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Time perception at resting state and during active motion: The role of anxiety and depression

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ABSTRACT

Background: Time perception and motion intensity are interrelated factors that may influence symptom expression and severity in case of various psychiatric conditions, including anxiety and depression.
Aims: The present study aimed to 1) explore the associations between the intensity of physical activity, time perception, impulsivity, anxiety and depressive symptoms, and to 2) investigate the extent to which resting state motion intensity can be used to identify the assessed psychiatric conditions.
Methods: 20 healthy controls and 20 psychiatric patients (with either anxiety or depression-related diagnoses) were included in the study and filled out a questionnaire consisting of validated anxiety, depression and impulsivity measures. Time perception was measured by a computerized time production task, whereas motion intensity was analyzed by a motion capture and analysis software. Respondents were randomly assigned to an experimental (with active motion task) and non-experimental group (resting state conditions). Both subgroups were repeatedly assessed, in order to explore changes in motion intensity, time perception and psychiatric symptom levels.
Results: Random forest regression analysis identified the level of impulsivity, depression and anxiety as the strongest predictors of resting state motion intensity, while a path analysis model indicated that controls and psychiatric patients show different pathways regarding the connection between motion intensity changes, time production ratio alterations and symptom reduction.
Conclusions: Our study implies the importance of distinguishing between clinical and subclinical severity of psychiatric symptoms when considering the association between motion intensity, time perception, anxiety and depression. Potential transdiagnostic relevance of resting state motion intensity is also addressed.

1. Introduction

The ability of perceiving time (including circadian, interval, and millisecond timing) is a fundamental function for many species, affecting the sleep-wake cycle, appetite, motor control, speed estimation, and risk perception (e.g. Zhang et al., 2014; Burge and Geisler, 2015; Monroe et al., 2017; Starling, 2019), and as such, time perception (TP) should be considered a multifactorial phenomenon. As an attempt to summarize some of the key genetic, neurobiological and cognitive psychological factors identified in the past years, Fig. 1 illustrates an integrative model of TP.

With regard to the scope of the current research, the impact of physical activity on both TP and the current mood is of heightened importance. As Behm and Carter highlighted in their review (2020), physical activity influences TP through a number of factors (e.g., age, intensity of exercise, contraction types, body temperature, gender, etc.), implying a complex relationship between TP and motion experiences. From a psychiatric point of view, the majority of former findings indicated dilated TP (e.g. Yoo and Lee, 2015; Kent et al., 2019a; Choi et al., 2021) in case of both anxiety and depression, although time dilation was linked to high-arousal negative stimuli in case of anxiety and low-arousal negative stimuli in case of depression, suggesting symptom-specific subtle differences in the subjective experience of dilated time. As Thönes and Oberfeld further noted (2015), the duration

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of the estimated time is also decisive in terms of TP: depressed individuals, for instance, might show a tendency of overproducing short and underproducing long duration intervals. Considering the beneficial effects of physical exercise on anxiety and depression, available meta-analyses (Kvam et al., 2016; Aylett et al., 2018) support the relevance of implementing exercise as a complementary therapy in psychiatric care.

The aim of the present study was two-fold. As a primary goal, we aimed to examine the associations between the intensity of physical activity, TP and specific mental states (anxiety and depressive symptoms) in a clinical and non-clinical sample, in order to provide a possible explanatory model for the beneficial therapeutic effects of physical activity among psychiatric patients, through changes in the inner sense of time. As a secondary goal, we aimed to investigate the extent to which locomotor activity measured at resting state can be informative regarding the presence of anxiety and depressive symptoms. Clinical observations and empirical findings support the assumption that anxiety and depression may influence the patient's locomotor activity (Lyra et al., 2016), with anxiety characterized by muscular tension, inner turmoil, and restlessness resulting in, for instance, recurring self-soothing behaviors (e.g. Uvnäs-Moberg et al., 2015), such as frequent self-tooching and leg bouncing, while former subtle face and gesture analysis approaches identified reduced facial expressions and head movements in depressed patients (Kacem et al., 2018). Besides anxiety and depression, we selected impulsivity as a potential covariate, as impulsivity is a relevant correlate of both TP (Paasche et al., 2019) and the intensity of physical activity (Castañer et al., 2020).

2. Materials and methods

2.1. Sample and procedure

The clinical subsample of our study consisted of treatment seeking individuals diagnosed with either anxiety disorders, mood disorders, or mixed anxiety and depressive disorder. These participants were recruited from the patients of the National Institute of Mental Health, Neurology and Neurosurgery – Nyírő Gyula Hospital (Budapest, Hungary). Control subjects were students of the Faculty of Health Sciences of Semmelweis University (Budapest, Hungary), and were invited via mailing lists. Exclusion criteria included any psychiatric diagnosis in these cases. Considering the limited sample size of the study, respondents from both subgroups were randomly assigned to either the

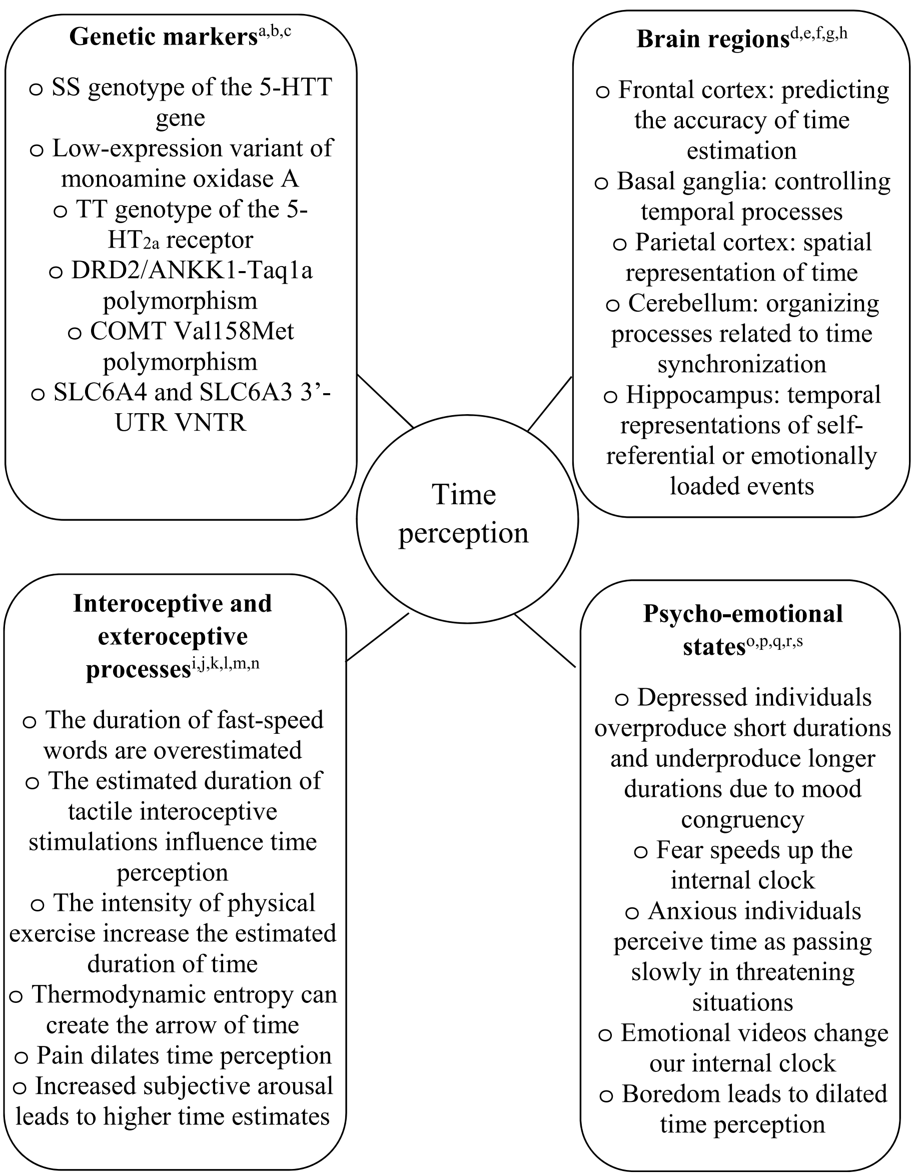

Fig. 1. An integrative model of time perception
Sources: [a]Sysoeva et al., 2010; [b]Wiener et al., 2011; [c]Bartholomew et al., 2015; [d]McFarland and Glisky (2009); [e]Jones et al., 2008; [f]Magnani et al., 2010; [g]Del Olmo et al. (2007); [h]Kraus et al., 2013; [i]Zhang et al., 2014; [j]Di Lernia et al. (2018); [k]Edwards and McCormick (2017); [l]Ghaderi, 2019; [m]Rey et al., 2017, [n]Schwarz et al., 2013; [o]Kent et al., 2019a, [p]Fayolle et al., 2015; [q]Yoo and Lee (2015); [r]Özgör et al., 2018; [s]Zakay, 2014.

experimental group (i.e. resting state at first measurement and active motion task at second measurement) or the non-experimental group (i.e. resting state at both measurement points) by following the method of block randomization. Block randomization is usually applied in case of small samples in order to still ensure equal subgroup sizes. Blocks represented predetermined group assignments (experimental vs. non-experimental). As regards to block size, which is a multiple of the number of subgroups, we selected an 8 block-solution for our study. The active motion task of the experimental group (consisting of healthy controls and psychiatric patients in equal numbers) was to ride an indoor minibike for 2 min during the time production task. All participants were video recorded during both the resting state and/or the active motion task during this 2 × 2 minute time interval. These videos were then analyzed with a motion capture and analysis software. A computerized time production task was applied as a measure of TP. The research adhered to all ethical principles for the conduct of research with humans outlined by the Declaration of Helsinki. Ethical approval was provided by Semmelweis University Regional and Institutional Committee of Science and Research Ethics (ethical approval number: SE RKEB 49/2021).

2.2. Measures

Basic demographic variables consisted of age, gender, perceived socioeconomic status (1 = much below the average; 7 = much higher than the average) and educational background (1 = elementary school or less; 7 = PhD or postdoctoral degree).

2.2.1. Current mood: depression and anxiety measures

Depression severity was assessed by the 9-item Hungarian version of the Beck Depression Inventory (BDI-9) (Beck et al., 1961; Rózsa et al., 2001). Respondents evaluate nine statements regarding their current mood on a 4-point Likert scale (1 = not at all; 4 = completely true). In the current study we used the total score of BDI-9 as a measure of depression severity. Good internal consistency of the total scale justified its application (Chronbach's alpha = 0.88).

Anxiety level was measured by the Spielberger State Anxiety Inventory (STAI-S) (Spielberger et al., 1970; Szigethy and Takács, 2015). STAI-S consists of 20 items, and uses a 4-point Likert scale (1 = almost never, 4 = almost always). The scale's total score (with a maximum of 80 points) was used as an estimate of the current severity of anxiety. Excellent internal consistency was found for the total scale (Chronbach's alpha = 0.91).

Changes between pre- and post-experimental situations were measured by using the depression and anxiety scores of the Emotion Thermometers (ET) (Mitchell et al., 2010). ET is mostly used and adopted for the population of oncological patients as a visual analog screening tool to identify emotional disorders. It consists of five subscores (from 0 to 10) representing the level of distress, anxiety, depression, anger, and a need for help. Participants were instructed to circle the number on each scale that best desribes their actual emotional state.

2.2.2. Impulsivity

As a potential confounder/covariate of both TP and the intensity of physical activity, impulsivity was measured by the 21-item Barratt Impulsiveness Scale Revised (BIS-R-21) (Kapitány-Fövény et al., 2020), a brief version of the Barratt Impulsiveness Scale (Patton et al., 1995), one of the most widely used measure of impulsivity. The scale, using a 4-point Likert scale (1 = rarely never/never; 4 = almost always/always), consists of three subscales with acceptable internal consistency identified in the present study: 1) Cognitive impulsivity (Chronbach's alpha = 0.65); 2) Behavioral impulsivity (Chronbach's alpha = 0.75); 3) Impatience/restlessness (Chronbach's alpha = 0.68). We used the total score of the scale as a general estimate of the level of impulsivity (Chronbach's alpha = 0.65).

2.2.3. Time perception: a time production task

A computerized verbal time production task was used as a measure of TP. Participants counted the seconds aloud, while the investigator administered the respondents' current time estimations at six measurement points (at 15, 30, 45, 60, 75 and 90s) indicated by a flashing signal on screen. In this way, it became possible to compare chronological/objective and subjective time. The whole computerized task lasted for 2 min (with a brief instruction part at the beginning), and it was repeated again after the participants had filled out the questionnaire. Similarly to the approach followed by O'Regan et al. (2017), a time production ratio was calculated: each time interval produced by the respondents were divided by the actual, chronological intervals. A time production ratio smaller than 1 represented underproduction, whereas a score above 1 implied overproduction of time duration. Within the confines of this trial, overproduction of time meant that the participant showed an accelerated rate of counting the seconds (i.e. estimating and producing more seconds than the actual elapsed time), suggesting a *faster* perception of time, in other words, acceleration. Since, unlike many other researchers, we did not apply any distractors and therefore allowed counting during the time production task, participants eventually evaluated the passage of time in small time units throughout the 90 s duration of the task. Chronometric counting is usually regarded as a confounder in the study of human TP as it may conceal existing timing alterations and result in deviations from the scalar property of temporal processing (e.g. Riemer et al., 2022). The reason why we still allowed chronometric counting was based on the insights that 1) the engagement in counting can have methodological benefits as well, such as participants may apply the same strategy (e.g. Perbal et al., 2003), 2) counting is indeed a *natural* human strategy to employ in TP tasks (Ben-Soussan and Glicksohn, 2018), while adding distractors (e.g. by using a dual-task paradigm) can introduce a different unnaturalistic confound, 3) counting, but not timing, activates the primary motor cortex (Hinton et al., 2004), while, as recent evidence highlights, the experience of time itself is computed within the motor system (Wiener et al., 2019), and 4) timing with and without counting may still lead to comparable results (Barholomew et al., 2015). Finally, as an analogue to the formula describing the deviation from a balanced time perspective suggested by Jankowski et al. (2020), perceptive deviation from chronological time was calculated as the square root of the sum of squared differences between one's subjective time production scores, and the objective time points, both at baseline and second measurements.

2.2.4. Motion capture and analysis

The Kinovea v.0.8.15., an open source, freely available motion analysis software under GPLv2 license, was used for motion capture and analysis. Motion distance data was first exported to Excel and then measured as the average deviation from a fixed point - located on either the knees or the hand - in terms of x (i.e. horizontal movement) and y axis (i.e. vertical movement) score ranges. In both cases, the following formula was applied: =SQRT(AVERAGE(POWER(cell range; 2))). We also created a variable labeled as 'motion distance', calculated as the mean of both leg (such as tapping or bouncing) and arm motions' (such as scratching or stretching) distance values. This variable thus represented the intensity of the overall movements captured during either the resting state or the active motion test situations.

2.3. Statistical analyses

Descriptive and basic comparative statistics were computed in relation to subgroup differences. In order to use the anxiety and depression subscores of the ET as measures of active motion induced changes, we first explored their correlation with the STAI-S and BDI-9 total scores, using Spearman's rank correlation analyses. A similar statistical approach was used to investigate the associations between perceptive deviation from chronological time at baseline measurement and the severity of psychiatric symptoms. All of these calculations were performed in SPSS v. 26 (IBM Corp, 2019).

As a second step, we performed random forest regression analysis using the RandomForestSRC package (Ishwaran and Kogalur, 2021). Resting state motion intensity was entered as the dependent variable while the following variables were entered as predictors: age, gender, clinical grouping variable (clinical vs. control), ET anxiety, ET depression, STAI total, BDI total, BIS-R-21 total, perceptive deviation from chronological time, and time production ratio. Nodesize and the number of variables randomly selected as candidates for splitting a node were selected to achieve the lowest out of bag error. The forest consisted of 500 trees. We applied swor (sampling without replacement) resampling to grow the trees and all variables were included. Minimal Depth and permutation Variable Importance measures (VIMPs) were calculated (Ehrlinger, 2016; Ishwaran, 2007).

Finally, as a structural equation modelling (SEM) approach, a path analysis model was tested to explore structural relationship between group membership (control vs. clinical), differences in motion intensity and time production ratio (covariates) and the differences in ET anxiety and depression scores between first and second measurements. A case-wise/full-information ML (maximum likelihood) estimation with nlminb optimization was used. A model was acceptable if root-mean-square error of approximation (RMSEA) < 0.08, comparative fit index (CFI) > 0.95, non-normed fit index or Tucker-Lewis index (TLI) > 0.95. For this model, the *lavaan* (Latent Variable Analysis) package (Rosseel, 2012) was used. Besides the aforementioned model fit indices, best performing models were selected on the basis of lower BIC (Bayesian Information Criterion) scores, and avoiding over-fitting/saturation by reducing the number of explanatory variables.

Calculations were performed with R 4.0.5 (The R Core Team, 2021).

3. Results

3.1. Sample characteristics

Altogether, 40 participants were included in the study (20 healthy controls and 20 psychiatric patients), with a majority of female respondents (57.5%). The mean age was 28.6 (SD = 6.97). The two subgroups showed no significant differences in terms of age ($t = 1.82$, $p > 0.05$), gender distribution ($\chi2 = 2.56$, $p > 0.05$), educational background ($U = 182$, $p > 0.05$), perceived socioeconomic status ($U = 199$, $p > 0.05$), impulsivity level ($t = 1.67$, $p > 0.05$) or motion intensity captured at baseline resting state measurement ($t = 0.67$, $p > 0.05$). Significant differences, however, occurred in case of the level of anxiety ($t = 5.84$, $p < 0.001$; $t = 4.43$, $p < 0.001$) and depression ($t = 3.93$, $p < 0.001$; 4.62, $p < 0.001$) as measured by STAI-S and BDI-9 total scores and the ET subscores, respectively, the level of perceptive deviation from chronological time ($t = 3.08$, $p < 0.01$) and time production ratio ($t = 2.59$, $p < 0.05$) at baseline resting state measurement.

As regards to the distribution of psychiatric diagnoses within the clinical subgroup, 6 patients were diagnosed with major depressive disorder (30%), 5 patients with generalized anxiety disorder (25%), 4 patients with mixed anxiety-depressive disorder (20%), 3 patients with panic disorder (episodic paroxysmal anxiety) (15%), 1 patient with anxiety disorder, unspecified (5%), 1 patient with recurrent depressive disorder (5%). Regarding randomized assignments to the experimental and non-experimental conditions, both subgroups consisted of 20 participants (with 10 healthy controls and 10 psychiatric patients randomly assigned to each condition). Table 1 summarizes detailed sample characteristics and differences between the subgroups of healthy controls and psychiatric patients.

3.1.1. Concurrent validity of the emotion thermometer subscores

Regarding the results of Spearman's rank correlation analyses in terms of the associations between anxiety and depression levels measured by the STAI-S and BDI and the ET anxiety and depression subscores, moderate correlations between STAI-S and ET anxiety ($r_S = 0.56$, $p < 0.001$) and between BDI-9 and ET depression ($r_S = 0.47$, $p < 0.01$) indicated acceptable concurrent validity, and therefore justified the use of the ET indices as measures of active motion induced changes.

Table 1
Sample characteristics and subgroup differences.

		Healthy controls (n = 20)	Psychiatric patients (n = 20)	χ2 test/ independent sample *t*-test/ Mann Whitney *U* test
Demographics	Age Mean (SD)	26.65 (6.34)	30.55 (7.19)	t = 1.18
	Gender distribution n of female (%)	14 (70)	9 (45)	χ2 = 2.56
	Level of education Mean (SD)	5.20 (0.41)	5.25 (0.91)	U = 182
	Perceived socioeconomic status	4.60 (0.88)	4.60 (0.99)	U = 199
Time perception and motion data	Baseline motion intensity Mean (SD)	18.86 (6.09)	20.80 (11.47)	t = 0.67
	Perceptive deviation from chronological time at baseline measurement Mean (SD)	15.11 (8.95)	28.44 (17.14)	t = 3.08**
	Time production ratio Mean (SD)	0.89 (0.07)	0.81 (0.13)	t = 2.59*
Level of anxiety and depression	STAI-S total score Mean (SD)	33.75 (6.52)	50.75 (11.27)	t = 5.84***
	BDI-9 total score Mean (SD)	14.60 (3.49)	21.55 (7.10)	t = 3.93***
	ET: baseline anxiety score Mean (SD)	1.90 (1.17)	4.70 (2.58)	t = 4.43***
	ET: baseline depression score Mean (SD)	1.25 (1.07)	4.85 (3.31)	t = 4.62***
Level of impulsivity	BIS-R-21 total score Mean (SD)	40.80 (7.72)	44.85 (7.60)	t = 1.67

***p < 0.001, **p < 0.01. Note: Although nonparametric comparative analyzes were rank-based (education and socioeconomic status), the table shows mean values in these cases as well for ease of intelegerpretation.

3.1.2. Intercorrelations between time perception measures and psychiatric symptoms

Perceptive deviation from chronological time significantly correlated with BDI total score ($r_S = 0.48$, $p < 0.01$), BIS total score ($r_S = -0.29$, $p < 0.05$) and resting state locomotor activity ($r_S = -0.35$, $p < 0.05$). Time production ratio was a significant correlate of resting state locomotor activity ($r_S = 0.42$, $p < 0.01$), BIS total score ($r_S = 0.32$, $p < 0.05$), and BDI total score ($r^S = -0.44$, $p < 0.01$), implying that participants showing greater movement intensity and higher impulsivity are more likely to overproduce time, while those with more severe depressive symptoms tend to underproduce it. Anxiety (STAI-S total) and impulsivity (BIS total) were also significant correlates ($r_S = 0.44$, $p < 0.01$). Impulsivity showed no significant connection with the level of depression ($r_S = -0.18$, $p > 0.05$).

3.1.3. Predicting resting state motion intensity

Tuning of the Random Forest identified the lowest error rate on the training dataset with 2 as nodesize and 2 as the mtry parameter (i.e. the number of randomly sampled variables at each split). Random forest model achieved an error rate of 11.38%. The highest variable importance factor was linked to BIS-R-21 total (13.173), the BDI total (8.40), and the STAI total (4.98679), followed by ET anxiety (2.788), time production ratio (2.574), ET depression (1.943), gender (1.399), clinical grouping variable (clinical vs. control) (0.037), perceptive deviation from chronological time (0.0249) and age (1.221). The importance of these variables were also backed by the rank order of the minimal depth values. An overall nearly linear positive association was detected with STAI total und BIS-R-21 total and an overall nearly linear negative association with BDI total score (Fig. 2).

3.1.4. Results of the path analysis model

Fit indices (RMSEA< 0.08, CFI >0.95, TLI >0.95) indicated a well-fitting model. Different pathways were identified in case of controls and psychiatric patients. Differences in motion intensity was a significant negative estimate of anxiety changes (Beta = −0.06, std. Error = 0.03, $p < 0.05$) only among controls, that is, higher motion intensity predicted greater reduction in anxiety (T2-T1). Furthermore, changes in time production ratio was a positive predictor of depression symptom changes in case of controls (Beta = 10.10, std. Error = 3.55, $p < 0.01$), but a negative predictor of the same in case of psychiatric patients (Beta = −8.53, std. Error = 3.40, $p < 0.05$). That means, that in case of healthy subjects, a shift towards overproduction of time may be linked to an exacerbation of depressive symptoms, while an under productive tendency in case of psychiatric patients may be associated with the same. Fig. 3 illustrates the results.

4. Discussion

Our results indicated that the extent of resting state locomotor activity is highly dependent on the level of impulsivity, depression and anxiety. Based on the findings of our random forest regression analysis, impulsivity and anxiety were, as expected, associated with enhanced resting state motion intensity, while depression showed an inverse association with the same. Former observations identified physical passivity in depression, and assigned important implications to reduced psychomotor performance, such as changes in the affective movements in maternal caregiving interactions (Young et al., 2015). Motion capture and analysis is a promising and fastly evolving approach in contemporary psychiatry that is able to infer intrapsychic processes from subtle bodily signals, such as the rate and direction of eye movements, changes in head movements, or facial expressions. Motion analysis may even identify mood episodes at an earlier stage, or detect dementia at its prodromal phase (Collier et al., 2018). Our observations similarly implicate that motion analysis of resting state locomotor activity can be

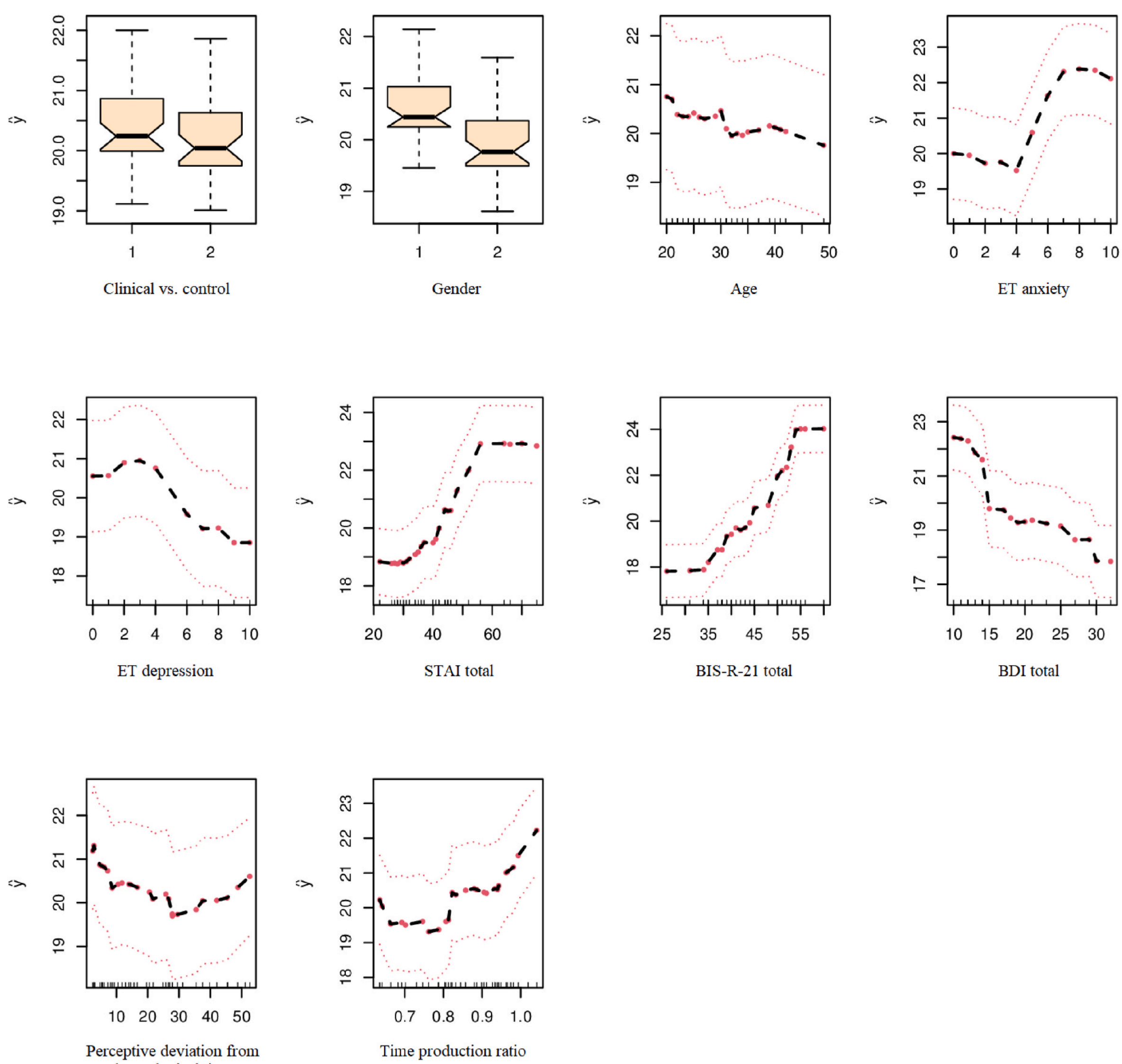

Fig. 2. Partial dependence plots. The yhat on the y-axis represents the predicted resting state motion intensity values. Pointed red lines represent the 95% error bounds, Marks on the x-axis indicate the data distribution. Red dots represent the OOB (out of box) predicted values.

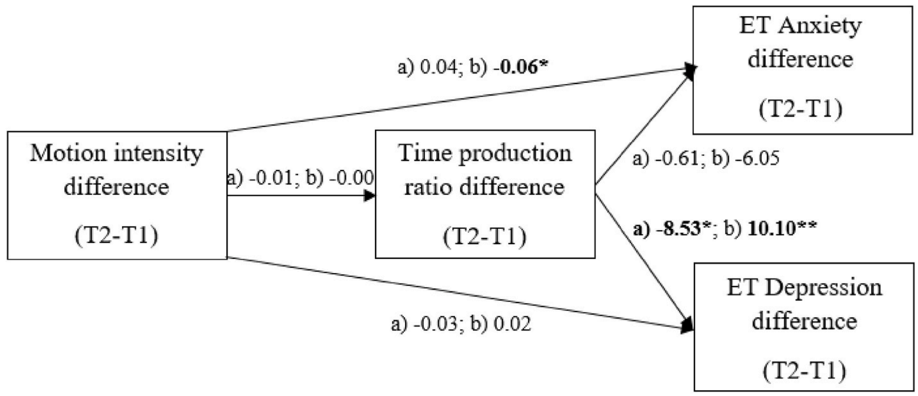

Fig. 3. Different pathways within the control and clinical subsample
Note: *p < 0.05, **p < 0.01; a) SEM estimates for clinical subgroup; b) SEM estimates for control subgroup. Significant estimators are boldfaced.

a useful means in diagnostic work, aiding the estimations of anxiety, depression and impulsivity levels. However, due care and diligence is needed when interpreting the results of motion analysis, as resting state locomotor activity provides transdiagnostic and not disorder-specific information about the current mental state of the individual. To exemplify this phenomenon with our own research results, higher locomotor activity was associated with both anxiety and impulsivity, while the goal of increased activity – or even hyperkinesis in more severe impulsivity cases - may be similar in both disorders: to reduce internal tension or ease the feeling of restlessness. The result that impulsivity was a stronger predictor of enhanced resting state locomotor activity than anxiety, suggests that the level of resting state locomotor activity (including voluntary and unintentional motions) can express or represent certain disorders in a dimensional way, in which higher than average resting state activity may primarily indicate conditions such as anxiety, ADHD, or even early signs of psychosis (Dean et al., 2018), while lower than average resting state locomotor activity may indicate the presence of, for instance, depression, or the negative symptoms of schizophrenia (Kupper et al., 2010).

Considering the associations between deviations from chronological time (including the under- and overproduction of time) and psychiatric symptoms, impulsivity and depression showed an opposite relationship with TP, with impulsive respondents characterized by greater motion intensity tend to overproduce time, while depressed individuals tend to underproduce it.What we call *overproduction* in this study, is an accelerated rate of counting (i.e. the participants perceived time to pass faster than in reality), and as such, this is the exact opposite of what is called overproduction in numerous studies. At the same time, since we allowed chronometric counting, the participants actually evaluated the passage of time in short time units (i.e. constantly estimating shorter durations) as sequenced by the ryhtm of counting. Still, a much more complex, multifactorial association between TP and mood disorders can be hypothesized. Our path analysis results further confirmed this assumption, as the clinical and control groups showed opposite directions in terms of the association between time production ratio and depressive symptom changes, with only the clinical subgroup showing a significant connection between a shift towards underproductive tendencies and the worsening of depressive symptoms. The fact that the clinical subgroup showed a higher perceptive deviation from chronological time and a stronger tendency to underproduce time than healthy controls, might imply that alterations in TP can be a general difference between the clinical population and healthy individuals. Underproduction of temporal intervals within this trial assumed slower perception of time, a marked characteristic of depressed individuals. As Cáceda et al. (2020) pointed out, time slowing may be triggered by psychological pain, possibly leading to the feeling of inescapability, a risk factor for suicidal behavior as well. Additionally, and to add a further dimension: conscious awareness might also have temporal limits. As for instance Wittmann suggested (2016), in the range of milliseconds, we try to differentiate between simultaneous or temporally ordered events (i.e. Wittmann calls it the *functional moment*); in the range of up to 2–3 s, we are able to temporally segmentate the experience which leads us to the conscious awareness of the moment (i.e. the *experienced moment*), while in the range of up to 30–100 s (e.g. the approximate duration we measured in the present study), working memory processes contribute to the continuity of the experience and thus the sense of *mental presence*. If chronometric counting is considered as an estimation of shorter durations, our participants actually perceived each moment of the trial as an experienced moment, implying that the perceived slowing in depressed participants (or their worsening symptoms) might be related to their perception of the experienced moment (2–3s in duration). In that sense, our results are comparable to the findings of Kent et al. (2019a), who argue that the experienced moment is dilated in depressed individuals but the mental present is accelerated.

Locomotor activity was a significant positive correlate of the overproduction of time. This is consistent with the findings of others (e.g. Edwards and McCormick, 2017), namely, that the intensity of physical exercise may increase the estimated duration of time. The most plausible explanation for this phenomenon – as it was presented by Behm and Carter as well (2020) – relies on scalar expectancy theory, that is, with increasing number of pulses collected in the “accumulator” due to motion-induced hyperarousal, the amount of processable neural information grows, and this evokes the feeling that more time has passed than in reality. Our findings may also be linked to former observations that more time is generally perceived when arousal levels are higher (e.g. Mella et al., 2011; Gil and Droit-Volet, 2012). With regard to the potential beneficial impacts of active motion on immediate psychiatric symptom reduction, the results of our path analysis model - and taking into account baseline differences between the control and the clinical subgroups in the level of psychiatric symptoms - may suggest that motion intensity can only reduce less severe, subclinical symptoms.

4.1. Limitations and future considerations

The primary limitation of the study clearly lies in the low number of respondents, negatively influencing the generalizability of the findings. This becomes a critical issue especially when we talk about the interpretation of the results of multivariate statistical analyses. Furthermore, changes in anxiety and depressive symptoms were examined immediately after the active motion task, without follow-up testing that could have been used to estimate the temporal duration of the outcomes. TP can be measured in a number of other ways in addition to the time production task. Potential TP paradigms encompass the measurement of verbal time estimation, detection of time shifts (O'Regan et al., 2017), applying temporal bisection tasks, and so on. Moreover, we hypothesized that alterations in TP depend on motion intensity and psychiatric symptoms, however, a number of factors beyond our control may as well explain changes in TP. Such factors include marked individual differences, context effects, learning effects, and timing strategies (e.g. interval-vs. beat-based perception) (Matthews and Meck, 2014). Finally, time production tasks generally ask the participants to indicate the start and/or end of the interval without asking them to count all the way through (e.g. Thönes and Stocker, 2019), which makes our findings (obtained with a less traditional time production task without assessing shorter intervals under 10 s) more difficult to compare with the results of others, even if they used similar methodology (i.e. measuring a 90s interval and allowing counting as well), such as the study of Kent et al. (2019b).

Based on our findings and the reviewed body of knowledge, we assumed that resting state motion intensity may function as a transdiagnostic dimension, differentiating between various psychiatric conditions. Future research is, however, needed to adequately address this issue. In order to increase the accuracy of motion-based predictions, further behavioral factors should also be monitored, such as vocal parameters, eye movements, or respiratory rates.

5. Conclusions

Our experimental study demonstrated that motion intensity may be associated with both subjective time experience and the changes of psychiatric symptoms. Different pathways, however, were identified in case of healthy controls and psychiatric patients, implying the relevance of distinguishing between clinical and subclinical severity of psychiatric symptoms. Future research on the extent to which resting state motion activity can be used as a transdiagnostic dimension is encouraged.

Contributors

Máté Kapitány-Fövény designed the study and wrote all drafts with Anna Kiss and Orsolya Bokk. Mihály Sulyok designed the analysis and corrected the manuscript drafts. Anna Kiss and Orsolya Bokk were involved in data collection. Máté Kapitány-Fövény and Mihály Sulyok performed the statistical analyses.

Data availability statement

The analyzed dataset is available at: https://github.com/msulyok/Time-motion-depression-and-anxiety.

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Declaration of competing interest

Authors declare no conflict of interest.

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References

Aylett, E., Small, N., Bower, P., 2018. Exercise in the treatment of clinical anxiety in general practice - a systematic review and meta-analysis. BMC Health Serv. Res. 18 (1), 559. https://doi.org/10.1186/s12913-018-3313-5.

Bartholomew, A.J., Meck, W.H., Cirulli, E.T., 2015. Analysis of genetic and non-genetic factors influencing timing and time perception. PLoS One 10 (12), e0143873. https://doi.org/10.1371/journal.pone.0143873.

Beck, A.T., Ward, C.H., Mendelson, M., Mock, J., Erbaugh, J., 1961. An inventory for measuring depression. Arch. Gen. Psychiatr. 4, 561–571. https://doi.org/10.1001/archpsyc.1961.01710120031004.

Behm, D.G., Carter, T.B., 2020. Effect of exercise-related factors on the perception of time. Front. Physiol. 11, 770. https://doi.org/10.3389/fphys.2020.00770.

Ben-Soussan, T.D., Glicksohn, J., 2018. Gender-dependent changes in time production following quadrato motor training in dyslexic and normal readers. Front. Comput. Neurosci. 12, 71. https://doi.org/10.3389/fncom.2018.00071.

Burge, J., Geisler, W.S., 2015. Optimal speed estimation in natural image movies predicts human performance. Nat. Commun. 6, 7900. https://doi.org/10.1038/ncomms8900.

Cáceda, R., Carbajal, J.M., Salomon, R.M., Moore, J.E., Perlman, G., Padala, P.R., Hasan, A., Delgado, P.L., 2020. Slower perception of time in depressed and suicidal patients. Eur. Neuropsychopharmacol 40, 4–16. https://doi.org/10.1016/j.euroneuro.2020.09.004.

Castañer M, Aiello S, Prat Q, Andueza J, Crescimanno G, Camerino O. Impulsivity and physical activity: a T-Pattern detection of motor behavior profiles. Physiol. Behav., 219, 112849. https://doi.org.10.1016/j.physbeh.2020.112849.

Choi, J.W., Lee, G.E., Lee, J.H., 2021. The effects of valence and arousal on time perception in depressed patients. Psychol. Res. Behav. Manag. 14, 17–26. https://doi.org/10.2147/PRBM.S287467.

Collier, S., Monette, P., Hobbs, K., Tabasky, E., Forester, B.P., Vahia, I.V., 2018. Mapping movement: applying motion measurement technologies to the psychiatric care of older adults. Curr. Psychiatr. Rep. 20 (8), 64. https://doi.org/10.1007/s11920-018-0921-z.

Dean, D.J., Samson, A.T., Newberry, R., Mittal, V.A., 2018. Motion energy analysis reveals altered body movement in youth at risk for psychosis. Schizophr. Res. 200, 35–41. https://doi.org/10.1016/j.schres.2017.05.035.

Del Olmo, M.F., Cheeran, B., Koch, G., Rothwell, J.C., 2007. Role of the cerebellum in externally paced rhythmic finger movements. J. Neurophysiol. 98 (1), 145–152. https://doi.org/10.1152/jn.01088.2006.

Di Lernia, D., Serino, S., Pezzulo, G., Pedroli, E., Cipresso, P., Riva, G., 2018. Feel the time. Time perception as a function of interoceptive processing. Front. Hum. Neurosci. 12, 74. https://doi.org/10.3389/fnhum.2018.00074.

Edwards, A.M., McCormick, A., 2017. Time perception, pacing and exercise intensity: maximal exercise distorts the perception of time. Physiol. Behav. 180, 98–102. https://doi.org/10.1016/j.physbeh.2017.08.009.

Ehrlinger, J., 2016. ggRandomForests: Visually Exploring Random Forests, 2016, R package version 2.0.1. https://CRAN.R-project.org/package=ggRandomForests.

Fayolle, S., Gil, S., Droit-Volet, S., 2015. Fear and time: fear speeds up the internal clock. Behav. Process. 120, 135–140. https://doi.org/10.1016/j.beproc.2015.09.014.

Ghaderi, A.H., 2019. Heat transfer, entropy and time perception: toward finding a possible relation between subjective and objective time. Med. Hypotheses 122, 172–175. https://doi.org/10.1016/j.mehy.2018.11.018.

Gil, S., Droit-Volet, S., 2012. Emotional time distortions: the fundamental role of arousal. Cognit. Emot. 26 (5), 847–862. https://doi.org/10.1080/02699931. 2011.625401.

Hinton, S.C., Harrington, D.L., Binder, J.R., Durgerian, S., Rao, S.M., 2004. Neural systems supporting timing and chronometric counting: an FMRI study. Brain Research, Cognitive Brain Research 21 (2), 183–192. https://doi.org/10.1016/j.cogbrainres.2004.04.009.

IBM Corp, 2019. IBM SPSS Statistics for Windows. IBM Corp, Armonk, NY. Version 26.0.

Ishwaran, H., 2007. Variable importance in binary regression trees and forests. Electronic Journal of Statistics 1, 519–537. https://doi.org/10.1214/07-EJS039.

Ishwaran, H., Kogalur, U., 2021. *Fast Unified Random Forests for Survival, Regression, and Classification (RF-SRC)*. R Package Version 2.13.0. https://cran.r-project.org/package=randomForestSRC.

Jankowski, K.S., Zajenkowski, M., Stolarski, M., 2020. What are the optimal levels of time perspectives? Deviation from the balanced time perspective-revisited (DBTP-r). Psychol. Belg. 60 (1), 164–183. https://doi.org/10.5334/pb.487.

Jones, C.R., Malone, T.J., Dirnberger, G., Edwards, M., Jahanshahi, M., 2008. Basal ganglia, dopamine and temporal processing: performance on three timing tasks on and off medication in Parkinson's disease. Brain Cognit. 68 (1), 30–41. https://doi.org/10.1016/j.bandc.2008.02.121.

Kacem, A., Hammal, Z., Daoudi, M., Cohn, J., 2018. Detecting depression severity by interpretable representations of motion dynamics. IEEE International Conference on Automatic Face & Gesture Recognition 739–745. https://doi.org/10.1109/FG.2018.00116, 2018.

Kapitány-Fövény, M., Urbán, R., Varga, G., Potenza, M.N., Griffiths, M.D., Szekely, A., Paksi, B., Kun, B., Farkas, J., Kökönyei, G., Demetrovics, Z., 2020. The 21-item Barratt impulsiveness scale revised (BIS-R-21): an alternative three-factor model. Journal of Behavioral Addictions 9 (2), 225–246.

Kent, L., Van Doorn, G., Klein, B., 2019a. Time dilation and acceleration in depression. Acta Psychol. 194, 77–86. https://doi.org/10.1016/j.actpsy.2019.02.003.

Kent, L., van Doorn, G., Hohwy, J., Klein, B., 2019b. Bayes, time perception, and relativity: the central role of hopelessness. Conscious. Cognit. 69, 70–80. https://doi.org/10.1016/j.concog.2019.01.012.

Kraus, B.J., Robinson 2nd, R.J., White, J.A., Eichenbaum, H., Hasselmo, M.E., 2013. Hippocampal "time cells": time versus path integration. Neuron 78 (6), 1090–1101. https://doi.org/10.1016/j.neuron.2013.04.015.

Kupper, Z., Ramseyer, F., Hoffmann, H., Kalbermatten, S., Tschacher, W., 2010. Video-based quantification of body movement during social interaction indicates the severity of negative symptoms in patients with schizophrenia. Schizophr. Res. 121 (1–3), 90–100. https://doi.org/10.1016/j.schres.2010.03.032.

Kvam, S., Kleppe, C.L., Nordhus, I.H., Hovland, A., 2016. Exercise as a treatment for depression: a meta-analysis. J. Affect. Disord. 202, 67–86. https://doi.org/10.1016/j.jad.2016.03.063.

Lyra, V., Kallergi, M., Rizos, E., Lamprakopoulos, G., Chatziioannou, S.N., 2016. The effect of patient anxiety and depression on motion during myocardial perfusion SPECT imaging. BMC Med. Imag. 16 (1), 49. https://doi.org/10.1186/s12880-016-0153-9.

Magnani, B., Oliveri, M., Mangano, G.R., Frassinetti, F., 2010. The role of Posterior Parietal Cortex in spatial representation of time: a TMS study. Behav. Neurol. 23 (4), 213–215. https://doi.org/10.3233/BEN-2010-0298.

Matthews, W.J., Meck, W.H., 2014. Time perception: the bad news and the good. Wiley interdisciplinary reviews. Cognit. Sci. 5 (4), 429–446. https://doi.org/10.1002/wcs.1298.

McFarland, C.P., Glisky, E.L., 2009. Frontal lobe involvement in a task of time-based prospective memory. Neuropsychologia 47 (7), 1660–1669. https://doi.org/10.1016/j.neuropsychologia.2009.02.023.

Mella, N., Conty, L., Pouthas, V., 2011. The role of physiological arousal in time perception: psychophysiological evidence from an emotion regulation paradigm. Brain Cognit. 75 (2), 182–187. https://doi.org/10.1016/j.bandc.2010.11.012.

Mitchell, A.J., Baker-Glenn, E.A., Granger, L., Symonds, P., 2010. Can the Distress Thermometer be improved by additional mood domains? Part I. Initial validation of the Emotion Thermometers tool. Psycho Oncol. 19 (2), 125–133. https://doi.org/10.1002/pon.1523.

Monroe, A.E., Ainsworth, S.E., Vohs, K.D., Baumeister, R.F., 2017. Fearing the future? Future-oriented thought produces aversion to risky investments, trust, and immorality. Soc. Cognit. 35 (1), 66–78. https://doi.org/10.1521/soco.2017.35.1.66.

O'Regan, L., Spapé, M.M., Serrien, D.J., 2017. Motor timing and covariation with time perception: investigating the role of handedness. Front. Behav. Neurosci. 11, 147. https://doi.org/10.3389/fnbeh.2017.00147.

Özgör, C., Şenyer Özgör, S., Duru, A.D., Işoğlu-Alkaç, Ü., 2018. How visual stimulus effects the time perception? The evidence from time perception of emotional videos. Cognitive Neurodynamics 12 (4), 357–363. https://doi.org/10.1007/s11571-018-9480-6.

Paasche, C., Weibel, S., Wittmann, M., Lalanne, L., 2019. Time perception and impulsivity: a proposed relationship in addictive disorders. Neurosci. Biobehav. Rev. 106, 182–201. https://doi.org/10.1016/j.neubiorev.2018.12.006.

Patton, J.H., Stanford, M.S., Barratt, E.S., 1995. Factor structure of the Barratt impulsiveness scale. J. Clin. Psychol. 51 (6), 768–774. https://doi.org/10.1002/1097-4679(199511)51:6<768::AID-JCLP2270510607>3.0.CO;2-1.

Perbal, S., Couillet, J., Azouvi, P., Pouthas, V., 2003. Relationships between time estimation, memory, attention, and processing speed in patients with severe traumatic brain injury. Neuropsychologia 41 (12), 1599–1610. https://doi.org/10.1016/s0028-3932(03)00110-6.

R Core Team, 2021. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. URL. https://www.R-project.org/.

Rey, A.E., Michael, G.A., Dondas, C., Thar, M., Garcia-Larrea, L., Mazza, S., 2017. Pain dilates time perception. Sci. Rep. 7 (1), 15682 https://doi.org/10.1038/s41598-017-15982-6.

Riemer, M., Vieweg, P., van Rijn, H., Wolbers, T., 2022. Reducing the tendency for chronometric counting in duration discrimination tasks. Atten. Percept. Psychophys. https://doi.org/10.3758/s13414-022-02523-1.

Rosseel, Y., 2012. Lavaan: an R package for structural equation modeling. J. Stat. Software 48 (2), 1–36.

Rózsa, S., Szádóczky, E., Füredi, J., 2001. [Psychometric properties of the Hungarian version of the shortened Beck Depression Inventory]. A Beck Depresszió Kérdőív rövidített változatának jellemzői a hazai mintán. Psychiatr. Hung. 16, 379–397.

Schwarz, M.A., Winkler, I., Sedlmeier, P., 2013. The heart beat does not make us tick: the impacts of heart rate and arousal on time perception. Atten. Percept. Psychophys. 75 (1), 182–193. https://doi.org/10.3758/s13414-012-0387-8.

Spielberger, C.D., Gorsuch, R.L., Lushene, R.E., 1970. Manual for the State-Trait Anxiety Inventory. Consulting Psychologist Press, Palo Alto, CA.

Starling, S., 2019. Neuronal clock coordinates appetite. Nat. Rev. Endocrinol. 15 (5), 253. https://doi.org/10.1038/s41574-019-0196-4.

Sysoeva, O.V., Tonevitsky, A.G., Wackermann, J., 2010. Genetic determinants of time perception mediated by the serotonergic system. PLoS One 5 (9), e12650. https://doi.org/10.1371/journal.pone.0012650.

Szigethy, K., Takács, Sz, 2015. Figyelemfelhívás egy hibás publikációra és javaslat a korrekcióra. Psychiatr. Hung. 3 (2), 56–62.

Thönes, S., Oberfeld, D., 2015. Time perception in depression: a meta-analysis. J. Affect. Disord. 175, 359–372. https://doi.org/10.1016/j.jad.2014.12.057.

Thönes, S., Stocker, K., 2019. A standard conceptual framework for the study of subjective time. Conscious. Cognit. 71, 114–122. https://doi.org/10.1016/j.concog.2019.04.004.

Uvnäs-Moberg, K., Handlin, L., Petersson, M., 2015. Self-soothing behaviors with particular reference to oxytocin release induced by non-noxious sensory stimulation. Front. Psychol. 5, 1529. https://doi.org/10.3389/fpsyg.2014.01529.

Wiener, M., Lohoff, F.W., Coslett, H.B., 2011. Double dissociation of dopamine genes and timing in humans. J. Cognit. Neurosci. 23 (10), 2811–2821. https://doi.org/10.1162/jocn.2011.21626.

Wiener, M., Zhou, W., Bader, F., Joiner, W.M., 2019. Movement improves the quality of temporal perception and decision-making. eNeuro 6 (4). https://doi.org/10.1523/ENEURO.0042-19.2019. ENEURO.0042-19.2019.

Wittmann, M., 2016. The duration of presence. In: Mölder, B., Arstila, V., Øhrstrøm, P. (Eds.), Philosophy and Psychology of Time, Studies in Brain and Mind, vol. 9. Springer, Cham. https://doi.org/10.1007/978-3-319-22195-3_6.

Yoo, J.Y., Lee, J.H., 2015. The effects of valence and arousal on time perception in individuals with social anxiety. Front. Psychol. 6, 1208. https://doi.org/10.3389/fpsyg.2015.01208.

Young, K.S., Parsons, C.E., Stein, A., Kringelbach, M.L., 2015. Motion and emotion: depression reduces psychomotor performance and alters affective movements in caregiving interactions. Front. Behav. Neurosci. 9, 26. https://doi.org/10.3389/fnbeh.2015.00026.

Zakay, D., 2014. Psychological time as information: the case of boredom. Front. Psychol. 5, 917. https://doi.org/10.3389/fpsyg.2014.00917.

Zhang, Z., Jia, L., Ren, W., 2014. Time changes with feeling of speed: an embodied perspective. Front. Neurorob. 8, 14. https://doi.org/10.3389/fnbot.2014.00014.