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Finding Patterns in Variability: Clustering Skin Conductance Responses to Identify Psychopathological Patterns

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Abstract

As current studies continue to provide evidence against the classic view of emotions, the search for new methods in affective science has become necessary. Approaches like the use of Representational Similarity Analysis (RSA), which are able to account for relationships between dimensions of data have proven to be useful tools in the continuous search for evidence of more recent theory of constructed emotions.

This paper examines the relationship between physiological variability in terms of skin conductance response (SCR) and psychopathological factors. This study applies unsupervised clustering to data sampled from two studies by Koppold et al. (2022; 2024), in order to find physiological clusters which might reflect mental health conditions.

Although significant results were found for both the physiological clustering and the psychopathological clustering, no significant results were obtained for a potential relationship between these sets of clusters.

While the physiological variability aligns with the constructed emotions framework, its connection to psychopathological markers remains inconclusive, suggesting the need for further research with more diverse samples.

Zusammenfassung

Da aktuelle Studien zunehmend Beweise gegen die klassische Emotionstheorie liefern, wird die Suche nach neuen Ansätzen in der affektiven Wissenschaft immer wichtiger. Verfahren wie die Representational Similarity Analysis (RSA), die Beziehungen zwischen verschiedenen Daten Dimensionen berücksichtigen können, haben sich als wertvolle Werkzeuge bei der Untersuchung der neueren Theorie der konstruierten Emotionen erwiesen.

Diese Arbeit untersucht den Zusammenhang zwischen physiologischer Variabilität, gemessen anhand der Hautleitfähigkeit (SCR), und psychopathologischen Faktoren. Hierfür wird eine unüberwachte Clusteranalyse auf Daten aus zwei Studien von Koppold et al. (2022; 2024) angewendet, um physiologische Cluster zu identifizieren, die möglicherweise auf psychische Gesundheitszustände hinweisen.

Obwohl signifikante Ergebnisse sowohl bei der physiologischen, als auch bei der psychopathologischen Clusterbildung erzielt wurden, konnte keine signifikante Beziehung zwischen diesen Clustergruppen festgestellt werden.

Während die beobachtete physiologische Variabilität die Theorie der konstruierten Emotionen unterstützt, bleibt der Zusammenhang zu psychopathologischen Markern unklar, was auf die Notwendigkeit weiterer Forschung mit vielfältigeren Stichproben hinweist.

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Introduction

Recent papers in affective science have shown support for the theory of constructed emotions (Hoemann et al., 2020; Koppold et al., 2024), which, in contrast to classic views on emotion, accommodates for potential variation in affective state within and between individuals. Evidence of a significant relationship between peripheral physiology and psychopathology has recently emerged as well (Koppold et al., 2022). This was illustrated by variations in skin conductance response (SCR) in participants who have experienced childhood maltreatment or recent life adversity (Koppold et al., 2022).

Given these current developments, this paper attempts to connect the intra-variability aspect of physiological emotional responses shown by Koppold et al. (2024) with possible mental health repercussions.

This is carried out by applying an unsupervised clustering algorithm to skin conductance response (SCR) data collected by Koppold et al. (2022; 2024), which accounts for intra-variability in participants in terms of their peripheral physiological responses in different trials.

The use of clustering under these circumstances could potentially have repercussions in many application fields, such as psychological diagnoses and work psychology, as clustering via physiological measures could facilitate diagnostic processes.

Although some studies have shown success in connecting mental health disorders with physiological patterns (Fisher et al., 2022), most have not accounted for intra-variability, which could provide a more well rounded picture of the affected individuals. In this paper, all of these factors will be taken into account.

Theoretical background

Emotion theories

When it comes to affective science, there is a deeply engrained debate which separates emotion scientists into functionalists and constructionists (Barrett, 2017). Functionalism derives from the classic view on emotions, relying on emotions being responses to environmental stimuli which arose as a product of evolution (Adolphs, 2016), but more recently another theory has gained traction in the attempt to better understand emotions: the theory of constructed emotions (Barrett, 2017).

Different from functionalism, constructionism does not view emotions as responses to given stimuli, but as concepts which are built and updated probabilistically in a context-dependent manner. Given this context dependency, the theory of constructed emotions implies that emotions are variable between and within individuals, which strongly opposes the universal physiological patterns suggested by functionalists. To better understand these theories, let us illustrate the two conflicting views with an example.

Imagine two middle schoolers prepare to present a science project to their class. Student A constantly wipes their palms to try and control the building sweat, their heartbeat is accelerated and they cannot seem to stay still. Meanwhile, student B is still and has dry hands. When asked if they feel afraid, both say yes. The two main streams of thinking that have emerged in emotion research would explain the scenario above quite differently from each other. In the following sections, let us dive into brief explanations of each of these prominent theories.

The Fingerprint Hypothesis

The idea that each emotion has their own unique characteristics has been around for a long time, with studies mentioning the potential universality emotions already in the 1960s (Ekman, 1992). In recent years, the theory of basic emotions (Ekman & Cordaro, 2011) and functionalism (Adolphs, 2016) have attempted to bring the fingerprints hypothesis into modern psychology.

According to Ekman and Cordaro (2011), there are 7 basic emotions: happiness, sadness, disgust, surprise, fear, anger, and the most recently added, contempt. Each of these emotions is uniquely identifiable and universal. They are shown via specific facial expressions (Le Mau et al., 2021), for example, anger would be showcased by frowning and happiness by smiling, and each of them is representative of a unique pattern of activity in the brain (Le Mau et al., 2021).

The basic emotions view implies that all individuals have the same physiological reactions to specific emotional situations. Functionalism would explains these physiological circuits as having developed as evolutionary mechanisms to regulate behaviour, which developed over thousands of years to attend to survival needs posed by environmental challenges (Adolphs, 2016).

In addition to patterns in the brain, emotions are associated with distinct autonomic nervous system (ANS) patterns (Kreibig, 2010), which link the emotional responses to peripheral responses such as heart rate increasing when one experiences fear, which according to this theory, triggers the sympathetic nervous system.

These theories can be encompassed by the fingerprint hypothesis, which states that each emotion is unique and has a distinct pattern in the brain, implying that all individuals experience the same emotions under specific circumstances.

According to the fingerprint hypothesis, the scenario of the students above could simply be explained by a matter of intensity. It is possible that the ANS circuits for fear are activated in both students A and B, but student A possibly sees the scenario of presenting in front of their class as more threatening than student B, and thus, student A has a stronger reaction. Note that according to this theory, the emotion circuits for fear would be activated regarded of this intensity difference.

This hypothesis represents what is known as an inductive approach. It starts off from a point of perception based categories and assumes these categories must have distinct physiological patterns (Barrett, 2017).

The Populations Hypothesis

In contrast to the fingerprint hypothesis, a recent view proposing variability in emotions has emerged. Lisa Feldman Barrett's theory of constructed emotion (2017) proposes a shift from the classic inductive to a deductive approach. The fingerprint hypothesis assumes the existence of the basic emotions and attempts to find their biological bases from these concepts. Barrett argues that these concepts are arbitrary, and that to truly move forward emotion research, one should start at the brain. Thus, the theory of constructed emotions starts with the function and structure of the brain, and then moves to the biological bases of emotions.

This implies that what we know as emotions are simply conceptual categories (Barrett, 2017). They are variable instances agglomerated due to their common objective, not due to their cause. Thus, it is logical that the same emotion, or rather, the same conceptual category of that emotion, could have different underlying physiological patterns in different people. According to Barrett (2017), emotions are concepts built on context-dependent instances, and are not strictly linked to specific physiological patterns.

This theory is representative of what is known as the populations hypothesis, which assumes that to investigate emotions, one must assume that there exists variability between individuals. The key would be to find structure within this assumption of variability.

This assumption collides with the fingerprint hypothesis, as the classic view assumes that each emotional category has a distinct pattern in the brain. If that were to be the case, every person would show the same ANS activation patterns for each emotion.

Coming back to the earlier scenario, this populations hypothesis could explain the different physiological states of students as variations. Student A and student B could simply have different conceptual categories in regard to what they have learned as fear. As the construction of an emotion is dependent on individual experiences, it would be expected that students A and B could have similar, overlapping concepts of the emotion fear, which however evoke different physiological patterns.

A glimpse into the evidence

While the classic view of emotions has been around for a long time, and thus, has several papers supporting it, many of those papers have fallen victim to time. Papers such as the classic “Pan-cultural elements in facial displays of emotion” by Ekman et al. (1969) used outdated methods which are all but impossible to reproduce nowadays. Meanwhile, with advances in new computational methods in recent years, a stream of evidence has started to appear in support of the populations hypothesis.

Regarding the classic view staple of universal facial expressions of each emotion, a recent study by Le Mau et al. (2021) has found that “facial movements and perceptions of emotion vary by situation and transcend stereotypes of emotional expressions”. The authors investigated images of professional actors portraying emotions and have found that when showing typical emotions in extreme scenarios, actors’ facial expressions did not correspond to the prototype established from previous research which supports the classic view. Meanwhile, in milder scenarios, they found moderate reliability and moderate specificity for the prototypical expressions (Le Mau et al. 2021). This study provides some support for the context-dependency proposed in the theory of constructed emotions, and somewhat provides evidence against the idea of universal facial expressions.

Furthermore, a study using unsupervised clustering (Hoemann et al., 2020) was not able to find a conclusive number of emotions in participants which were accompanied during their daily activities with physiological monitors. The participants received prompts throughout their days in order to report on current emotions. Meanwhile, peripheral physiological measures such as interbeat interval (IBI) and cardiac output (CO) were taken. After performing both within and between participant analyses, the authors found no consistent number of clusters nor did they find consistency and specificity in emotion word usage (Hoemann et al. 2020). This provides support for the idea that emotional categories are variable and that looking for a set number of emotions might be misguided.

The studies discussed in this section highlight the evidence in research supporting variability in emotional responses, particularly the theory of constructed emotions, but they do not reveal any connections to mental health. In the following sections, this paper attempts to bridge this gap.

Accounting for variability: Representational Similarity Matrices as a tool

Arguably, the biggest challenge in researching the theory of constructed emotions is finding an approach that matches its innovation (Barrett, 2017). With current approaches, there is evidence supporting both the classical view of emotions as well as the theory of constructed emotions. However, as suggested by Barrett herself (2017), new methods that align with the concepts of constructionism must be developed so that research can move forward.

One of the staples of constructionism is the assumption that there is structure within variability (Hoermann et al. 2020), thus the key to investigating constructionism is finding methods that allow for the investigation of variability between and within participants, as the theory assumes that concepts of emotion are constructed individually and updated as individuals grow under different circumstances and environments. Due to this, Koppold et al. (2024) have proposed the use of representational similarity matrices (RSMs) to investigate variability in emotion research.

In their study, Koppold et al. (2024) use Representational Similarity Analysis (RSA) to build a Representational Similarity Matrix (RSM) which contains similarity scores based on the distances in vector space between participants' peripheral physiological reactions in different trials. The peripheral physiological reactions are represented by a measure of skin conductance response (SCR).

Koppold et al. (2024) analysed participant's scores under two circumstances. They calculated the RSM which accounted for intra-variability, by first sorting trials by arousal values, then calculating the SCR RSMs for individuals and finally averaging the values. For dismissing intra-variablity, Koppold et al. produced an RSM of averaged trials across participants.

The Nearest Neighbours (NN) model assumes that trials that are close to each other in the vector space will contain similar responses, independently of where in the vector space they are. This model is congruent with the fingerprint hypothesis, assuming that affective experiences that are analogous will evoke similar peripheral physiological responses.

The other model which was theorised was the Anna Karenina (AK) model, which assumes that trials that are close in the vector space don't necessarily evoke similar reactions, which is congruent with the populations hypothesis. It predicts that the responses will vary in accordance to their location in the arousal spectrum, expecting that similar affective experiences might correspond to divergent physiological responses. The initial assumption was that trials that are in the higher end of the arousal spectrum would produced more similar responses than those in the lower end. However, the authors found that the most appropriate model when considering intra-variability was the inverse AK model, which shows responses on the lower end of the arousal spectrum showing more similarity than those in the higher end.

When it came to the data that did not account for variability, the authors found that it resembled what would be expected according to the fingerprint hypothesis, the NN model (Koppold et al., 2024).

These results are relevant as they show that once variability is accounted for, the patterns that are expected when it comes to physiological measures representative of arousal shift. This could lead to new understanding in areas that have emotions as foundation, such as mental health research. With this in mind, let us take a look into another recent study by Koppold et al. (2022).

Psychopathological factors

A study by Koppold et al. (2022) found significant differences in physiological responses of individuals who had suffered childhood maltreatment as well as recent adversity, indicating a connection between psychopathology and affective physiological responses.

The authors found that individuals who had suffered childhood maltreatment shows reduced affect modulation in SCRs in relation to those who had not been exposed to childhood maltreatment. Furthermore, Koppold et al., (2022) found that individuals exposed to recent adverse events had the opposite response, showing increased affect modulated SCR.

This has lead to the idea that there might be physiological groups which relate specifically to psychopathological factors.

Research questions

This paper aims to investigate the relationship between inter-variable physiological data and psychopathological factors. This is to be carried out by applying a clustering algorithm to a SCR RSM. Specifically, the following three questions are to be answered.

1. What is the ideal number of clusters given the RSM?
2. How are the identified clusters characterised in terms of physiological responses?
3. Can the identified clusters be linked to psychopathological factors?

Methods

Data origin

All data used in this study was sampled from two papers by Koppold et al. (2022; 2024). What makes this paper possible is the participation of common participants in both studies. The psychopathological data was sampled from the 2022 study, which contained 685 participants in (424 female, 246 male; mean age = 25.36, SD age =5.57). This data was also used in the 2024 study, with an addition of 64 participants in a replication sample (51 women, 13 men; mean age = 23.43, SD age = 4.11). Out of these, there were 488 participants whose sample was used for the construction of the SCR RSM. The final sample contained 336 participants who participated in both studies.

Physiological data

What is referred to as physiological data from this point forward is the RSM containing the similarity scores SCR responses between trials for individual participants. It contains similarity scores for all 36 trials in all their different combinations, resulting in 1296 rows for each of the 488 participants.

Psychopathological data

What is referred to as psychopathological data from this point forward is the data containing participants' scores in various different questionnaires on mental health. Each of the questionnaires is briefly explained below.

The Childhood Trauma Questionnaire (CTQ) was used to assess negative emotional, physical childhood experiences, sexual abuse, and physical neglect (Koppold et al. 2022).

The List of Threatening Experiences (LTE) was used to assess recent adverse events occurring in the 12 months previous to testing (Koppold et al., 2022).

The Spielberger Trait Anxiety Scales (STAI) was used to assess trait anxiety (Koppold et al., 2022).

The Beck-Depression Inventory (BDI) was used to assess depression (Koppold et al., 2022).

Data analysis and results

Physiological data analysis

Preprocessing

As the physiological data was already manipulated by Koppold et al (2024), there was only a minimal need to further process it. The data was already properly scaled in terms of similarity scores.

Duplicates containing identical trial combinations were removed, resulting in a total of 666 rows for each participant.

Choice of model

Supervised vs. unsupervised models

There is an abundant amount of machine learning models in use in the world today. They range from classifying mammogram images to identify potential breast cancer patients (Jayandhi et al., 2022) to identifying exoplanets in space (Shallue & Vanderburg, 2018) and costumer segmentation for marketing strategy (Abdulhafedh, 2021).

These models are most commonly divided into two categories: supervised and unsupervised models. Supervised models analyse data that is labelled with the objective of eventually inferring these labels onto new data. This would be the case, for example, of the SVM model used by Jayandhi et al. (2022) to aid doctors in detecting breast cancer. Models such as this one have gained some popularity in psychological research in recent years (Sánchez-Reolid et al., 2022).

On the other hand, there are models that aim to detect patterns, in which case, there are no labels for the model to learn with. These models usually rely on common characteristics of different data points, or how the data points' positions on a multidimensional vector space can determine which potential group, or cluster, they belong to.

The K-means model

Although supervised machine learning models have gained some traction in psychology research in recent years (Sánchez-Reolid et al., 2022), unsupervised modelling is still mostly uncharted territory in the field (Sánchez-Reolid et al., 2022). A few pioneer studies have used clustering models in emotion research, such as Le Mau et al. (2021) and Hoemann et al. (2020), which were mentioned previously. However, these are outliers and research using unsupervised models is still new to this field.

For this paper, the K-means model was chosen. It clusters data points by grouping them around centroids. The number of clusters is predetermined, and the algorithm determined the best position of the centroids of these clusters (Kodinariya & Makwana, 2013). In the case of this study, the model forms groups based on the RSM matrix. Participants with similar relative scores should therefore be grouped together.

The K-means model is also the most widely used unsupervised machine learning tool in psychology research as of yet (Sánchez-Reolid et al., 2022). For this initial analysis of physiological clusters, K-means is an appropriate model, as it is simple and wide-spread.

The model works by dividing a sample into K clusters. Each of these clusters is determined based on the mean of the samples in the cluster, which are called centroids. In short, the model determines two ideal centroids so that each data point belongs to its most likely cluster. It aims to minimise the inertia, that is, the sum of the squared distances of each data point to their closest centroid.

The model choice here was based on simplicity and reproducibility, since, as previously mentioned, both clustering and the assumption of structure within variability are somewhat new in the field of emotion research.

A drawback of this model is having the number of clusters as an argument. That is, the algorithm itself is not proper to determine the ideal number of clusters. Because of this limitation, the number of cluster had to be determined via a combination of two methods which have proven to be reliable in previous clustering studies (Aladžuz et al, 2022).

Skin conductance response (SCR) cluster analysis

The optimal number of clusters, representing the most likely grouping of the physiological data, was determined to be 2. To determine this number, two different techniques were combined: the elbow method and the silhouette score.

The elbow method (Fig. 1A) was calculated by running the K-means algorithm for multiple possible cluster numbers and choosing the most appropriate number visually. For each iteration of the algorithm, the value of inertia is calculated. The final inertia for each cluster was plotted on the y-axis, while the number of clusters is plotted on the x-axis (Kodinariya & Makwana, 2013). Theoretically, the optimal number of cluster would appear as an elbow in the line graph, which is the case at cluster 2.

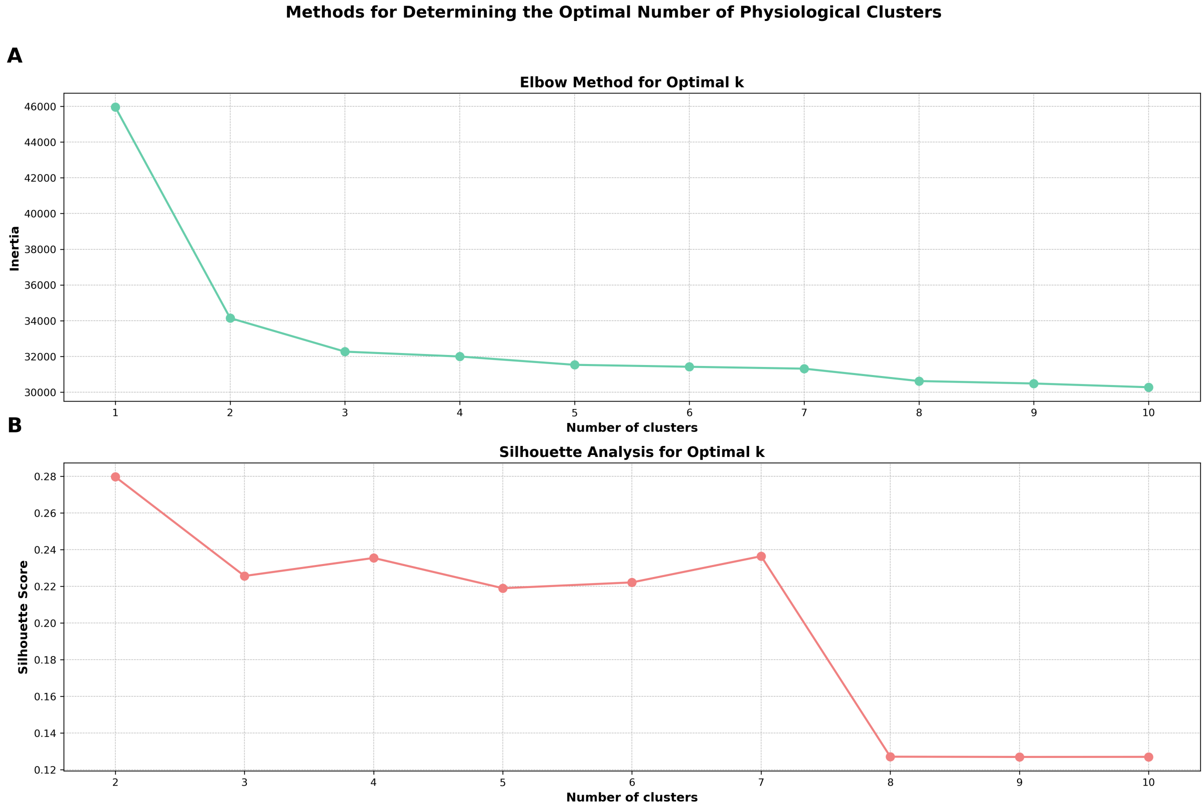

Fig. 1. Plots showing the two methods for determining the number of cluster. The upper plot (A) shows the elbow method while the lower plot (B) shows the silhouette analysis.

To support this choice, a silhouette analysis (Fig. 1B) was carried out as well. This method takes into account distances inside of potential clusters as well the between them (Kodinariya & Makwana, 2013).

The formula for the silhouette score S is shown below. In it, variable **a** represents the mean distance of the data points in a potential cluster to all other data points in the same potential cluster, while variable **b** represents the mean distance the data points in a potential cluster to all data points in the nearest potential cluster (Pedregosa et al., 2023).

$$S = \frac{b - a}{\max\{a, b\}}$$

After calculating the silhouette score for all potential clusters in the chosen range, the highest score is selected as most appropriate (Aladžuz et al, 2022). In this case, the highest silhouette score corresponds to 2 clusters, supporting the result obtained via the elbow method.

After having established the optimal number of clusters, the K-means algorithm could be applied to the RSM.

The algorithm yielded two clusters. As unsupervised models create categories based on euclidean distance in a vector space, it is not immediately clear what these clusters represent and whether they have any relation to the above mentioned psychopathological data. For now, they will remain with the generic labels of "Cluster 1" and "Cluster 2".

Cluster 1 has 248 participants with a mean similarity score of 2.13, while Cluster 2 has 240 participants with a mean similarity score of 2.50. The difference between these two clusters is statistically significant ($p<0.01$) and it shows a very large effect size ($d=-4.326987128037509$), indicating that the mean of Cluster 1 is smaller than Cluster 2, as is made clear in Figure 2. This was supported by a permutation test with 10000 permutations.

As Koppold et al. (2024) have used heat maps to represent their findings due to the nature of their research, here the data is also shown in heat maps, for the comparison to be clearer. Note that because of this 3D representation of data that is originally 2D, the matrices are symmetrical, that is, the upper and lower triangles are the same.

Observe that the values are shown in order of arousal. Low arousal data points are concentrated in the upper left corner of each map, while higher values are in the lower right corner. The colour bar to the right of each map represents the intensity of the correlation values, with darker values representing higher correlation values.

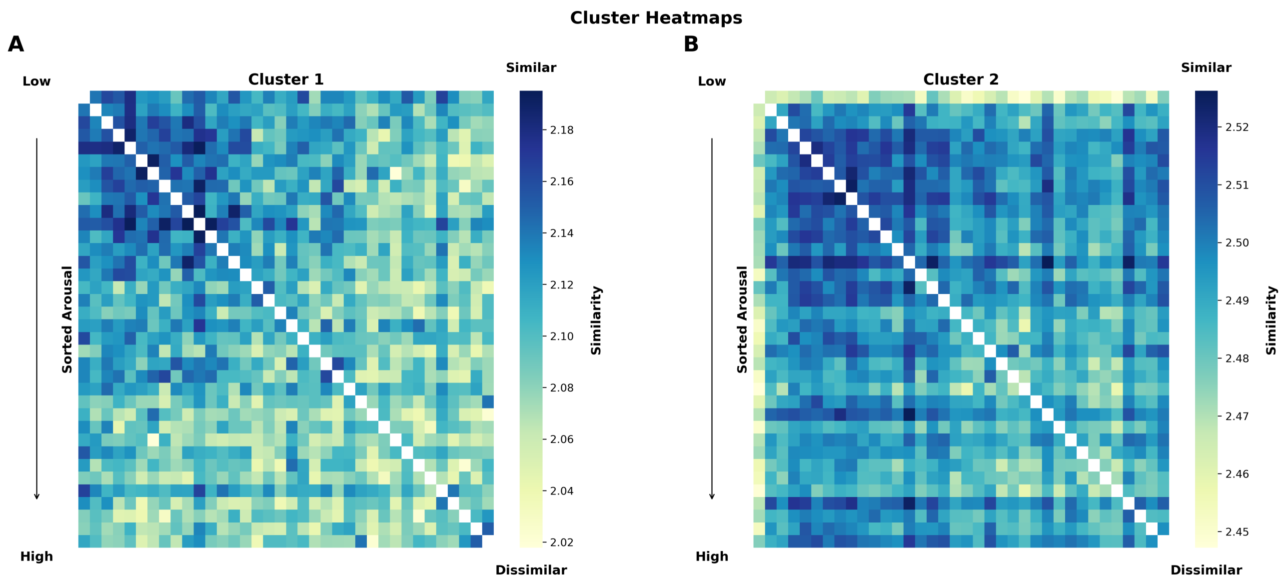

Fig. 2. Plots showing the resulting physiological clusters in the form of heatmaps. (A) Cluster 1. (B) Cluster 2.

By analysing the two clusters side by side, some differences stand out. Let us first take a look into the pattern which arises in Cluster 1 (Fig. 2A).

Cluster 1 reflects the pattern shown in the mean heat map of all participants, which is the pattern that Koppold et al. (2024) proposed for the populations hypothesis. This pattern, known as the inverted Anna Karenina (AK) model, represents similarity in physiological responses in the lower end of the arousal dimension, while the distances between responses of dimensionally close trials tend to increase along the diagonal, that is, as arousal increases.

Meanwhile, Cluster 2 (Fig. 2B) does not show this pattern as clearly as Cluster 1. Although the general trend of lower arousal showing a higher similarity between measures and higher arousal values being more scattered, there is more deviation from the expected inverse AK model.

This group shows much higher similarity values in general, as can be seen by the scores shown in the colour bar to the right of the plots. And within these higher similarity values, the values in the higher arousal region show higher similarity between dimensionally close trials than in Cluster 1.

Interestingly, Cluster 2 shows quite a bold outlier line, on the left and upper borders of the heat map. This border does not show the expected gradient, but only low similarity values in spite of the progression of arousal values, indicating that this could potentially reflect a systematic error.

Psychopathological data analysis

Different from the physiological data, the psychopathological data is comprised of several different questionnaire scores, and thus, requires more thorough preprocessing. Each of the different questionnaires has a different scale and answer style. For example, the BDI questionnaire consists of 21 questions on a 4 or 5 point Likert scale, while the LTE questionnaire is comprised of yes-or-no forced-choice style questions.

These questionnaires are also assessed differently from one another, which is why it is important to scale the data before moving on to the machine learning portion of the study.

To address this issue, the data was scaled using the function MinMaxScaler, from the Python package Scikit Learn (Pedregosa et al., 2023). This algorithm assures all columns are represented in a common scale, in this case, all original values are linearly transformed to be in the scale of 0 to 1. Their nature is conserved, while the new scale makes it possible for the questionnaires to be analysed as a whole.

Furthermore, before applying the K-means algorithm to the psychopathological data, a correlation analysis was performed as to discard any highly correlated (>0.8) columns in order to simplify the model. This analysis indicated that the features of CTQ emotional negative experience and CTQ emotional neglect were highly correlated with the sum of all CTQ questionnaires (as shown in the image below), and thus were removed previous to clustering.

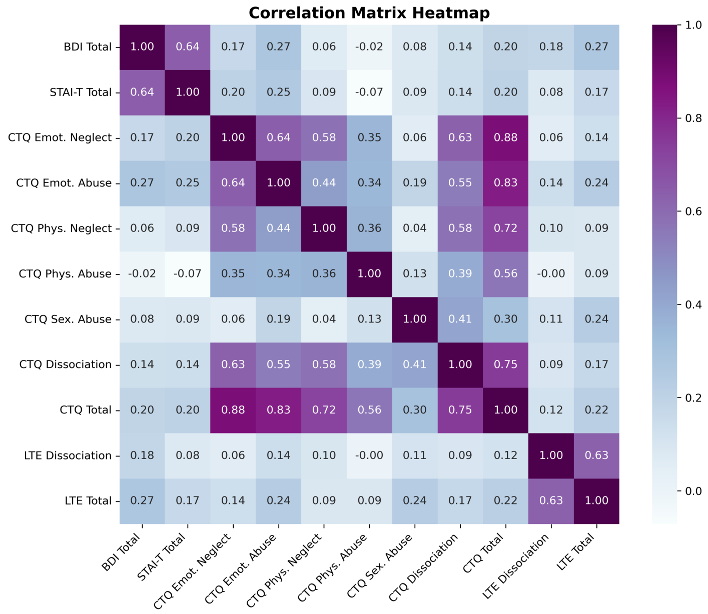

Fig. 3. Correlation matrix of all psychopathological features.

As this paper takes a deductive approach as suggested by Barrett (2017), it follows the assumption that one should start looking for emotions in the brain, before inferring any kind of emotional categories and their implications. Thus, there is no need to identify the optimal number of clusters for the psychophysiological data, as it should theoretically be a reflection of the physiological clusters which have been determined to be 2.

Once again, the K-means model from the Scikit Learn (Pedregosa et al., 2023) package was used to analyse the data. As intended, the algorithm yielded two clusters. Cluster 1 contains 358 participants and Cluster 2 contains 111 participants. Table 1 shows the mean of each psychopathological feature for each cluster.

The mean of all values, as well as the median (50%), indicate that both clusters are quite similar in terms of psychopathological factors and that most participants are mentally healthy. There are a few outliers, such as the maximum score of 44 in the BDI questionnaire for a participant of Cluster 1, but the general picture of both clusters is quite similar.

It is interesting to note that in the LTE questionnaire, the values for the participants are mutually exclusive, with Cluster 1 having participants which have experienced significant negative events, while Cluster 2 presents a score of 0 for all life events which may have recently caused stress.

In all other questionnaires, participants in both clusters tended to stay on the lower end of the spectrum, indicating no mental health issues.

	mean	std	min	50%	max
BDI Total					
Cluster 1	4.93	5.19	0.0	4.0	44.0
Cluster 2	2.82	3.74	0.0	1.0	21.0
STAI-T Total					
Cluster 1	35.81	8.17	21.0	34.0	69.0
Cluster 2	34.28	7.00	21.0	34.0	54.0
CTQ Emot. Neglect					
Cluster 1	8.71	3.80	5.0	8.0	25.0
Cluster 2	8.19	3.55	5.0	7.0	22.0
CTQ Emot. Abuse					
Cluster 1	7.85	3.12	5.0	7.0	25.0
Cluster 2	6.84	2.45	5.0	6.0	19.0
CTQ Phys. Neglect					
Cluster 1	6.40	2.13	5.0	5.0	20.0
Cluster 2	5.92	1.85	5.0	5.0	14.0
CTQ Phys. Abuse					
Cluster 1	5.45	1.29	5.0	5.0	16.0
Cluster 2	5.45	2.14	5.0	5.0	25.0
CTQ Sex. Abuse					
Cluster 1	5.47	1.65	5.0	5.0	18.0
Cluster 2	5.09	0.44	5.0	5.0	8.0
CTQ Dissociation					
Cluster 1	0.20	0.40	0.0	0.0	1.0
Cluster 2	0.12	0.32	0.0	0.0	1.0
CTQ Total					
Cluster 1	33.89	8.82	25.0	31.0	76.0
Cluster 2	31.49	7.44	25.0	29.0	64.0
LTE Dissociation					
Cluster 1	1.00	0.00	1.0	1.0	1.0
Cluster 2	0.00	0.00	0.0	0.0	0.0
LTE Total					
Cluster 1	2.01	1.21	1.0	2.0	8.0
Cluster 2	0.00	0.00	0.0	0.0	0.0

Table 1. Summary statistics of psychopathological factors for both psychopathological clusters.

In spite of these nuanced values, significant differences were found between clusters in the columns of BDI Total ($p<0.01$, $d=0.53$), with moderate effect size, STAI-T Total ($p<0.05$, $d=0.3$) with small effect size, CTQ Emotional Abuse ($p<0.01$, $d=0.39$) with moderate effect size, CTQ Sexual Abuse ($p<0.05$, $d=0.29$) with small effect size, CTQ Dissociation ($p<0.05$, $d=0.29$) with small effect size, CTQ Total ($p<0.05$, $d=0.31$) with moderate effect size, LTE Dissociation ($p<0.01$, d=infinite) with very large effect size and LTE Total ($p<0.01$, $d=1.85$) with very large effect size. This may be due to the size of the sample and the homogeneity of participants in terms of psychopathological scores.

In summary, Cluster 1, although minimally for most individuals, tends to be more affected by these psychopathological factors than Cluster 2.

Comparison of clusters

Now that the two datasets and their respective clusters have been analysed individually, let us compare the resulting clusters for each dataset with each other.

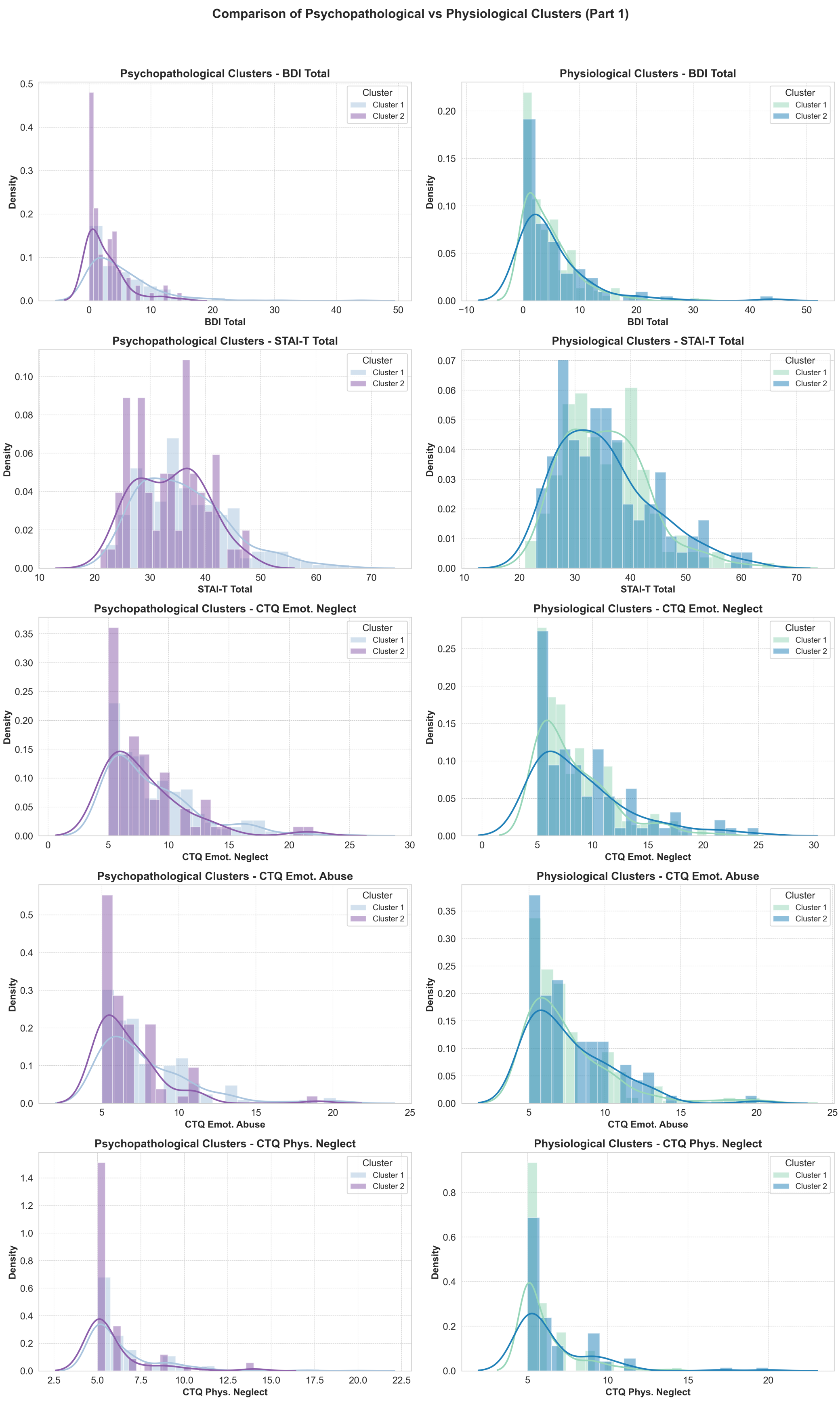

Fig. 4. Plots of psychopathological features for psychopathological (left) and physiological clusters (right).

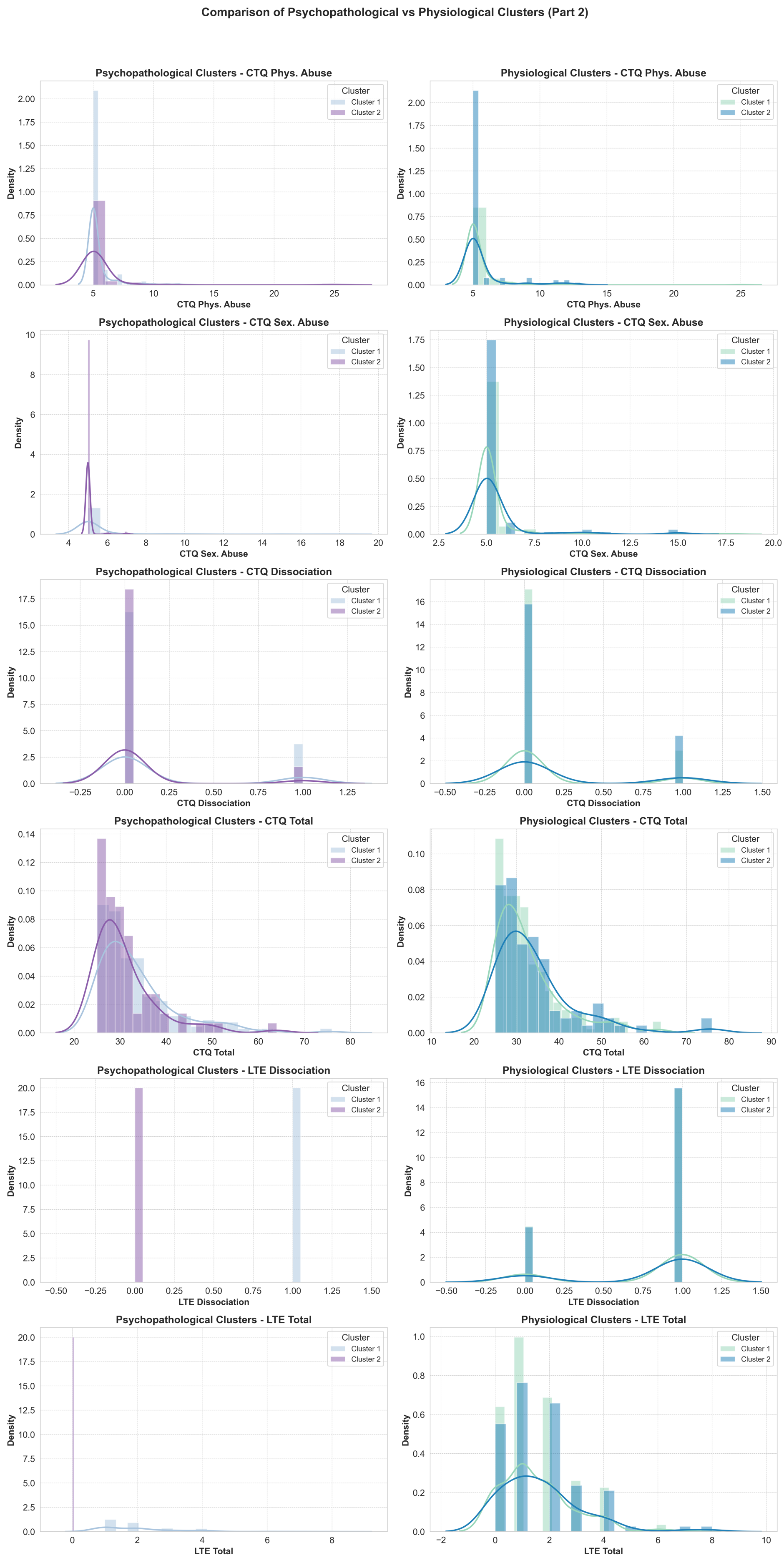

Fig. 5. Plots of psychopathological features for psychopathological (left) and physiological clusters (right).

While the physiological data presented groups of 248 and 240 participants, the psychopathological data was grouped into two very uneven clusters in terms of number of participants, with Cluster 1 having 358 participants and Cluster 2 111. When accounting for only the participants which were present in both datasets, these numbers drop to 241 and 95 (physiological clusters), and 261 and 75 (psychopathological clusters), totalling a number of 336 participants.

When comparing the overlapping participants between clusters of skin conductance response and psychological factors, there is an overlap of 61.9%; however, this value is not statistically significant ($p>0.05$).

In spite of this lack of statistical significance, let us visually examine these clusters in terms of psychopathological factors. Figures 4 and 5 show the distributions for the psychopathological clusters whose statistical measures we examined in the previous section, as well as the distributions of the physiological clusters, which were obtained via the k-Means algorithm for the skin conductance data.

The distributions (Fig. 4 and 5) for the psychopathological clusters support what the descriptive statistics had already indicated. For most factors, distributions are very even between clusters as well as skewed in the lower end, indicating most participants are mentally healthy, showing values which are not high enough to indicate the presence of depression (as per the BDI scores), anxiety traits (as per the STAI-T scores) and total childhood trauma (as per the CTQ Total scores).

There is a higher presence of participants with high depression scores in Cluster 1, as indicated by the long, flat tail on the right of the BDI distribution, as well as a higher presence of participants with high anxiety scores, as shown by the right hand tail on the STAI-T distribution.

Regarding childhood trauma scores, in spite of the lack of significant difference between clusters for physical abuse (CTQ Physical Abuse), it shows an interesting distribution, as Cluster 2 shows more affected individuals than Cluster 1, which is the opposite pattern as most other scores. However, for sexual abuse (CTQ Sexual Abuse) the pattern of Cluster 1 containing more affected individuals than Cluster 2 returns.

Finally, perhaps the most interesting distribution is the one for recent events of dissociation (LTE Dissociation), which, as indicated previously by the summary statistics, shows mutually exclusive values. Cluster 1 contains strictly affected individuals, while Cluster 2 contains strictly individuals which did not experience the event of dissociation.

In contrast to the psychopathological clusters, no significant difference between physiological clusters was found in terms of psychopathology.

For example, while the BDI distribution shows a longer tail for Cluster 2, indicating a higher presence of depression scores than in Cluster 1, the STAI-T distribution for Cluster 1 is more skewed to the right than Cluster 2, indicating the opposite pattern for anxiety.

This alternation of clusters with higher scores in psychopathology continues for the other factors, supporting the lack of significance found in psychopathology for the skin conductance response based clusters.

Interestingly, the strong pattern shown in LTE scores for the psychopathological clusters is not present for the physiological clusters. Just as in the other factors, the two clusters are somewhat evenly distributed, indicating once again no significant difference between physiological clusters.

Please note that for all plots in Figure 4, the histograms reflect the size of the clusters, which are sometimes uneven, as is the case for the psychopathological clusters. Thus, examining the distributions shows a more accurate picture of the shape of the data and the contrast between clusters.

Exploratory Data Analysis

Unfortunately, the physiological clusters did not reflect any psychopathological patterns, as examined in the previous section. However, there were significant differences in terms of psychopathology for the psychopathological clusters. Therefore, it is interesting to explore what these significantly different clusters may look like in terms of physiology. It is important to note that this is out of the original scope of this paper and thus should be taken as such.

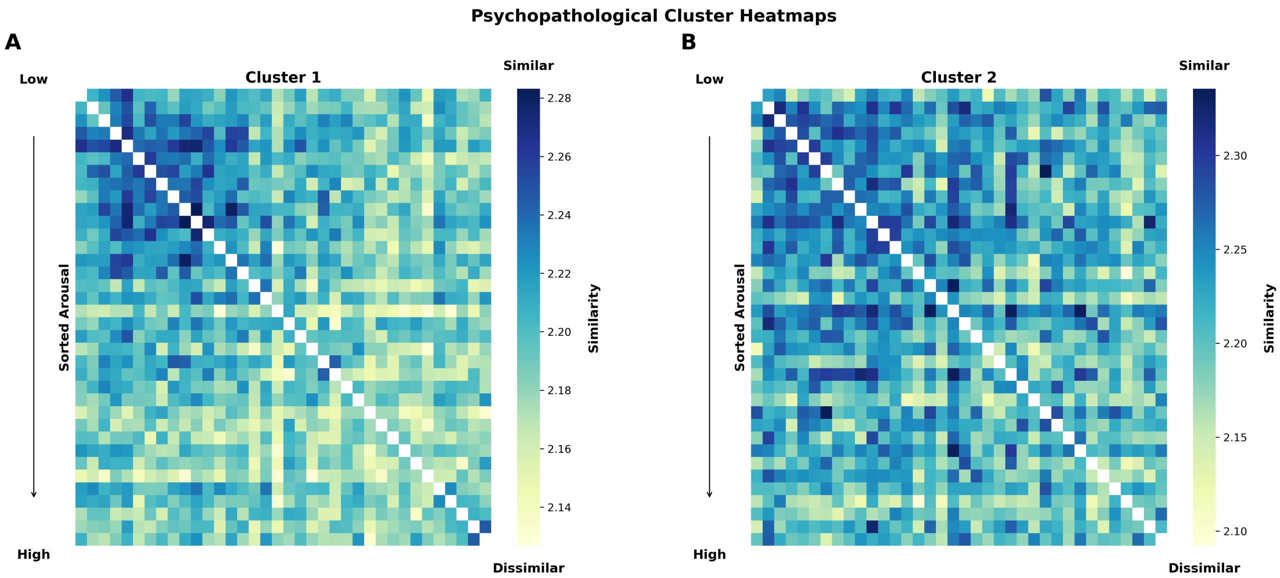

Fig. 6. Plots showing the physiological data for the psychopathological clusters in the form of heatmaps. (A) Cluster 1 (psychopathological). (B) Cluster 2 (psychopathological).

The plots above (Fig. 6) show what the psychopathological clusters look like in terms of skin conductance response, in the same style as the physiological clusters were previously shown.

As somewhat expected after the previous physiological data analysis and the results from Koppold et al. (2024), one of the clusters shows the inverse AK model. In this case, this is Cluster 1 (Fig. 6A), which have shown significantly higher scores in most psychopathological features in comparison to Cluster 2, as highlighted in the previous section.

Thus, Cluster 1 shows a higher similarity score for lower arousal values between dimensionally close trials, while the similarity decreases following the diagonal axis towards the lower right side of the plot, indicating that there is more divergence between physiological measures for trials containing more highly arousing images.

In contrast with the clear cut pattern of Cluster 1, it is difficult to recognise a pattern for Cluster 2 (Fig. 6B) initially. Upon closer inspection, it is possible to recognise a diluted version of the inverse AK pattern. This might indicate that individuals in Cluster 2 might more stable in their peripheral physiology responses, and thus present similarity between trials than those individuals in Cluster 1. However, it is important to note that Cluster 1 contains roughly three times the amount of participants than in Cluster 2. This might cause the pattern in Cluster 2 to be more diluted than in Cluster 1 simply because the sample is too small in Cluster 2.

Discussion

Accounting for variability in affective science is a fairly recent development, which comes with exciting new discoveries as well as many new challenges. While the fingerprint hypothesis is well established in the field of emotion science, navigating the new methods required to investigate the populations hypothesis and its potential repercussions demands creativity and meticulous examination of these potential new methods.

Following the success of Koppold et al. (2024) at using Representational Similarity Matrices (RSMs) to account for intra-variability in participants, this study aimed to expand their discoveries and look for repercussions in the field of mental health.

Koppold et al. (2024) found that, when using RSMs to account for intra-variability, the pattern of responses that emerged resembled the theorised inverse AK model. This model reflects an interesting relationship between skin conductance in dimensionally close trials. In low arousal trials, this relationship, as showcased by the distance in the vector space between SCR responses in different trials, are quite close to each other. However, as arousal rises, the responses start to diverge more frequently.

This pattern also arose in this paper. After having determined the optimal number of clusters given the RSM via a combination of the elbow method and silhouette analysis, the data was grouped with the k-Means algorithm (Pedregosa et al., 2023) to produce two clusters. One of these clusters, deemed Cluster 1 for clarity purposes, presented the inverse AK pattern quite clearly.

Interestingly, a second cluster, Cluster 2, did not show as strong a pattern and even diverged from it slightly, showing more similarity in the higher arousal dimension than what would be predicted by the inverse AK model. These two clusters are significantly different from each other and the effect size of this difference is also quite high, indicating that Cluster 2 tends to show a higher SCR similarity in dimensionally close trials than Cluster 1.

While Cluster 1 has its highest similarity scores at 2.18, Cluster 2 starts at its lowest point with a similarity of 2.45. This could be a due to participants in Cluster 2 simply showing more stability in their SCR responses in general, but to support this finding, further research is needed.

The psychopathological clustering has shown some promise in terms of results, having statistically significant differences between clusters in many of the analysed features. However, once the size of the effect is taken into account, it is clear that the effect is quite small. This is somewhat expected, given that the psychopathological data had strong tendencies toward the lower end of the spectrum of almost all questionnaires, reflecting the lack of participants psychopathological disorders in the sample.

Unfortunately, when the two sets of clusters (physiological and psychopathological) were analysed in direct comparison, they did not show a significant overlap, indicating no relation between them. This lack of matching clusters from the physiological and psychopathological datasets could potentially be explained by the lack of balance in the sample of participants.

Before sampling, potential participants were screened for mental health disorders. They were also quite young, with samples averaging 25.36 and 23.43 years, and caucasian. This lack of randomised sampling might have hindered potential discoveries which were quite heavily dependent on the presence of differences in mental health.

Some exploratory data analysis was carried out beyond the original scope of this paper to briefly examine if investigating peripheral physiological data from the psychopathological clusters would show any interesting patterns, which could potentially be investigated at some point in the future. However, this investigation lead once again to the inverse AK pattern for Cluster 1 (psychopathological), while Cluster 2 does not seem to show any visually stark pattern aside from, perhaps, a diluted version of the same inverse AK pattern, which could just be due to the reduced number of participants present in the latter cluster.

In conclusion, let us refer back to the proposed research questions.

1. What is the ideal number of clusters given the RSM?

As determined via the elbow method and the silhouette analysis, the ideal number of cluster was predicted to be 2. However, it is important to note that because of the homogeneity of the sample, it is possible that a different number of clusters would emerge in more randomised data.

2. How are the identified clusters characterised in terms of physiological and emotional responses?

The identified clusters are different from each other in terms of intensity of similarity scores. Cluster 1 shows the inverse AK pattern with somewhat low similarity scores in relation to Cluster 2. Cluster 2 shows a diluted version of the inverse AK pattern, but with higher similarity in the higher arousal region than Cluster 1.

3. Can the identified clusters be linked to psychopathological factors?

No. Unfortunately, the results here have been inconclusive, but this is likely to be a consequence of a sample which does not contain individuals with mental disorders.

Limitations and further research

Finally, this study presents several limitations. Firstly, the choice of model could have been a problem. As using RSMs in affective science is still in its early stages, it is difficult to gauge what the ideal model is for this type of data. The k-Means model was chosen for its simplicity, reproducibility and popularity in many fields that utilise unsupervised clustering, but it might not have been the best model in this case.

In data with so many dimensions it is sometimes difficult to determine its shape. Due to this issue, the data probably violates the assumption of globular clusters, which k-Means handles optimally (Pedregosa et al., 2023).

Other models were considered, such as Gaussian Mixed Models (Hoemann et al., 2020), but because of the very strong violation of the assumption that values be normally distributed, this model was discarded. In spite of this limitation, Gaussian Mixed Models has the advantage of not needing the number of clusters as a variable, so in a situation such as this, in which the number of clusters is initially unknown, it might be a good option, given that the data undergoes the required transformation.

It is possible that hierarchical clustering could offer some better results as well, but this would require further research to assess. In the future, it would perhaps be wise to carry out clustering of the inter-variable physiological data via multiple different clustering methods to achieve the best results before attempting to compare these clusters to psychopathological data.

Another limitation of this study presents itself in the psychopathological portion of the data. As mentioned above, only mentally healthy individuals took part in the study (Koppold et al., 2022). This caused the participants to be almost exclusively in the lower end of the spectrum of most psychopathological questionnaires, which makes it difficult to assess the true reflection of physiology in psychopathology. A more balanced sample, containing individuals with scores more evenly distributed across the different psychopathological factors could reveal underlying patterns which went undetected in this sample of mostly young and healthy university students (Koppold et al., 2024; Koppold et al., 2022).

Furthermore, the scaling of the different psychopathological questionnaires is varied. As psychopathological clusters showed mutual exclusivity in the factor of LTE Dissociation, it is possible that the method of scaling the data could be improved so that the balance between psychopathological questionnaire scales is more adequate.

Finally, a sample containing more peripheral physiological indicators, such as inter-beat interval, or respiratory sinus arrhythmia in addition to skin conductance response might provide a more well rounded picture of affective states. Without further investigation of variability with the inclusion of more physiological factors, it is impossible to determine to which extent peripheral physiology can inform on mental health.

This study has presented limitations, but the implications of finding physiologically distinct clusters that could connect to mental health disorders are exciting. Perhaps, a more sophisticated algorithm will be used to help diagnose and treat mental health issues in the future.

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Potsdam, 13th of September 2024

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