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Original article

Understanding individual differences in non-ordinary state of consciousness: Relationship between phenomenological experiences and autonomic nervous system

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ABSTRACT

Non-ordinary states of consciousness offer a unique opportunity to explore the interplay between phenomenological experiences and physiological processes. This study investigated individual differences in phenomenological and autonomic nervous system changes between a resting state condition and a non-ordinary state of consciousness (auto-induced cognitive trance, AICT). Specifically, it examined the relationship between self-reported experiences (e.g., absorption, visual representations) and heart rate variability (HRV).

Twenty-seven participants underwent electrocardiography recordings and completed self-report questionnaires during rest and AICT. A machine learning framework distinguished the rest and AICT states based on self-reported measures and HRV metrics. A linear mixed-effects model assessed inter-individual differences in HRV and self-reported phenomenology between the two states. Finally, the relationship between relative change in HRV and self-reported experiences was explored.

Results showed changes in self-reported phenomenology (accuracy=86 %; $p<.001$) and HRV (accuracy=73 %; $p<.001$) characterizing the AICT state compared to rest. The baseline level in phenomenology or HRV was associated with change amplitude during AICT. Moreover, relative change in HRV was associated with change in phenomenology.

The findings suggest that inter-individual differences at rest revealed a functional mechanism between phenomenology and the autonomic nervous system during non-ordinary states of consciousness, offering a novel perspective on how physiological mechanisms shape subjective experiences.

Introduction

Non-ordinary state of consciousness (NOC) is an umbrella term encompassing various techniques and states (such as meditation, hypnosis, psychedelics) that share characteristic modification of "ordinary" consciousness (Timmermann et al., 2023). Due to its psychopathological characterization by several authors in 20th-century psychiatry, NOC has long faced resistance from both the public and the scientific community, who equated it with a psychotic episode (Jutras, 2017; Stoyanov et al., 2019; Telles-Correia & Sampaio, 2016). However, these misconceptions were largely due to the fact that the study of NOC was conducted from a third-person perspective, which excluded access to the subject's phenomenological experience. Recently, these misconceptions were dismissed, and NOC have been recognized as states of consciousness that are worth studying and have therapeutic potential (Timmermann et al., 2023). New techniques, such as the auto-induced cognitive trance

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(AICT), train people to self-induce NOC through willpower without psychoactive agents, and propose integrating NOC as a technical practice devoid of cultural contexts (Grégoire et al., 2021; Lafon et al., 2018). This state is typically characterized by a loss of sense of agency, automatic movements, heightened sensations and perceptions, and spontaneous vocalizations (Grégoire et al., 2021, 2024; Lafon et al., 2018). This approach allows a large number of people to practice AICT after four days of training. However, the phenomenological content during AICT remains unclear and poorly understood.

The literature on phenomenological experiences of NOC is based on two types of studies: (i) the study of the content of lived experiences (phenomenological narratives), often explored through qualitative methods, and (ii) the study of the psychological structure of these experiences (such as absorption, dissociative altered sensory perception), often explored through self-reported psychometric questionnaires. Qualitative studies showed that the content of these experiences is highly dependent on the context (set and setting, e.g., induction method, framework, purpose) and the socio-cultural environment (Costin & Ennis-McMillan, 2022; Ember & Carolus, 2017; Timmermann et al., 2023). The use of self-reported psychometric questionnaires revealed that NOC involve changes in different psychological components, including absorption (Ballew & Omoto, 2018; Lifshitz et al., 2019; Vanhaudenhuyse et al., 2019), dissociation (Dienes et al., 2009; Lynn & Green, 2011; Peres et al., 2012; Vanhaudenhuyse et al., 2019), altered perception of time (Meissner & Wittmann, 2011; Vanhaudenhuyse et al., 2019), altered sense of agency (Timmermann et al., 2023), automatic thinking and enhanced imagination (Gosseries et al., 2024; Peters & Price-Williams, 1983; Preller & Vollenweider, 2018). Additionally, changes in self-perception, such as ego dissolution/inflation and feelings of oceanic boundlessness have also been reported (Carhart-Harris, 2018; Carhart-Harris et al., 2014). However, the change in phenomenological experience during NOC exhibits important inter-individual differences.

Some authors have suggested that this inter-individual variability in phenomenal experience under NOC might be explained by inter-individual variability at rest (Kumar & Pekala, 1988; Pekala & Kumar, 2000). This phenomenon has been explored in the context of hypnosis, where it has been shown that at rest (eyes closed), some individuals report a richer phenomenological experience than others, leading to more profound phenomenological experiences during hypnosis (Kumar & Pekala, 1988; Vaitl et al., 2005). This suggests that the magnitude of phenomenological experiences during the hypnotic process may be linked to individual predispositions that are already present at rest. Moreover, individuals who are more highly hypnotizable experience a greater increase in phenomenological experience after hypnosis induction compared to those who are less hypnotizable (Kumar & Pekala, 1988; Vaitl et al., 2005). This highlights that inherent traits can be associated with inter-individual differences in state changes. However, these hypotheses have never been verified concerning other forms of NOC (including AICT) and have never been linked to any physiological mechanisms.

One biological system that has received particular attention in relation to NOC is the autonomic nervous system (ANS). The ANS is one of the main systems responsible for maintaining physiological homeostasis and can both influence and be influenced by lived experiences (Kreibig, 2010). The ANS plays a key role in influencing interoceptive mechanisms, which provide critical sensory information that the brain uses to construct conscious perception (Meissner, 2011; Meissner & Wittmann, 2011). Despite this understanding of the ANS's influence on interoception and lived experience, the detailed mechanisms underlying these interactions remain poorly understood and NOC offer a unique window into this relationship by enabling the observation of variations in lived experience associated with changes in ANS activity.

Various studies have investigated changes in the ANS to understand the effects of NOC, often using heart rate variability (HRV) as a measure. HRV is the most reliable and non-invasive method to monitor ANS activity, allowing researchers to extract a wide range of physiological markers, including time-domain, frequency-domain, and non-linear metrics These metrics have been demonstrated by a substantial body of research to reflect direct effects on the ANS (Beauchaine & Thayer, 2015; Makivić et al., 2013; Sacha et al., 2013; Singer, 2010).

As such, systematic changes in the ANS during NOC have been reported (Aubert et al., 2009; Brown et al., 2021; Christodoulou et al., 2020; Debenedittis et al., 1994; Jerath et al., 2006; Krygier et al., 2013; Rådmark et al., 2019). However, results are discrepant, with some studies reporting an increase (Aubert et al., 2009; Brody et al., 1998; Olbrich et al., 2021) and others a withdrawal of parasympathetic nervous system (PNS) activity (Bonnelle et al., 2024; Oswald et al., 2023). The two main limitations of these studies are that baseline ANS activity is often not accounted for when observing changes during NOC, and these changes are not directly linked to phenomenological experiences. A recent work reported an increase in sympathetic nervous system activity and a withdrawal in PNS activity, associated with 'spiritual experience' and 'insightfulness' during the psychedelic experience (Bonnelle et al., 2024). However, it remains unclear whether this physiological effect is attributable to the substance (i.e., psychedelics) or the lived experience during the psychedelic experience.

In our previous work (Oswald et al., 2023), we found comparable ANS effects during AICT, which is a non-psychoactive form of NOC. One possible mechanism linking changes in the ANS to alterations in conscious states could be the lived experience and its content. In this study, we aimed to address this issue by exploring whether changes in physiological activity might plausibly be associated with changes in phenomenology. By examining this relationship, we hope to shed light on potential mechanisms underlying the dynamic interplay between physiology and conscious experience.

To elucidate this question, we collected a comprehensive list of self-reported characteristics of phenomenological experiences as well as physiological measurements of the ANS during AICT. These data were collected both at rest and during the AICT state to clearly observe individual variations from resting state. The aim of this study is twofold: i) to describe and identify the phenomenological experience features that are most predictive of the AICT state compared to the resting state using a machine learning framework, by extracting feature importances contributing to distinguishing the two states; ii) to link the changes in phenomenological experiences with the changes in the ANS.

Methods

This study was conducted using a previously published dataset (Grégoire et al., 2024; Kumar et al., 2024; Oswald et al., 2023) for HRV data, and the initial sections (participants and training, procedure, electrocardiogram recordings, heart rate variability data preprocessing and feature extraction) of this methodology are similar and have been adapted and reformulated in line with a previous work (i.e., Oswald et al., 2023).

Participants

We included 27 adult participants (23 females, mean age 45±13 years; range 24–72 years), all native French speakers, highly proficient at entering an AICT state, and regularly practicing AICT, averaging 28 months of practice (±339 months; range: 9–216 months). Before the study, participants were fully informed about the study's objectives and provided written consent. No incentives were offered for participation. The study received approval from the Ethics Committee of the Faculty of Medicine at the University of Liège (reference 2019/141) and was conducted in accordance with relevant guidelines and regulations.

AICT training

All participants underwent AICT training, which consisted of a sound-loop-based program designed to help people enter AICT. The goal of this training is to enable voluntary induction of AICT by will without the need for sound or movement cues. Participants lay on the floor with their eyes closed while listening to sound loops developed by the TranceScience Research Institute (www.trancescience.org), (i.e., designed electronic binaural sounds with pure tones between 100 Hz and 200 Hz and beat rates lower than 10 Hz, combined with voices and noises inspired by those produced during traditional Mongolian shamanic rituals) (Gosseries et al., 2020, 2024; Grégoire et al., 2021, 2024; Lafon et al., 2018). AICT can be induced in various ways, for example by making sounds (e.g., singing, protolanguage) or specific movements (e.g., stereotyped gestures, rapid eye movements). Gradually, participants find their personal inducer (e.g., movement of the hand, vocalization). Participants were then given the opportunity to continue practicing autonomously at home.

Procedure

Before the experiment, demographic data including age, sex, and other relevant details were collected. Participants were required to remain motionless during their trance due to electroencephalographic recording (not reported here). The experimental session consisted of five conditions: resting state ('Rest'), ordinary conscious state with auditory stimulation ('Rest-Auditory'), imagining a previous intense AICT without entering a trance state ('Imagination'), AICT, and AICT with auditory stimulation ('AICT-Auditory'). The first three conditions were counterbalanced among participants, while the last two were always conducted subsequently to avoid after-effects of AICT. During each condition, participants kept their eyes closed. In the 'Rest' and 'Auditory' conditions, they let their thoughts flow freely. In the 'AICT' and 'Auditory-AICT' conditions, participants induced and maintained AICT using their preferred techniques, which involved body movements and/or vocalizations, lasting between 2 and 10 min. Once in a trance state, participants remained motionless; if the trance faded, they re-induced it, extending the recording accordingly. Each condition lasted approximately 12 min.

After the experimental session, participants completed a self-report questionnaire to indicate whether they reached a trance state and to rate the intensity of their experience ('trance intensity'). They also completed a free recall task and other questionnaires. This study focused on two conditions: baseline resting state 'Rest', and 'AICT', and excluding the 'Imag' condition and the two 'Auditory' conditions due to their focus on a related project.

We collected physiological data, including electrocardiogram (ECG), electroencephalography (EEG), and respiration recordings (data not used in this work), using the EGI polygraph input box. ECG signals were recorded using the EGI polygraph input box embedded in Net Station software, with a sampling rate of 500 Hz and an input voltage range of ±2.5 V. A Lead II configuration was employed for electrode placement to ensure optimal R-wave detection. Signals were filtered with a 0.05–100 Hz bandwidth and synchronized with EEG data for precise time-locked analyses. These measurements captured physiological changes during the experimental conditions, providing detailed insights into the participants' physiological responses (Fig. 1).

Self-reported phenomenological measures

The questionnaire included 20 items (Table 1) administered after each experimental condition ('Rest' and 'AICT'), with responses recorded on a Likert scale from 0 to 10 (0=Not at all, 10=Completely). For analysis, we excluded questions 11, 12, 14, and 16 due to a lack of variance, as all responses were null across both conditions.

Machine learning

Multi-feature classification

To test the differences between the 'Rest' and 'AICT' conditions at both the phenomenological and physiological levels (i.e., HRV), we implemented a comprehensive multi-feature classifier that incorporated all questionnaire responses ($n = 16$) or HRV metrics as features ($n = 12$) to build a single model. To evaluate the individual contributions of each feature to the model, we employed a random forest algorithm (Breiman, 2001). This method estimates feature importance by averaging the relative ranks of each feature across the decision trees within the forest. To measure variability in feature importance, we repeated the training process 100 times. During each iteration, we utilized grid search with 5-fold cross-validation as part of a nested cross-validation approach, optimizing hyperparameters. We then used a polynomial law to estimate the p-value associated with the mean accurate decoding score. This approach provided valuable insights into the significance of each feature (phenomenological question or HRV metric) in influencing the overall

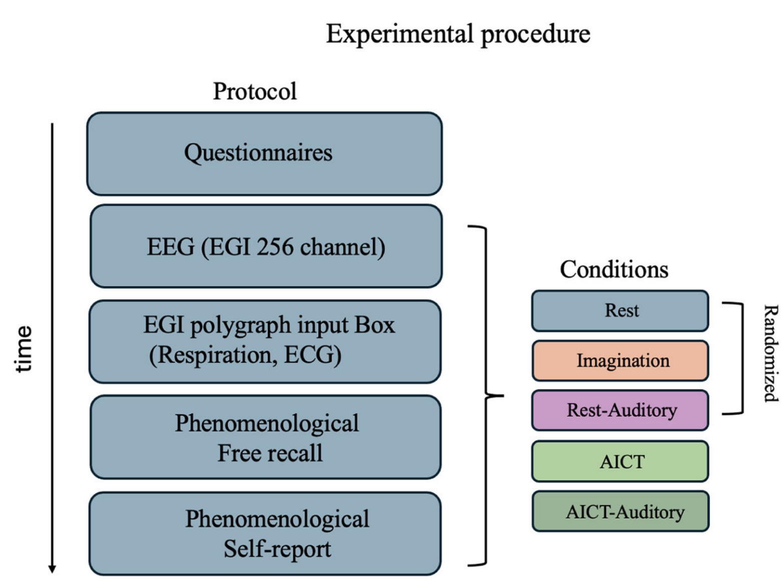

Fig. 1. Experimental Procedure. Participants completed five randomized conditions: 'Rest', 'Imagination', 'Rest-Auditory', 'AICT', and 'AICT-Auditory'. For each condition, data collection included a global questionnaire, EEG recording using a 256-channel EGI system, and physiological measures (respiration and ECG) using the EGI polygraph input box. Additionally, participants provided phenomenological data through free recall and self-reporting after each condition. The timeline of the protocol is depicted on the left, showing the sequential steps for each condition.

Table 1
Self-reported phenomenological questionnaire (20 items) collected after each experimental condition. *Excluded from the analysis due to a lack of variance.

	Label	Items
1	'External thoughts'	I was oriented towards the outside environment
2	'Inner thoughts'	I was oriented inwardly
3	'Retrospective thinking'	I imagined a scene or event that happened in the past
4	'Prospective thinking'	I was planning for the future
5	'Focus'	I was focused on my experience
6	'Imagined scene'	I thought of a scene that never happened
7	'Inner speech'	I heard my own voice (inner speech)
8	'Ambient noise'	I heard noises in the room or from outside
9	'Tactile sensation'	I experienced tactile sensations (e.g., numbness, stiffness)
10	'Visceral sensation'	I experienced visceral sensations (e.g., in my stomach)
11*	'Taste things'	I tasted things
12*	'Imaginary taste'	I imagined tastes
13	'Emotion'	I felt specific emotions
14*	'Observer/Agent'	I was either an observer or an agent in my experience
15	'Mind wandering'	I can't really say what I was thinking; my mind was just wandering
16*	'Imaginary smell'	I imagined scents
17	'Visualizations'	I had visual representations in my thoughts
18	'Absorption'	Level of absorption: How absorbed were you in your experience? How focused was your attention on the experience?
19	'Dissociation'	Level of dissociation: To what extent were you dissociated from your bodily reality/environment? (0: fully present in reality, in this room; 10: completely out of reality, totally disconnected from 'here and now')
20	'Altered time perception'	Estimate the duration of your experience (in minutes) (this duration was never mentioned to the participant)

performance of the classifier. By combining random forest and cross-validation techniques, we obtained robust and reliable feature importance estimates for our multi-feature classifier.

Heart rate variability (HRV) data preprocessing and feature extraction

ECG data for each condition ('Rest' and 'AICT') underwent preprocessing, including the application of a high-pass Butterworth filter (0.5 Hz cut-off, order 5) and powerline filtering to remove electrical interference. Five minutes of continuous clean data after the induction period were selected for further analysis. R-peak detection was performed to identify R peaks in the ECG signal, and RR intervals (time intervals between successive R peaks) were computed. Manual inspection was conducted to correct any abnormal detections. HRV features were extracted using Neurokit2, a Python package for advanced biosignal processing (Makowski et al., 2021). The following time domain HRV features were computed: heart rate and root mean square of the successive differences (RMSSD) of RR intervals. Frequency domain analysis was conducted using the Welch method to compute the power spectral density of RR intervals, extracting low-frequency (LF, 0.04–0.15 Hz) and high-frequency (HF, 0.15–0.4 Hz) bands. Normalized powers (nLF, nHF) were calculated by dividing the power in a given frequency band by the total power, and the LF/HF ratio was also computed. Additionally, we included HRV metrics targeting the ANS with indices characterizing both the sympathetic system (Baevsky stress index and cardiac sympathetic index (CSI)) and the parasympathetic system (cardio-vagal index (CVI) modified), as well as the sympatho-vagal balance (SD1/SD2 ratio). Nonlinear HRV metrics were assessed using fuzzy entropy and Lempel-Ziv complexity to quantify the entropy and complexity of the HRV time series, respectively. These procedures characterized cardiac parameters and HRV indices during different experimental conditions ('Rest' and 'AICT').

The selection of metrics was primarily based on our previous study (Oswald et al., 2023). However, in this study, we expanded the set of measurements to specifically target those reflecting sympathetic and parasympathetic activity, as well as metrics that capture the balance between these two systems. Additionally, we included other ANS measurements to facilitate comparisons with studies examining ANS changes in other NOC (Aubert et al., 2009; Bonnelle et al., 2024; Debenedittis et al., 1994; Ganguly et al., 2020).

Statistical analysis

Inter-individual differences

To analyse inter-individual differences between the baseline state and AICT, we used a linear mixed model with two measurement points (i.e., 'Rest' and 'AICT') for each feature, whether related to self-reported phenomenology or HRV. We also explored the relationship between the intercept and the linear coefficient between the two time points. To calculate this coefficient, we used the following formula:

$$Coef(int, slope) = \frac{cov\ (int, slope)}{sd(int) * sd(slope)}$$

We calculated this coefficient for each feature across all subjects, then extracted a null distribution using a Bootstrap method with 400 repetitions ($n = 400$) to establish a confidence interval associated with each coefficient.

Reducing dimensionality: principal component analysis

To test our hypothesis regarding the link between phenomenological variations (Δ phenomenology) and HRV variations during AICT (Δ HRV), we performed dimensionality reduction on the phenomenological data using principal component analysis (PCA), retaining 90 % of the explained variance. Here Δ was computed by subtracting individual 'AICT' values from 'Rest' values. We then focused on the first principal component (PCA1), which accounts for 23 % of the total explained variance, as a candidate to test the regression between phenomenological variations (Δ phenomenology PCA1) and HRV variations across each metric (Δ HRV). For multiple comparisons, we applied the FDR correction method ($p<.05$).

Results

Changes in self-reported phenomenological experiences during 'Rest' and 'AICT'

All participants reported being able to reach a trance state in the 'AICT' condition, with a mean reported intensity of 6.72 (SD=1.77; min=3; max=10). Fig. 2a shows the average self-reported scores across participants for each item (i.e., 20 items) and each condition (i.e., 'Rest' and 'AICT'). The multivariate classification implemented to distinguish between 'Rest' and 'AICT' was performed with a decoding accuracy of 86 % ($p<.001$). The ranking of output features by their importance derived from the classification model is illustrated in Fig. 2b. During 'AICT' compared to 'Rest', we observed a mean increase in altered time perception, inner thoughts, visualizations, absorption, dissociation, emotion, tactile sensations, and visceral sensations, while external thoughts, mind wandering, ambient noise, focus, prospective thinking, and retrospective thinking showed a mean decrease. Emotion, altered time perception, dissociation and ambient noise were the four most important phenomenological features contributing to the discrimination between 'Rest' and 'AICT' (Fig. 2b).

Inter-individual differences in self-reported phenomenological experiences between 'Rest' and 'AICT'

Table 2 presents all linear mixed models for each phenomenological feature. All features, except focus, inner speech, and visualization, show

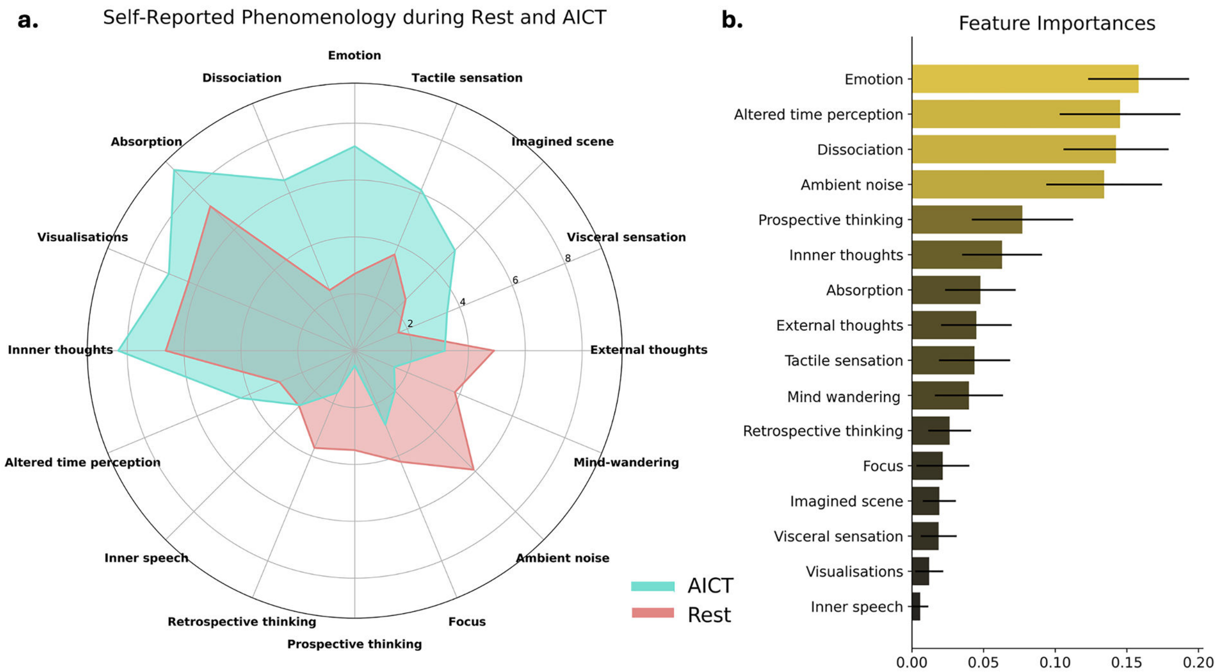

Fig. 2. Change in phenomenological self-rating at rest and during auto-induced cognitive trance (AICT). a. The left panel shows the mean self-reported scores for each feature across all subjects, with 'AICT' in red and 'Rest' in blue. **b.** The right panel displays feature importances derived from a multivariate classification performed using a random forest classifier to distinguish between 'Rest' and 'AICT', with a decoding accuracy of 86 % ($p\leq.001$).

Table 2
Linear mixed model between 'Rest' and 'AICT' with intercept and slope coefficient for each self-reported phenomenological feature.

Phenomenological features	Time effect (coef)	P-value	Intercept & slope (coef)	[CI] 95 %
External thoughts	*−0.568*	*.022**	*−.9345*[#]	*[−.9270, −.6558]*
Inner thoughts	*0.728*	*.005**	*−.9487*[#]	*[−.9457, −.6802]*
Retrospective thinking	*−0.618*	*.019**	*−.9487*[#]	*[−.9447, −.7389]*
Prospective thinking	*−0.980*	<0.001*	*−.9487*[#]	*[−.9451, −.7413]*
Focus	*−0.409*	*.108*	*−.9360*[#]	*[−.9321, −.7403]*
Imagined scene	*0.602*	*.013**	*−.9323*[#]	*[−.9253, −.7359]*
Inner speech	*−0.017*	*.942*	*−.9067*	*[−.9127, −.5307]*
Ambient noise	*−1.129*	<0.001*	*−.9349*	*[−.9355, −.6959]*
Tactile sensation	*0.719*	*.002**	*−.9304*[#]	*[−.9250, −.7493]*
Visceral sensation	*0.578*	*.024**	*−.9416*[#]	*[−.9262, −.7357]*
Emotion	*1.205*	<0.001*	*−.9430*[#]	*[−.9366, −.7515]*
Mind wandering	*−0.792*	*.002**	*−.9486*[#]	*[−.9479, −.7798]*
Visualizations	*0.236*	*.335*	*−.9240*[#]	*[−.9232, −.5866]*
Absorption	*0.868*	*.001**	*−.9487*[#]	*[−.9452, −.7018]*
Dissociation	*1.193*	<0.001*	*−.9487*	*[−.9542, −.7701]*
Altered time perception	*−1.022*	<0.001*	*−.9124*[#]	*[−.9075, −.6704]*

*: p val<0.05; #: coefficient outside the 95 % confidence interval (CI).

significant ($p<.05$) changes over time between 'Rest' and 'AICT'. Additionally, Table 2 provides the coefficients reflecting the strength of the association between the intercept and slope for each feature. All features, except inner speech, ambient noise, and dissociation, show coefficients outside the 95 % confidence interval. Fig. 3 shows linear models between 'Rest' and 'AICT', using a median split to illustrate changes based on high or low values at rest.

Changes in HRV during 'Rest' and 'AICT'

Fig. 4a reports the mean z-scores for each HRV metric investigated across all participants during rest and AICT. The performance of our multivariate classifier achieved an accuracy of 73 % ($p<.001$). Feature importance ranking revealed that a normalized high-frequency of HRV (HFn) played a predominant role, followed by cardiac entropy (fuzzy entropy), the LF/HF ratio, heart rate, and high-frequency HRV (HF), as the most discriminative features between the 'Rest' and 'AICT' conditions (Fig. 4b).

Inter-individual differences in HRV between 'Rest' and 'AICT'

Table 3 presents all linear mixed models for each HRV feature. All features, except RMSSD, LF, SD1/SD2, and CVI and Baevsky index show significant ($p<.05$) changes over time between 'Rest' and 'AICT'. Additionally, Table 3 provides the coefficients reflecting the strength of the association between the intercept and slope for each feature. Only HF, LFn, CSI, fuzzy entropy, and LCZ complexity show coefficients outside the 95 % confidence interval. Fig. 3 shows linear models between 'Rest' and 'AICT', using a median split to illustrate changes based on high or low values at rest.

Association between changes in self-reported phenomenological experiences and HRV measures

We report a significant association between self-reported phenomenological experiences and HRV measures in two different ways. First, after applying PCA to reduce the dimensionality of 17 self-reported

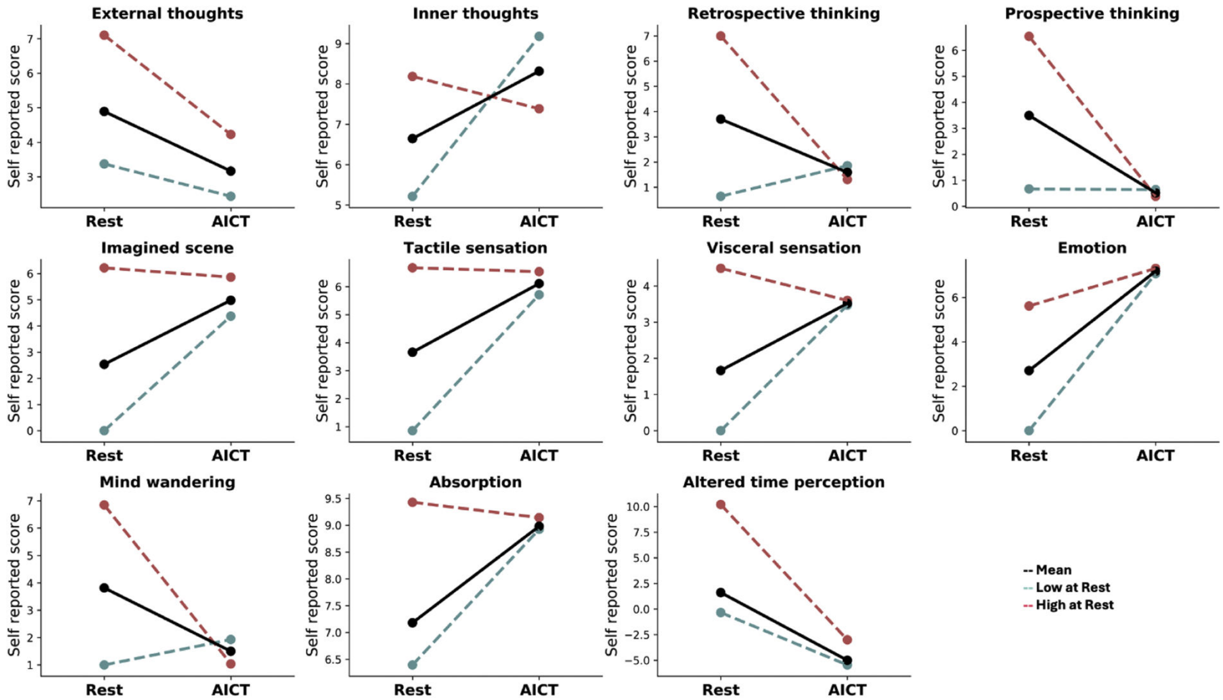

Fig. 3. Linear mixed model reports changes between 'Rest' and 'AICT' conditions for each phenomenological feature. Only models showing significant coefficients between intercept and slope (i.e., outside the 95 % confidence interval) from *Table 2* were plotted**.** A median split (black line) was used to separate individuals into high ratings at rest (red dotted line) and low ratings at rest (blue dotted line).

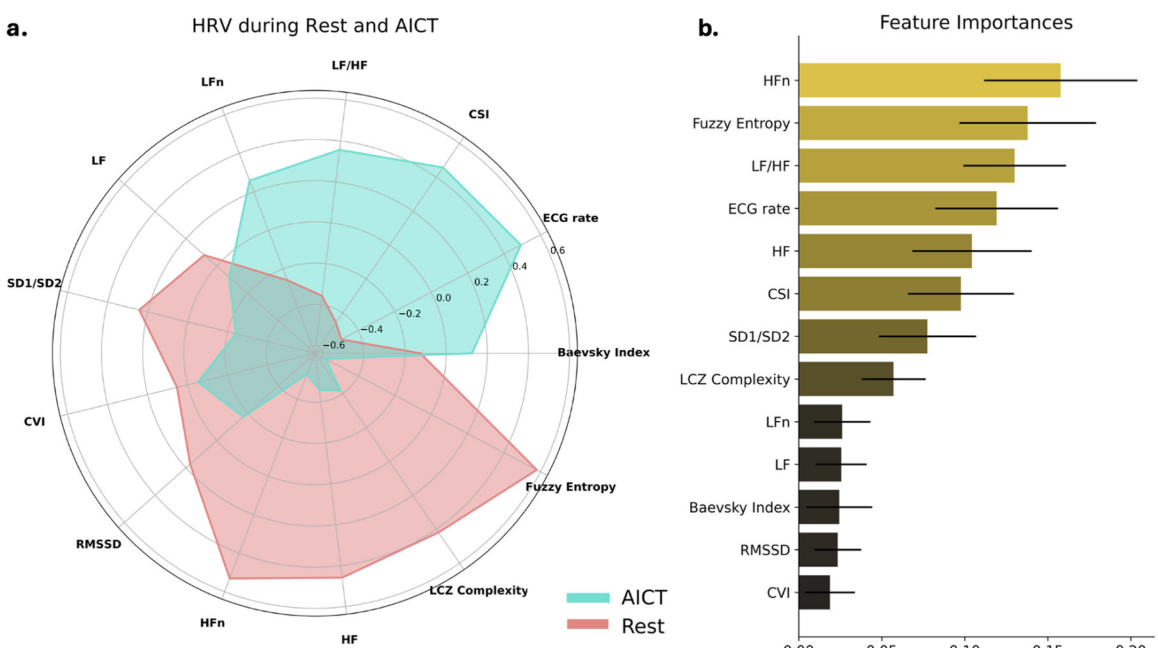

Fig. 4. Change and inter-individual variability in heart rate variability (HRV) at rest and during auto-induced cognitive trance (AICT). a. The left panel shows the mean self-reported scores for each feature across all subjects, with 'AICT' in red and 'Rest' in blue. b. The right panel displays feature importances derived from a multivariate classification performed using a random forest classifier to distinguish between 'Rest' and 'AICT', with a decoding accuracy of 73 % ($p \leq .001$).

phenomenological experience features, we retained the components that explained 90 % of the variance (Fig. 6a). We focused on the first component (PCA1), which accounts for 23 % of the explained variance. The corresponding weighted features of PCA1 are shown in Fig. 6b. We then regressed PCA1 against HRV measures, and after FDR ($p<.05$) correction, only HFn ($R^2=0.31$, $p=.002$) remained significant (Fig. 6c). This indicates that Δ HFn is significantly associated with PCA1, which represents 23 % of the variance of all self-reported phenomenological components. Although LF ($R^2=0.25$, $p=.008$) and LFn ($R^2=0.18$, $p=.02$) showed trends, they did not remain significant after FDR correction.

Second, we investigated the relationship between HF HRV and individual self-reported phenomenological items (Fig. 7). We found that Δ HF regress with external thoughts ($R^2=0.31$, $p=.002$), internal thoughts ($R^2=0.31$, $p=.002$), emotion ($R^2=0.31$, $p=.002$), absorption ($R^2=0.18$;

Table 3
Linear mixed model between 'Rest' and 'AICT' with intercept and slope coefficients for each HRV feature.

HRV features	Time effect (coef)	P-value	Intercept & slope (coef)	[CI] 95 %
ECG rate	0.995	<0.001*	−.8617	[−.8764, −.5306]
RMSSD	−0.349	.064	−.8588	[−.8923, −.4539]
LF	−0.164	.471	−.9060	[−.9071, −.6202]
HF	−0.927	<0.001*	−.9487#	[−.9467, −.6898]
LF/HF	0.720	<0.001*	−.8479	[−.9066, −.3391]
LFn	0.522	.023*	−.9160#	[−.9125, −.6057]
HFn	−1.071	<0.001*	−.8829	[−.8932, −.6106]
SD1/SD2	−0.488	.053	−.9356	[−.9456, −.3670]
CVI	−0.107	.598	−.8762	[−.8874, −.6474]
CSI	0.924	<0.001*	−.9487#	[−.9426, −.6315]
Fuzzy entropy	−1.170	<0.001*	−.9210#	[−.9170, −.5899]
LCZ complexity	−0.845	.001*	−.9487#	[−.9465, −.7028]
Baevsky index	0.253	.247	−.8975	[−.9084, −.4577]

*: p val<0.05; #: coefficient outside the 95 % confidence interval (CI).

p=.02), dissociation (R^2=0.18; p=.02), and trance intensity (R^2 =0.17, p=.03). After FDR correction, external thoughts, inner thoughts, and emotion remained significant (p<.05), while absorption, dissociation, and trance intensity were not significant (p=.09) and only show trends. This result indicates that individuals whose HF varies least during AICT also vary the most in self-reported internal thoughts, emotion, absorption, dissociation, and report greater trance intensity.

Discussion

This study provides new insights into the relationship between phenomenological experiences and physiological processes during NOC. By comparing rest and AICT states, we observed significant changes in heart rate variability (HRV) and self-reported phenomenology. Notably, baseline measures and relative changes in HRV were closely associated with variations in self-reported experiences, shedding light on the functional mechanisms that connect ANS activity to the dynamics of conscious states.

Change in self-reported phenomenology during AICT

Our results suggest that certain general characteristics emerge despite individual differences. The collected phenomenological elements seem to converge towards describing characteristics related to increased perceptual decoupling. This involves a significant reduction in general exteroceptive sensory characteristics (e.g., listening to external noises, awareness of the immediate external environment) in favour of an increase in characteristics related to interoceptive experiences (e.g., visceral and tactile sensations). Moreover, AICT also seems to indicate a cognitive disengagement associated with reasoning (e.g., reduction in prospective and retrospective thoughts, and particular focus) and more of an intuitive cognitive state linked to a significant increase in perceived emotions, enhanced imagination, absorption, and dissociation.

Our results are consistent with other studies reporting similar characteristics experienced during trance states (shamanic trance, Mahorikatan trance, African trance) (Gregoire et al., 2024; Krippner, 2020; Ng, 2000; Peters & Price-Williams, 1983) and other forms of NOC such as hypnotic states (Rainville & Price, 2003), meditative states (Brandmeyer et al., 2019; Lindahl et al., 2014; Lutz et al., 2015) or psychedelic states (Kochevar, 2023; Preller & Vollenweider, 2018). Our results also align with the theoretical models of the entropic brain theory (Carhart-Harris, 2018; Carhart-Harris et al., 2014), which supports the idea that internal, sensory phenomenology increases in NOC are due to a release of top-down inhibition of certain key brain structures.

Resting states: a key factor in inter-individual variations

Our results show that variations in self-reported phenomenology during AICT are strongly linked to participants' baseline phenomenology at rest, with consistency across most items, suggesting a general mechanism related to lived experiences. This is the first time such an effect is highlighted through self-reported phenomenology related to AICT and shows that the resting state itself contains information revealing that a trait that can be associated with change during this state. These findings align with anthropological research (Friedman & Hartelius, 2013; Tart, 1980), indicating that individual resting states should be considered when assessing the effects of NOC. Similar studies in hypnosis show that individuals with higher hypnotizability and absorption traits report richer experiences than those with lower traits (Kumar & Pekala, 1988).

This result shows that participants who display the most significant changes during AICT are those who rate themselves lowest on these scales at rest. This suggests a possible mechanism of compensation or self-regulation. Individuals who experience various emotions and easily enter absorption or dissociation states at rest show minimal changes during AICT. Therefore, this state only slightly enhances the basal state. In contrast, those with fewer felt emotions and more externally oriented thinking (e.g., using greater goal-oriented, prospective, or retrospective thinking) may experience greater shifts during AICT due to increased disinhibition. This suggests that phenomenological variation is an adaptation from the resting state.

Since these measures are self-reported, it is possible that the AICT state alters how participants assess their experiences rather than the experiences themselves. However, from a therapeutic perspective, this can be equivalent, as stimulating positive and favourable beliefs can be beneficial in certain situations, notably by triggering cascades of self-regulation in the ANS (Kreibig, 2010; Meissner, 2011; Porges, 2009).

Autonomic nervous system adaptations

In this study, we revisited HRV metrics to focus on the sympathetic (HR, Baevsky stress index, CSI) and parasympathetic (PNS) indices (RMSSD, HF, HFn, CVI), along with sympatho-vagal balance (LF, LFn, SD1/SD2). Previous findings of PNS withdrawal and slight sympathetic engagement during AICT were reproduced (Oswald et al., 2023). However, new insights, enabled by multi-feature classification, revealed that PNS metrics were more influential in distinguishing rest from AICT. These variations suggest that PNS activity plays a critical role in the observed physiological changes during AICT. Inter-individual comparisons between baseline and changes during AICT (Fig. 5) show that baseline variability is linked to the slope coefficient. This effect is strongest in PNS measures (HF, fuzzy entropy, LCZ complexity), as well as sympatho-vagal (LFn) and sympathetic measures (CSI). This suggests that baseline physiological differences play a significant role in how participants' autonomic systems respond to AICT.

This finding aligns with the idea that PNS variations reflect resilience and physiological adaptability, predicting physiological, metabolic, and psychological flexibility (Beauchaine & Thayer, 2015; Thayer et al., 2009, 2012). Participants with higher PNS levels at rest (greater ANS resilience) show the most significant PNS withdrawal during AICT, indicating a greater capacity for autonomic variation. Conversely, those

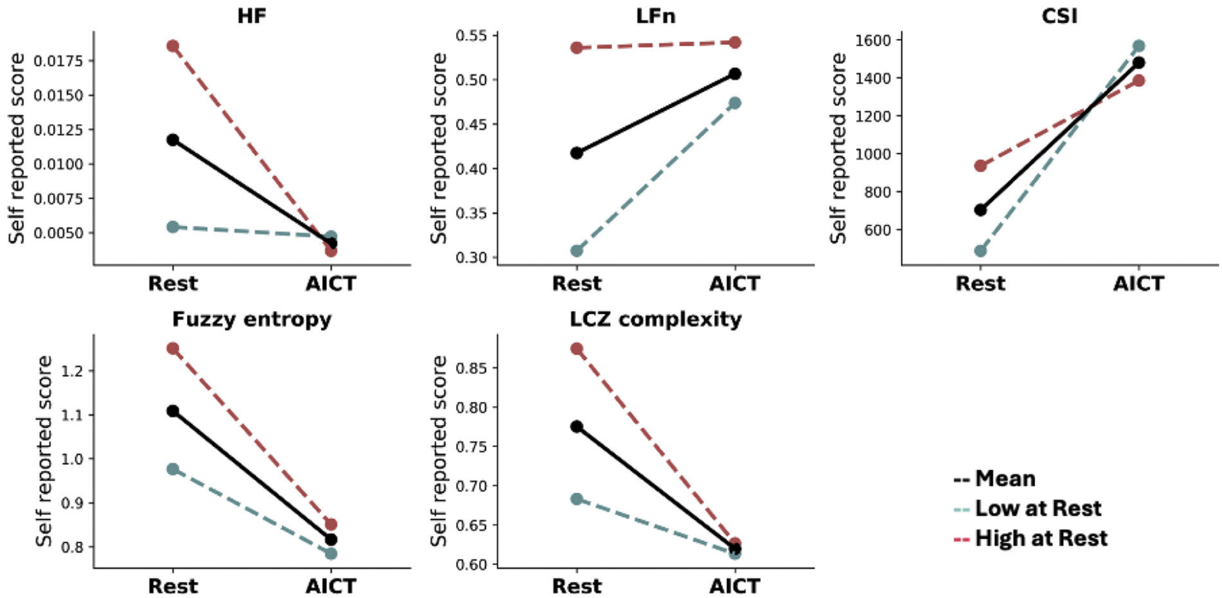

Fig. 5. Linear mixed model reports changes between 'Rest' and 'AICT' conditions for each HRV feature. Only models showing a significant coefficient between intercept and slope (i.e., outside the 95 % confidence interval) from *Table 3* were plotted. A median split was used to separate individuals into high ratings at rest (red) and low ratings at rest (blue).

with lower PNS levels at rest show minimal changes during trance. This effect is unique to the PNS, not seen in sympathetic measures, suggesting modulation specifically targeting this physiological system. A recent study on psychedelics reported a similar withdrawal of the parasympathetic system compared to baseline (i.e., before induction) and placebo (Bonnelle et al., 2024). However, they did not investigate inter-individual differences (Bonnelle et al., 2024). No other studies report a similar effect in ANS inter-individual modulation across NOC.

Association between subjective experience and parasympathetic modulation

Our main goal was to link self-reported phenomenology with physiological changes during AICT. Our results support this connection, showing that the overall variation in phenomenology features significantly regress with changes in high-frequency normalized HRV (HFn) (Fig. 6). Additional analyses revealed that internal and external thoughts, as well as emotions, had a strong relationship with HF, with trends also observed for absorption, dissociation, and trance intensity (Fig. 6). This highlights the role of PNS modulation in subjective experiences during AICT.

Moreover, our results showed that greater PNS variation between rest and AICT was linked to fewer changes in phenomenological experiences. Conversely, participants with minimal phenomenological changes experienced significant PNS withdrawal during AICT. This suggests an inverse relationship between physiological and phenomenological variations. This inverse relationship between phenomenology and physiology aligns with recent HRV research, particularly polyvagal (Porges, 2007, 2009) and vagal tank theory (Laborde et al., 2018), which suggest that vagal reserve at rest is crucial for psycho-emotional adaptation to stressful events. Our data may reflect a self-regulation mechanism where an adaptive central nervous system modulates PNS activity across states, influencing the extent of phenomenological experiences during AICT. This supports the idea that physiological flexibility is linked to variations in subjective experiences during NOC.

This interpretation of NOC is innovative and requires further validation, particularly through longitudinal studies tracking participants over time as they engage in regular practice. Future research should

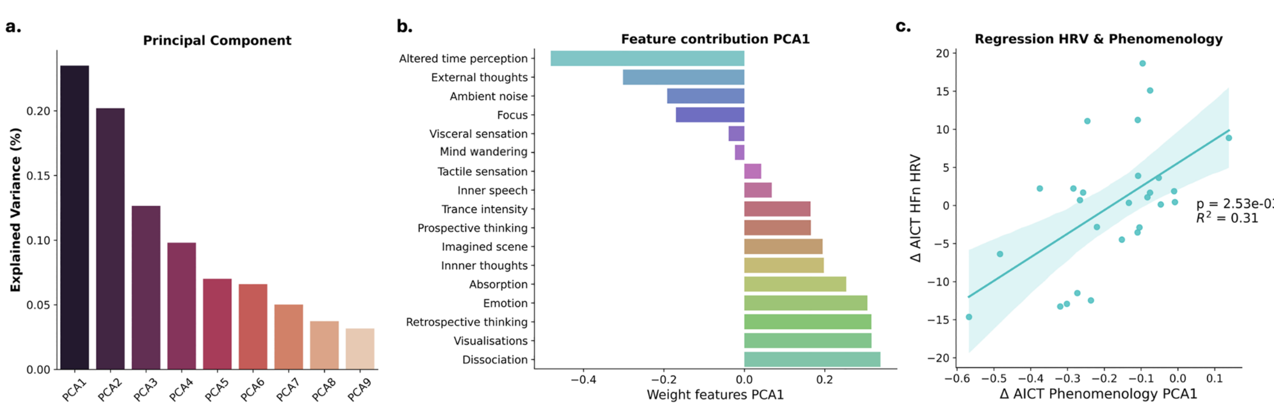

Fig. 6. Interrelation between self-reported phenomenological experiences and HRV measures during auto-induced cognitive trance (AICT). a. All principal component analyses (PCA) obtained after dimensionality reduction, accounting for 90 % of the explained variance with all Δ self-reported phenomenological features, b. Contribution of each self-reported phenomenological feature (or weighted matrix) ordered by value for PCA1, the first principal component (23 % explained variance) c. Regression between the variation (Δ) of self-reported phenomenological experiences during AICT (PCA1) and the variation (Δ) of HFn (HRV) during AICT. The regression results indicate R^2=0.31, which remains significant after FDR correction ($p \leq .05$).

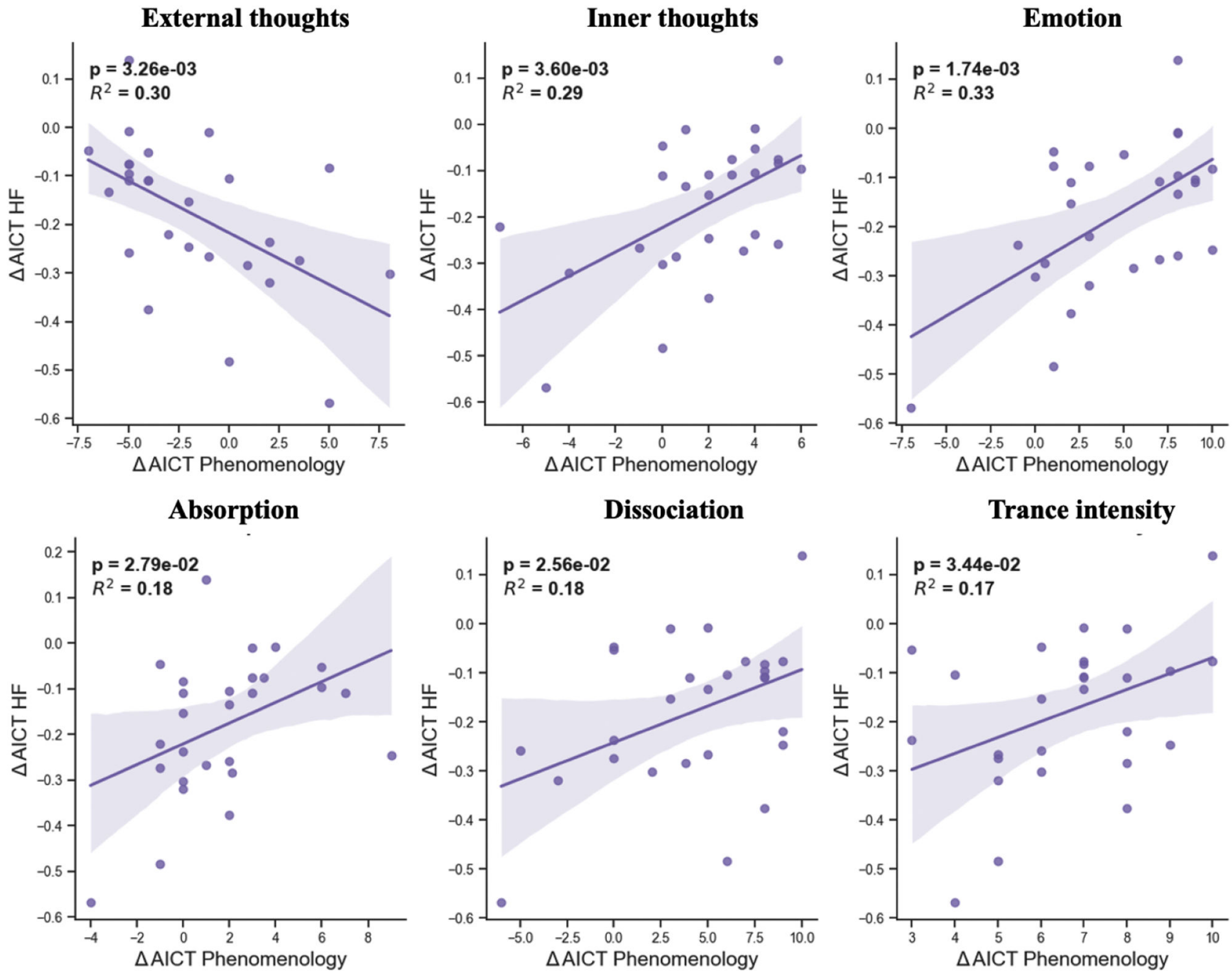

Fig. 7. Interrelation between parasympathetic nervous system and **self-reported phenomenological experiences during auto-induced cognitive trance (AICT).** Results for regressions between variation (Δ) of HFn (HRV) and variation (Δ) of self-reported phenomenological experiences during AICT; external thought (R^2=0.30; p=.003), inner thought (R^2=0.29; p=.003), emotion (R^2=0.33: p=.001), absorption (R^2=0.18; p=.02), dissociation (R^2=0.18; p=.02), and trance intensity (R^2=0.17, p=.03). After FDR correction, external thought, inner thought, and emotion remained significant ($p \leq .05$), while absorption, dissociation, and trance intensity were not significant (p=.09).

explore how baseline phenomenological and physiological measures evolve with practice. Additionally, identifying personality traits linked to greater variation in trance states could help to target populations that are more responsive to these experiences, with potential therapeutic benefits.

Clinical perspectives

The findings of this study offer promising avenues for clinical and health psychology. AICT, by facilitating perceptual decoupling and self-regulation through autonomic nervous system (ANS) modulation, may have therapeutic potential in managing stress, anxiety, and conditions involving dysregulated interoception, such as somatic symptom disorders or chronic pain.

For instance, the observed link between baseline ANS states and the magnitude of change in phenomenology suggests that tailored interventions could be designed to optimize individual responses. Incorporating AICT into therapeutic practices might provide patients with tools to achieve greater physiological and emotional balance, potentially complementing existing approaches such as mindfulness-based therapies, biofeedback, or hypnosis. Future research should explore how AICT could be adapted for specific clinical populations and evaluate its long-term efficacy and safety.

Limitations

Our study involved a small sample of AICT experts recruited by the programme leader (C.S.) based on her judgment of expertise. Future research should establish specific criteria for AICT expertise and replicate findings on a larger, more diverse, and longitudinal sample, including novices. All participants had read about AICT through C.S.'s books on Mongolian shamanic experiences, which may have introduced indirect suggestions (e.g., feeling possessed by an animal, encountering unknown people). We used single-question measures for phenomenology to reduce completion time and stay close to participants' real-time experiences, addressing issues with memory recall. While this method has its advantages, future studies could benefit from using validated psychometric tools to explore different facets of the lived experience and provide a deeper understanding of AICT-related phenomena.

Conclusion

This study highlights the diverse changes that occur during NOC, specifically with AICT. Our findings reveal distinct phenomenological changes, particularly perceptual decoupling during AICT compared to rest, alongside physiological modulation of ANS activity. Importantly, baseline states significantly influence the magnitude of these changes.

The observed inverse relationship between PNS activity and lived experiences points to a dynamic self-regulation mechanism linking physiological processes to phenomenological states. This provides direct evidence of the intricate interplay between ANS activity and self-reported phenomenology, offering a novel perspective on how physiological mechanisms shape subjective experiences in NOC.

This study also provides insight into the therapeutic potential of AICT as a NOC and its use as a therapeutic tool. Tailoring interventions to target patients based on their baseline ANS states could enhance the effectiveness of NOC-based therapies. Future research on the therapeutic potential of NOC will be essential to elucidate the physiological mechanisms underlying these transformative states.

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Artificial intelligence disclosures

The text was revised and corrected using ChatGPT-4.

Materials

All data ECG and self-report data are available upon request at avanhaudenhuyse@chuliege.be and ogosseries@uliege.be. Script analysis: A GitHub repository consolidates all Python scripts used for machine learning, regression, and visualization (https://github.com/LIKACT/Phenomenology-Heart-rate-variability-in-Auto-Induced-Cognitive-Transe-AICT-).

Ethics disclosures

Before the study, participants were fully informed of its objectives and provided written consent. No incentives were offered for participation. The study was approved by the Ethics Committee of the Faculty of Medicine at the University of Liege (reference 2019/141) and conducted in accordance with relevant guidelines and regulations.

Authors contributions

Design of the study: O. Gosseries, A. Vanhaudenhuyse. Data collection: O. Gosseries, A. Vanhaudenhuyse, C. Martial, J. Annen. Data analysis: V. Oswald, K. Jerbi, O. Gosseries, A. Vanhaudenhuyse.Manuscript writing: V. Oswald. Reviewing paper: O. Gosseries, A. Vanhaudenhuyse, C. Martial, V. Oswald, K. Jerbi, C. Sombrun, J. Annen.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Victor Oswald reports financial support was provided by TranceScience Research Institute post doctoral grant. Corine Sombrun reports financial support was provided by TranceScience Research Institute founder. All the other authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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