accurate classification of sad emotions. However, the NSSI model showed a preference for areas adjacent to these prominent facial features. This suggests altered emotion perception in adolescents with NSSI that manifests through potential avoidance of relevant facial information, thereby influencing their emotional response to emotion-inducing situations.

Regression analysis showed that, as participants' self-rated ability to regulate their own emotions increased, all facial clusters became more important for emotion recognition, indicating a lack of avoidance strategy. Adolescents who do not have difficulty regulating emotion are expected to not engage in perceptual avoidance of emotionally challenging states in others, as they can adaptively regulate their own emotional reactions. Individuals who value emotions tended to use facial information less selectively, possibly indicating a broader focus on emotional cues. Interestingly, individuals with higher self-perceived abilities in recognizing emotions in others tended to focus less on the eye region and more on the mouth region, suggesting that adeptness in discerning emotional cues may lead to quicker avoidance of emotionally stimulating stimuli. Recognizing the negative emotional state of others early may enable individuals to avoid confrontations by leaving distressing situations promptly, potentially aiding in their emotion regulation. As C3 was predominantly utilized by the patients, this effect is evident within the patient group. Similar results were identified for age and school type, indicating a transition towards emphasizing the mouth area, potentially as a development and experience-based coping strategy to avoid emotionally intense stimuli, such as the eyes (Bayless et al., 2011; McCrackin et al., 2023). Notably, neither comorbidities nor group membership could explain the altered emotion perception in patients, which might suggest that the altered perception of emotion in adolescents with NSSI was present before the onset of the mental illness, potentially serving as a risk factor for its development. Similar findings were reported by Brotman et al. (Brotman et al., 2008), who examined emotion recognition in patients with bipolar disorder, adolescents at genetic risk for bipolar disorder, and healthy controls. The at-risk group exhibited deficits in classifying emotional facial expressions comparable to the patient group, and both significantly differed from the control group (Brotman et al., 2008).

4.1. Strengths and limitations

This study is the first in the literature to examine whether emotion processing is altered in adolescent NSSI patients during emotional stimulus perception using the bubble technique. The threshold design customizes stimuli based on each participant's performance level, generating individualized stimulus materials that enhance the machine learning model's ability to discern emotional perception differences between patients and controls. Additionally, this design allows for the prompt detection of sudden changes in response patterns, such as those caused by impulsivity or response bias, ensuring data integrity throughout the analysis. Through an innovative machine learning approach, subtle patterns were identified in patients' emotion perception, surpassing traditional methods such as reaction time and response accuracy. By eliminating reliance on reaction times, the method reduces biases from impulsive responses, enabling a more accurate assessment of emotional recognition. Machine learning techniques, particularly image classifiers, excel at capturing subtle emotional cues, such as barely visible emotional expressions, which are critical in this study. Operating at the pixel level, these classifiers detect fine variations, including micro-expressions, that standard analyses might overlook, increasing the likelihood of identifying group differences. The machine learning models were trained using images reflecting the exact spatial frequency information necessary for emotion recognition by the groups, enabling the identification of clear and methodologically sound differences in perception. Furthermore, the study's strength lies in its integration of behavioral methods, validated questionnaires, and diagnostic interviews, facilitating a comprehensive analysis of factors influencing emotion perception in NSSI patients. The study also benefits from a representative sample of highly burdened adolescents with NSSI, ensuring accurate diagnoses validated by experienced clinical experts.

Despite thorough planning and execution, this study has limitations that may impact the interpretation of results. Primarily, the physiological features of highly expressive facial emotions vary significantly. To enhance the comparability of stimuli, emotions were presented at reduced intensity in the bubble experiment. As a result, the emotion perception of NSSI patients may align with controls when presented at full intensity or with additional cues such as facial movements or gaze directions. Moreover, achieving group equivalence was challenging despite non-significant age differences. This suggests a potential influence of age or development on our results, possibly masking group disparities. Another limitation of this study is the unequal statistical power between the models for cluster generation and the person-specific models for the LMM analysis. Due to the lower test power, subtler effects or interactions between predictors and DV in the LMM may not have been detected. While we controlled for various comorbidities associated with NSSI, we did not specifically assess childhood trauma. Given the established association between childhood maltreatment and altered emotion perception, we therefore cannot exclude the possibility that such traumatic experiences may have contributed to changes in emotion perception in our participants. Additionally, because NSSI is more prevalent among females, we included only female participants in this study. Consequently, we cannot draw conclusions about whether emotion perception is similarly altered in male patients with NSSI. Moreover, although most participants were receiving treatment, we did not gather information on the duration of treatment or any medications prescribed, nor did we determine whether the therapeutic focus included enhancing emotion recognition. Certain therapeutic approaches, such as dialectical behavior therapy and schema therapy, focus on training emotional competence and perception (Fassbinder et al., 2016), which may obscure additional group differences due to therapy status. Therefore, future research should explore how therapy status influences emotion perception in individuals with NSSI. Targeted training in emotion recognition could potentially reduce group differences and support adaptive emotion regulation, which might alleviate NSSI behaviors over time.

5. Conclusion

In conclusion, this study identified altered emotion perception in adolescents with NSSI, which was marked by reduced recognition of sad facial expressions due to the use of different spatial frequency information. Our results suggest that altered emotion perception in patients is skill-based and influenced by individual experiences and developmental processes.

CRediT authorship contribution statement

Alexandra Otto: Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Irina Jarvers:** Writing – review & editing, Methodology, Conceptualization. **Stephanie Kandsperger:** Writing – review & editing, Resources, Conceptualization. **Robert Bosek:** Software, Methodology. **Jens Schwarzbach:** Supervision, Methodology. **Romuald Brunner:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Gregor Volberg:** Writing – review & editing, Validation, Supervision, Software, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jad.2024.12.055.

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