Naturalistic viewing increases individual identifiability based on functional brain network connectivity

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Abstract

Naturalistic viewing (NV) is currently considered a promising paradigm for studying individual differences in functional brain organization. While whole brain functional connectivity (FC) under NV has been relatively well characterized, so far little work has been done on a network level.
Here, we extend current knowledge by characterizing the influence of NV on FC in fourteen meta-analytically derived brain networks considering three different movie stimuli in comparison to resting-state (RS). We show that NV increases identifiability of individuals over RS based on functional connectivity in certain, but not all networks. Furthermore, movie stimuli including a narrative appear more distinct from RS. In addition, we assess individual variability in network FC by comparing within- and between-subject similarity during NV and RS. We show that NV can evoke individually distinct NFC patterns by increasing inter-subject variability while retaining within-subject similarity. Crucially, our results highlight that this effect is not observable across all networks, but rather dependent on the network-stimulus combination. Our results confirm that NV can improve the detection of individual differences over RS and underline the importance of selecting the appropriate combination of movie and cognitive network for the research question at hand.

Keywords

Naturalistic viewing; Network functional connectivity; Identification algorithm; Individual differences; Movie watching; Resting-state

1. Introduction

Understanding functional brain organization is a major goal of human neuroscience. Typically, researchers have focused on commonalities between individuals and used group-averages to reveal the shared neural underpinnings of certain brain functions. In recent years, the interest in individual functional brain architecture has grown. At the same time, neuroimaging has shifted from mapping brain functions towards investigating interactions within distributed brain networks by considering functional brain connectivity. Specifically, functional connectivity studies yielded insight into the foundation of individual brain organization[1–4]. However, it is yet unclear which paradigms are best suited to study individual differences.

Most research on FC has been done on connectivity patterns occurring during resting state (RS), where participants lie in the scanner without any particular task or any external stimulation [4–10]. In contrast to task-based studies, RS is thought to reveal the intrinsic brain organization[11]. In addition, the ease of implementation of RS data allows for the relatively quick acquisition of large healthy and clinical samples due to low demands on participants. Although the RS paradigm has provided a variety of insights into the organization of the human brain, it also comes with limitations: In the absence of a task, RS is likely influenced by spontaneous thoughts of the participant [12,13]. Furthermore, experimental decisions such as instructing participants to keep their eyes open or closed can affect the measurement[14]. Finally, various studies have shown that individual FC during RS is heavily influenced by state effects [15].
To address these limitations, naturalistic viewing (NV) has been suggested as a promising tool for the study of individual differences [16,17]. During NV, participants are instructed to watch a movie clip without any additional task. Therefore, NV reduces the variability induced by spontaneous thought content of the subject, because all participants are presented with the same stimulus [18]. By more closely mimicking conditions under which the brain naturally operates, NV promises to capture more ecologically valid neuronal responses. Despite the more synchronized neural response across participants individual differences in FC still persist. Using “fingerprinting” [19] or identifiability as a proxy for individual differences, Vanderwal et al., (2007) demonstrated that NV shows better identification accuracy than RS [20]. Furthermore, Finn et al., (2021) showed that the implementation of NV data outperforms RS in predicting trait-like phenotypes, thus suggesting that individual variability might be enhanced during NV [21]. Different attempts have been made to explain why NV might enhance FC variability. For instance, Geerligs et al., (2015) argued that the differences in interpretation of a given movie content might promote individual FC variability[15]. Van de Meer and colleagues[22] suggested that NV might impose richer brain state dynamics and therefore more distinct connectivity profiles, which in turn might better reflect phenotypes of interest than brain states during RS. Naturalistic Viewing paradigms provide further advantages over conventional RS: By increasing participant engagement, NV reduces fatigue and head movement during the measurement [21,23]. In addition, movie-watching can increase scanner tolerability for cohorts which might either struggle with staying still (e.g ADHD patients) or completing demanding tasks (subjects with cognitive impairments)[24].

Current literature evinces the potential for naturalistic viewing as a useful paradigm for studying individual brain architecture. So far, most studies primarily focused on whole-brain connectivity reflecting a holistic view on brain functions. However, brain architecture is commonly seen as

segregated into modular clusters of spatially distinct areas constituting functional networks [25]. These networks represent specific cognitive domains, such as memory[26], social cognition [27] and executive function[28]. Therefore, investigating networks functional connectivity (NFC) increases the interpretability of findings over whole-brain connectivity. Furthermore, connectivity in different networks likely yields distinct patterns of variance in reaction to NV stimuli. For example, a functional network related to the processing of emotions should react differently to a movie scene with strong emotional content, as compared to the motor network.
There are several methods for defining functional networks [10,11,29], one of which are meta-analytically defined networks[30]. The latter have the advantage of representing the most likely core nodes involved in a given cognitive function, because they incorporate convergent information from a multitude of studies[24]. Thus, studying NFC in meta-analytical networks might grant robust insights into the effects of naturalistic viewing on individual variability, which has not been studied yet.

The present study aims to investigate the influence of NV on individual variability in NFC. To this end, we compare several measures of individual variability (e.g. identifiability and inter- and intra-subject variability) between three different movie stimuli and RS across three scanning sessions on the basis of various meta-analytical networks covering affective [5,8,31,32], social [5,27,33], executive [6,28,34,35], memory [7,26] and motor[36] functions. As a first step, we examined the similarity of connectivity profiles evoked by different movies and RS. Secondly, we assessed the identifiability of subjects based on NFC-patterns evoked by NV or RS. Subsequently, we investigated to what extent identifiability is affected by network size. Finally, we compared the effect of different movies and RS on inter- and intra-subject variability.

2. Material and Methods

Participants

36 healthy right-handed and ambidextrous adults were scanned at the Centre for Translational MR Research, National University of Singapore. Two subjects were excluded for having incomplete sessions, leaving a final cohort at 34 (19 females, mean age 27 + / - 2.7 years). Exclusion criteria were neurological or psychiatric diagnoses, significant visual or hearing impairment, alcohol or caffeine consumption 6 hours prior to the scan and self-reporting of bad sleep the night before the scan days. All participants underwent three identical testing sessions within a one-week interval. Subjects gave written, informed consent and were compensated for their participation. The study was approved by the institutional review board of the National University of Singapore.

Data acquisition

The data was acquired on a Siemens Magnetom PrismaFit 3-Tesla with a 20-Channel head coil. Structural images were collected using an MP-RAGE sequence (TR=2300ms, TE =2,28ms, TI=900ms, flip-angle=8°) and 1mm voxel size. All RS and NV runs used the same echo planar imaging sequence (TR=719ms, TE=30ms, flip-angle=52°, slices=44, FOV=225x225 mm^2) resulting in 2.96x2.96x3 mm voxel size. Data were retrieved from collaborators at the National University of Singapore, and structured in the form of a DataLad dataset, a research data management solution providing data versioning, data transport, and provenance capture (Halchenko et al.)[37]. Each of the three testing sessions per participant, which were conducted within a seven day period, comprised three NV runs and two RS scans. The order of scans was identical on all three days, starting with a structural scan, followed by 5 functional scans in the order of RS 1, *Inscapes*, *Circus*, *Indiana Jones* and RS 2, with each functional scan lasting for 10 minutes. All movies had been cut to the same length. For RS scans, participants were asked to lay as still as possible and think of nothing in particular, while keeping their eyes open. Instructions for the NV scans were to watch the movies while staying as still as possible. For all scans, participants were asked to not fall asleep during the measurement. The movie clips were presented via a mirror that was mounted on the head coil and the sound was played through headphones. *Inscapes* is a nonverbal, non-social series of animated abstract shapes created by Vanderwal et al. which was looped to match the 10 minutes duration [38]. *The Circus* (United Artists Digital Studios, 1928, directed by Charlie Chaplin) is a silent black-and-white film which depicts the protagonist being chased by the police and unintentionally causing comic situations during his escape. *Indiana Jones and the Temple of Doom* (Paramount Pictures, 1984, directed by Steven Spielberg) shows the opening scene of the movie during which the protagonist has to fight off several hitmen who are trying to kill him. Foam wedges were fitted around each subject's head for comfort and to decrease movement. For all subsequent analyses, only the first RS scan (RS1) was used.

Data preprocessing

Preprocessing of MRI data was performed using fMRIPrep, version 20.1.1[39]. In brief, the T1-weighted volumes were corrected for intensity non-uniformity and skull-stripped. The extracted brain images were then transformed into Montreal Neurological Institute (MNI) space and motion corrected using Advanced Normalization Tools (ANTS)[40]. The functional data was motion-corrected with MCflirt[41] and subsequently co-registered to the native T1-weighted image using boundary based registration with six degrees of freedom from Freesurfer[42]. Subsequently, ICA-AROMA[43] was used on the MNI-aligned BOLD images to remove motion artifacts and applied an isotropic Gaussian kernel of 6mm FWHM (full-width half-maximum) for spatial smoothing. Global signals were extracted within the CSF, the WM, and the whole-brain masks and regressed from the preprocessed fMRI data for each subject.

Network functional connectivity

For each subject, NFC matrices were constructed for each of the 14 meta-analytical networks, comprising nine to 23 nodes (a detailed description of the networks can be found in the supplements). Isotropic 5mm spheres were created around the local maxima of each meta-analytical network node and the mean time series were subsequently extracted. Only gray matter voxels were included. Pearson's correlation coefficient (PCC) between all node pairs was calculated to generate a n-times-n connectivity matrix per subject and condition, where n denotes the number of nodes of the respective network.

Representational Dissimilarity Matrix (RDM) analysis

To investigate how patterns of inter-individual differences in NFC vary across conditions (RS and three different NV conditions), we applied a RDM analysis. The present analysis closely followed the methods described by Kriegskorte et al [44]. The procedure can be summarized in three steps. First, the correlation between the FC patterns of every possible pair of subjects is calculated for each condition and network. Second, to generate a measure of dissimilarity, the correlation distance (1-r) is computed. Third, the dissimilarity values for all subject pairs are assembled into an RDM (as a subjects * subjects size matrix) that serves as the signature of the given condition.
To visually compare RDMs, we employed Uniform Manifold Approximation and Projection (UMAP)[45], a technique for dimensionality reduction and visualization. Instead of preserving large-scale structures, UMAP seeks to preserve local neighborhood distances. To this end, a pre-set number of nearest neighbors are specified and the distances to these neighbors is represented as a weighted graph, with the nearest neighbors being assigned with higher weights. UMAP then finds a low-dimensional representation of the data that best preserves these neighborhoods. We here applied UMAP to the previously described RDMs. By grouping closely related RDMs together, UMAP allowed us to visualize which conditions evoked similar responses.

Assessment of identifiability

Assessment of identifiability was closely based on the methods described by previous papers [19,20]. The FC matrices belonging to the same session and condition were grouped, resulting in 12 databases (three sessions times the four conditions). For every combination of two databases, Pearson's correlation between the FC matrix of one subject from the first database and every other FC matrix from the second database was calculated. The two FC matrices with the highest correlation were considered to be from the same subject. Identification accuracy was defined as the frequency of correctly identified subjects divided by the total number of subjects. Afterwards, the accuracies were averaged across session pairs to quantify the identifiability per condition and network.

Influence of network size

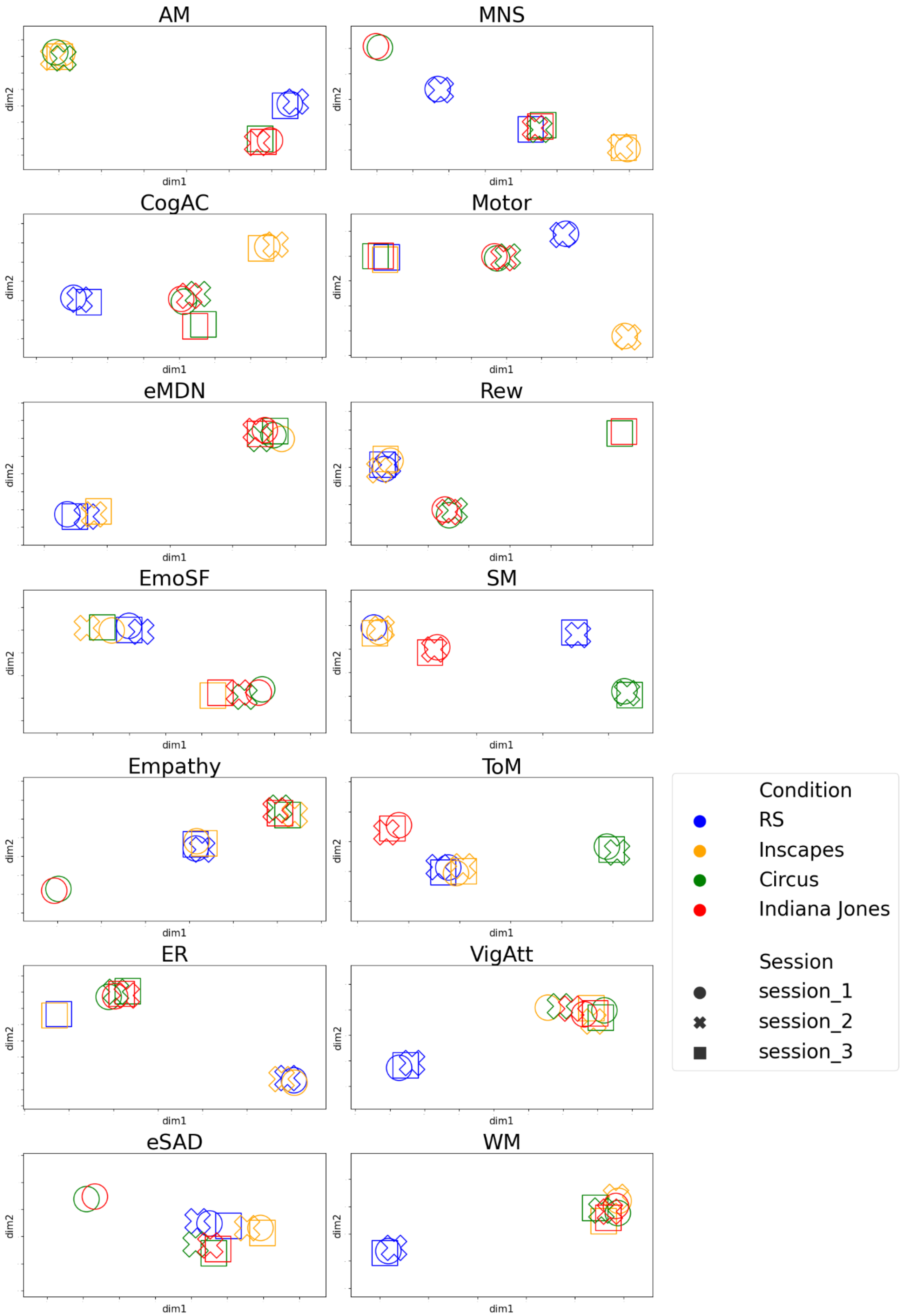
To ensure that the differences in identification accuracy between networks were not just reflections of network size, we systematically compared identifiability in artificially created networks, constituting up to 50 nodes. Artificial networks were created by randomly choosing coordinates from the MNI152 gray matter mask and creating a 5mm sphere around them. The mean Euclidean distance between nodes from the meta-analytically defined networks was calculated (14.62 mm) and set as the minimal distance between nodes for the artificial networks. Thereby, the randomly chosen nodes were prevented from overlapping whilst preserving some degree of spatial comparability between artificial and meta-analytically defined networks. This process was repeated 100 times for each network size. Subsequently, identification accuracies for all networks and the different conditions were calculated to evaluate 1) how network size influences identification accuracy, 2) how identifiability between the different conditions behaves in artificial networks and 3) how the meta-analytically defined networks compare to the artificial networks.

Within- and between subject correlation

Within-subject correlations were calculated as Pearson's correlation between the FC matrices of the same subject across session pairs (e.g. Ses-1 to Ses-2, Ses-1 to Ses-3) and then averaged. This process was performed for each of the four conditions (RS and the three movie stimuli) separately. For each network, a one-way ANOVA was computed with condition (RS, *Inscapes*, *Circus*, *Indiana Jones*) as within-subject factor to evaluate the effect of condition on within-subject correlations within the specific networks. Subsequently, Tukey's HSD test was performed to reveal which of the conditions significantly differed. The between-subject correlations were defined as the mean PCC between the FC matrix of one subject and every other subject's FC matrix from the same session and condition. For each network, a one-way ANOVA was computed with condition (RS, movie1, movie2, movie3) as between-subject factor to evaluate the effect of condition on between-subject correlations within the specific networks. Subsequently, Tukey's HSD test was performed to reveal which of the conditions significantly differed.

3. Results

3.1 Similarity of different movies and RS connectivity profiles.



AM
MNS
CogAC
Motor
eMDN
Rew
EmoSF
SM
Empathy
ToM
ER
VigAtt
eSAD
WM
dim1
dim2
Condition
RS
Inscapes
Circus
Indiana Jones
Session
session_1
session_2
session_3

Figure 1. UMAP representation of the RDMs of the different conditions in each network. (AM =Autobiographical Memory, CogAC = Cognitive Attention Control,eMDN=extended Multiple Demand Network, EmoSF= Emotional Scene and Face Processing, ER = Emotion Regulation, eSAD=Extended Social-affective Default, MNS = Mirror Neuron System, Rew = Reward, SM = Semantic Memory, ToM = Theory of Mind, VigAtt= Vigilant Attention, WM = Working memory)

We investigated the similarity of different conditions by embedding the respective RDMs into a low dimensional space (UMAP).The UMAP representation showed that RS was embedded separately from all NV conditions in AM, CogAC, VigAtt and WM, and separately from most NV conditions in MNS and Motor networks. In eMDN, EmoSF, ER, eSAD, Rew and ToM networks, RS shows overlaps with the movie *Inscapes*. On the other hand, the movies *Circus* and *Indiana Jones* tended to cluster together in (AM, CogAC, eMDN, Empathy, ER, eSAD, MNS, Motor, Rew). We did not observe any evidence for a systematic session-effect, as RDMs of the same session (session 3) were only embedded together in the motor network.

3.2 Identification accuracies in meta-analytic networks

Network	RS	Inscapes	Circus	Indiana Jones	Node Number
SM	95.1%	95.1%	97.1%	**98.0%**	23
CogAC	93.6%	90.2%	94.1%	**96.6%**	19
ToM	93.1%	90.7%	**95.1%**	94.6%	15
AM	**94.1%**	92.2%	93.1%	92.6%	22
WM	**96.1%**	93.6%	88.7%	92.2%	23
Rew	**96.1%**	90.7%	86.3%	90.2%	23
EmoSF	88.7%	85.8%	86.8%	**94.6%**	24
eMDN	85.8%	85.8%	79.9%	**86.8%**	17
Empathy	**86.3%**	81.4%	79.9%	81.9%	18
ER	81.9%	80.9%	72.1%	**83.3%**	14
VigAtt	80.4%	74.0%	73.5%	**80.9%**	16
MNS	**77.0%**	76.5%	71.1%	**77.0%**	11
eSAD	59.8%	52.9%	54.4%	**64.7%**	12
Motor	27.9%	30.4%	**30.4%**	27.5%	9

Table 1. Identification accuracies per network and modality, averaged across sessions. Networks are in order of highest average accuracy. The highest identification accuracy in each network is denoted in bold. (AM =Autobiographical Memory, CogAC = Cognitive Attention Control,eMDN=extended Multiple Demand Network, EmoSF= Emotional Scene and Face Processing, ER = Emotion Regulation, eSAD=Extended Social-affective Default, MNS = Mirror Neuron System, Rew = Reward, SM = Semantic Memory, ToM = Theory of Mind, VigAtt= Vigilant Attention, WM = Working memory)

Identifiability of subjects was assessed based on NFC-patterns evoked by NV or RS. Overall, individual FC matrices could be matched across sessions with moderate to high accuracy with identification accuracies ranging from 52% to 100%. The motor network represented an exception with low identification accuracies across conditions (27.5% - 30.4%). In ten out of 14 networks, identifiability was highest in either the *Circus* or *Indiana Jones* NV conditions. Among the naturalistic stimuli, *Indiana Jones* led to the highest identification accuracies in eight of the networks (SM, CogAc, EmoSF, eMDN, ER, VigAtt, MNS, and eSAD). The top three highest accuracies were achieved using NV, with FC matrices using the *Indiana Jones* movie reaching the highest accuracy (98%) in the SM network. Generally, networks with more nodes tended to achieve higher accuracies.

3.3 Identification accuracies for different network sizes

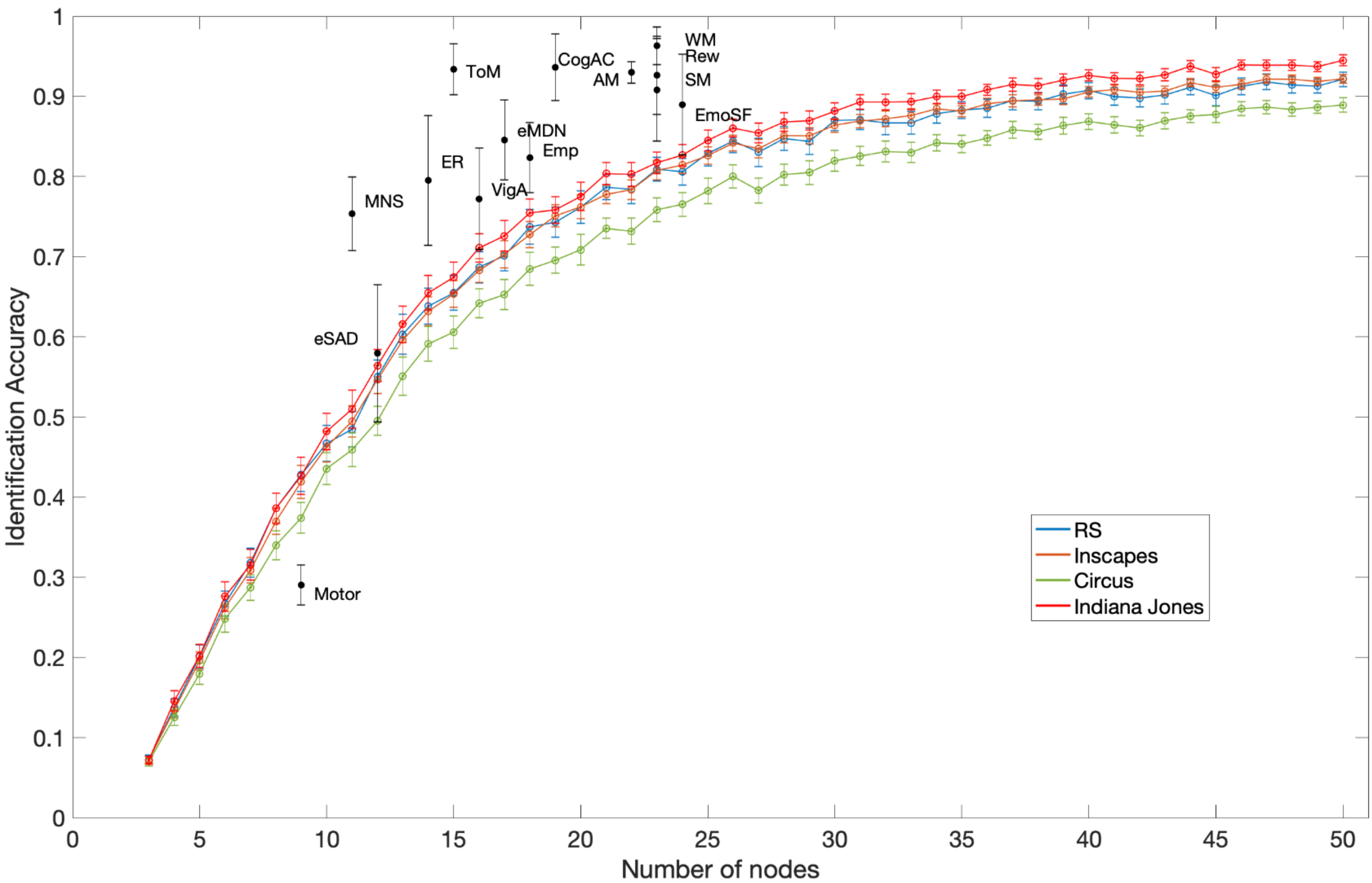


Fig. 2 Identification accuracies in artificial networks. The figure depicts the network size as the number of nodes (x-axis) against averaged identification accuracy (y-axis) for each of the four conditions (RS = blue; Inscapes = orange; Circus = green; Indiana Jones = red). Black dots denote the mean identification accuracy of meta-analytically defined networks, averaged across conditions and placed at their respective node count.

To evaluate the effect of network size on identification accuracy, we compared the meta-analytic networks against a sample of random networks with sizes between 3 and 50 nodes. Identifiability in artificial networks showed how network size influences identification accuracy for all modalities (Fig 2). A continuous increase of identification accuracy can be seen for all conditions up until a network size of 20 nodes, where the increase rate stabilizes. All networks, apart from the Motor network, achieved higher accuracies than the artificially created networks of the same size, regardless of condition. Furthermore, identification accuracies for the *Indiana Jones* movie exceeded those of the other three conditions, regardless of network size.

3.4 Within- and between-subject correlations

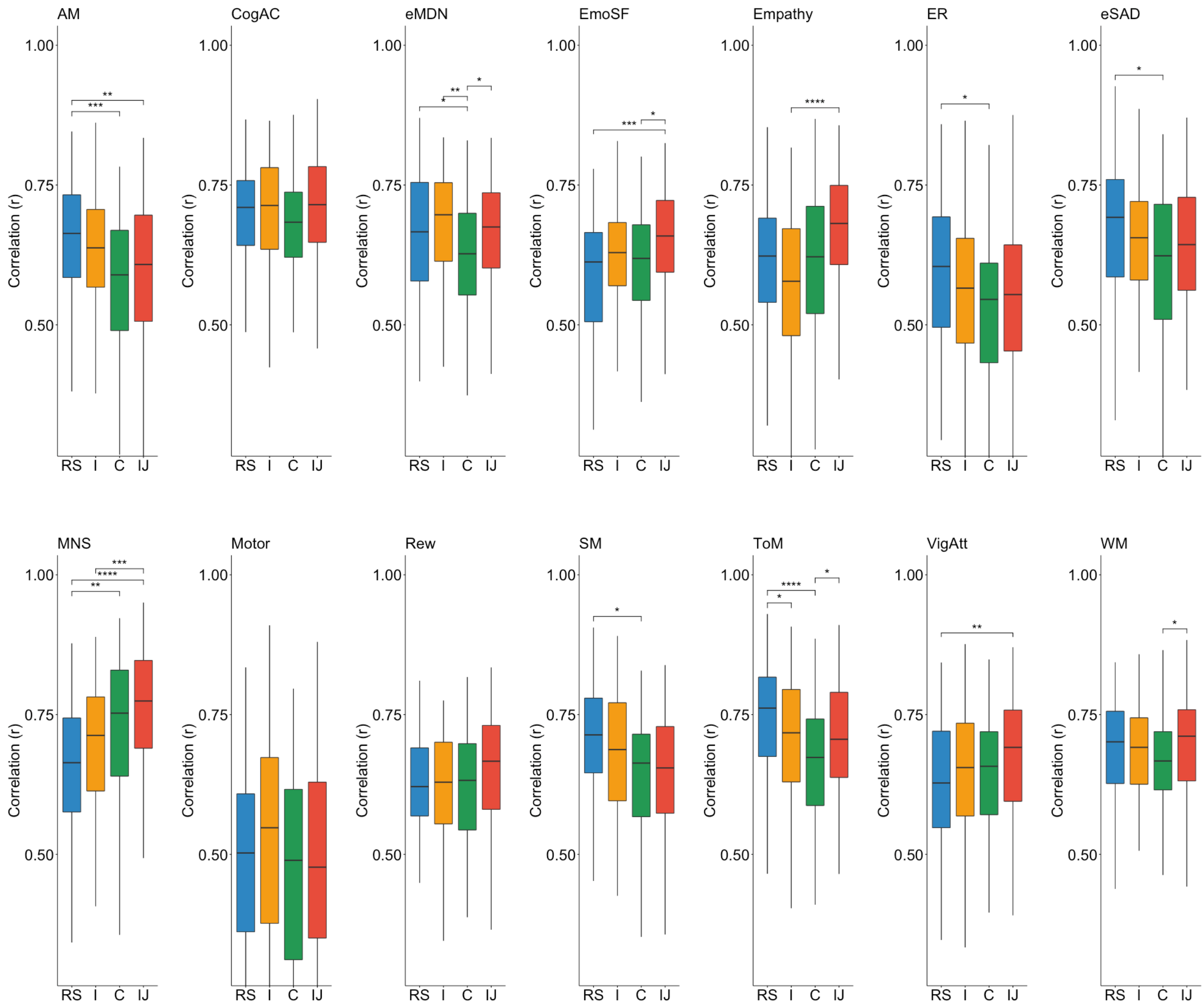


Figure 3. Within-subject correlations for the meta-analytically defined networks. Correlations across all session pairings are depicted. (RS= Resting State, I = Inscapes, C = Circus, IJ = Indiana Jones, AM =Autobiographical Memory, CogAC = Cognitive Attention Control,eMDN=extended Multiple Demand Network, EmoSF= Emotional Scene and Face Processing, ER = Emotion Regulation, eSAD=Extended Social-affective Default, MNS = Mirror Neuron System, Rew = Reward, SM = Semantic Memory, ToM = Theory of Mind, VigAtt= Vigilant Attention, WM = Working memory)

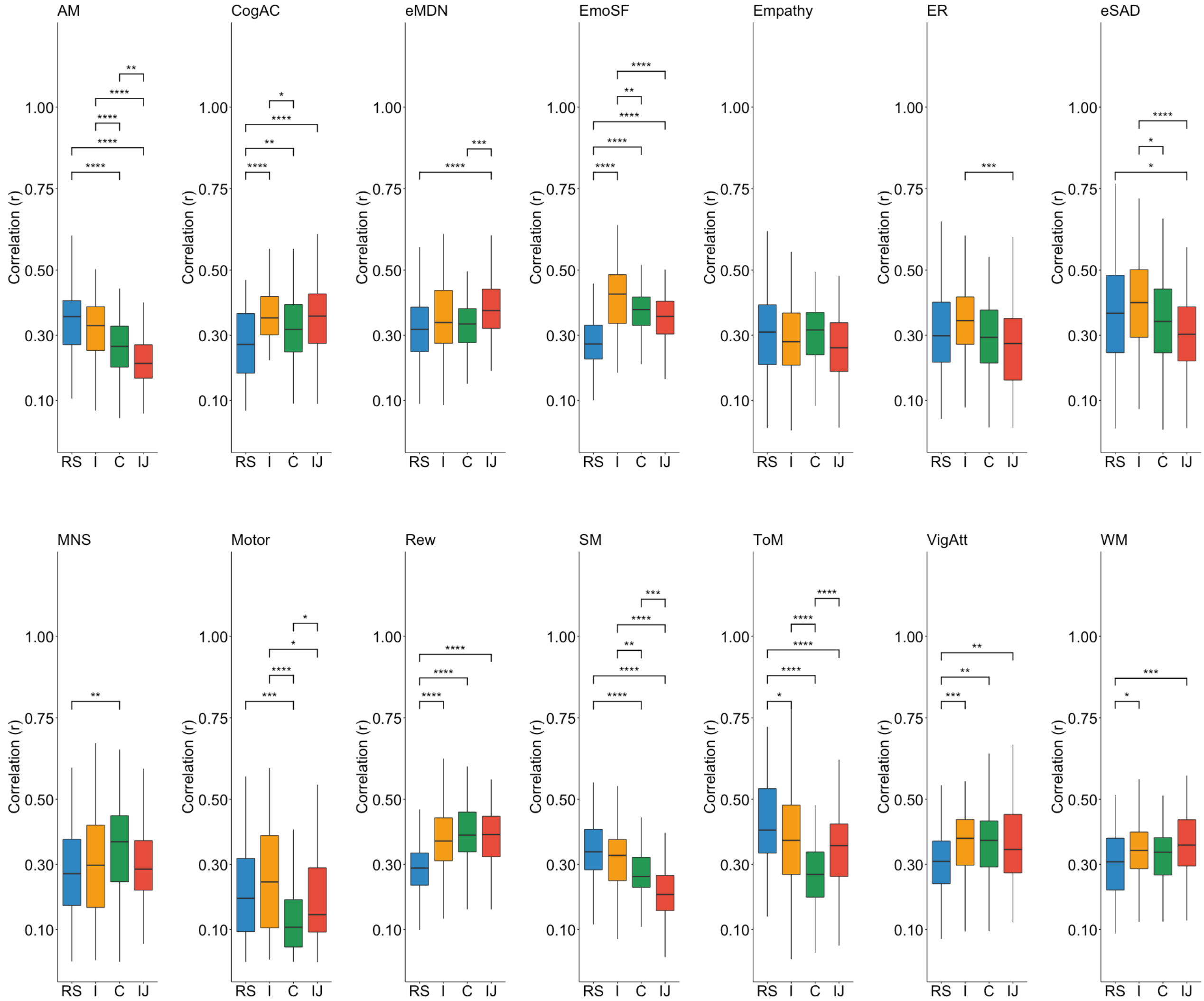


Figure 4. Between-subject correlations for the meta-analytically defined networks. Correlations for all sessions are depicted. (RS= Resting State, I = Inscapes, C = Circus, IJ = Indiana Jones, AM =Autobiographical Memory, CogAC = Cognitive Attention Control,eMDN=extended Multiple Demand Network, EmoSF= Emotional Scene and Face Processing, ER = Emotion Regulation, eSAD=Extended Social-affective Default, MNS = Mirror Neuron System, Rew = Reward, SM = Semantic Memory, ToM = Theory of Mind, VigAtt= Vigilant Attention, WM = Working memory)

We calculated within-subject correlations, as a measure of how similar subjects are to themselves across sessions, and between-subject correlations, as a measure of similarity between subjects. The average within-subject correlations for RS and NV ranged between 0.5 and 0.8, with the exception of the Motor network (0.1 - 0.6), indicating a high level of similarity of connectivity patterns across sessions. For multiple networks, most prominently the MNS network, within-subject correlations strengthened from RS < *Inscapes* < *Circus* < *Indiana Jones*.

RS state differed from one or more movie conditions in various networks: RS showed significantly higher within-subjects correlations compared to *Indiana Jones* (AM), *Inscapes* (ToM) and *Circus* (AM, eMDN, ER, eSAD, SM, ToM). In contrast, some movies showed significantly higher within-subject correlations than RS in emoSF (*Indiana Jones*), MNS (*Indiana Jones* and *Circus*) and VigAtt (*Indiana Jones*).

In several networks certain movies differed from one another, with significantly higher correlations of *Inscapes* compared to *Circus* in the eMDN network; and higher correlations in *Indiana Jones* compared to *Circus* in eMDN, emoSF, ToM, WM; and higher correlations in *Indiana Jones* compared

to *Inscapes* in Empathy and MNS networks. *Circus* never showed significantly higher correlations compared to any other movie in any network.
RS and the movie *Inscapes* exhibited similar correlations across networks. Overall, the movie *Indiana Jones* tended to stand out in that it was the only condition that showed significantly higher within-subject correlations than RS in several networks (EmoSF, MNS, and VigAtt). On the contrary, the movie *Circus* often led to decreased within-subject correlations in comparison to the other conditions.

Between-subject correlations were generally lower than those previously observed on a whole-brain basis, ranging from below 0.1 to 0.75. In several networks, the opposite pattern of what was observed for within-subject correlations can be seen, such that increasingly complex stimuli weaken between-subject correlations (AM, ER, eSAD and SM). In other networks, the three movies synchronized neural responses across subjects, increasing between-subject correlations in comparison with RS (CogAc, EmoSF, Rew and VigAtt).
Comparing within- and between-subject correlations, it is evident that increased within-subject correlations did not automatically lead to decreased between-subject correlations (and vice versa), such that a subject's scan can be highly individual (or reliable) and still share substantial overlap with others.
RS state differed from one or more movie conditions in various networks: RS showed significantly higher between-subjects correlations compared to *Indiana Jones* (AM, eSAD, SM, ToM), *Inscapes* (ToM) and *Circus* (AM, Motor, SM, ToM). In contrast, other networks showed significantly higher between-subject correlations than RS for *Indiana Jones* (CogAC, eMDN, EmoSF, Rew, VigAtt,WM), *Inscapes* (CogAC, emoSF, Rew, VigAtt, WM,) and *Circus* (CogAC, EmoSF, MNS, Rew, VigAtt).
In several networks certain movies differed from one another, with significantly higher between-subject correlations of *Inscapes* compared to *Circus* in the AM, CogAC, EmoSF,eSAD, Motor, SM, and ToM; and higher correlations in *Inscapes* compared to *Indiana Jones* in AM, EmoSF, ER, eSAD, Motor and SM; and higher correlations in *Indiana Jones* compared to *Circus* in eDMN and ToM; and higher correlations in *Circus* compared to *Indiana Jones* in AM, Motor and SM networks.

4. Discussion

In the current study we examined and compared the NFC evoked by different NV stimuli and RS with respect to similarity of connectivity profiles, individual identifiability, as well as within- and between-subject correlations. Our results showed that NV stimuli evoke connectivity profiles that are distinct from RS across different networks. NV stimuli, especially *Indiana Jones*, enhance the identifiability of individual subjects in the vast majority (10 of 14) of networks. Lastly, our results emphasize that the similarity of individuals to themselves and to others is highly dependent on the combination of condition and network.

4.1 Comparison of connectivity profiles during NV and RS

In this study, we compared NFC evoked by three different NV stimuli and RS. A low-dimensional embedding of NFC similarity across subjects showed that FC patterns during *Inscapes* are mostly similar to those during RS, while *Circus* and *Indiana Jones* exhibited distinct connectivity profiles across networks. The relative similarity of connectivity patterns during Inscapes and RS has been reported before: For instance, based on Pearson's correlations between FC matrices, *Inscapes* was shown to be more similar to RS than to another movie condition [20]. These authors argued that due to the abstract nature of the movie, participants might not engage in temporally synchronized cognitive processes, which is similar to RS[38]. Furthermore, our embedding shows little similarity of NFC during *Inscapes* and either *Circus* or *Indiana Jones* in the majority of networks. This is in line with the previous argument, as both *Circus* and *Indiana Jones* contain a narrative that is likely to increase synchronicity across subjects, as has been shown for verbal narratives (e.g. emotional speeches [46,47]).

4.2 Identifiability

To assess the stability of individual patterns on the network level, we calculated the identifiability of NFC matrices across the three movies and RS. Considering that NV has been shown to increase the reliability of individual FC patterns [15,48], we hypothesized that identifiability should be higher for movies as compared to RS. However, present results suggest that this is not the case for movies in general, but rather identification accuracy appears to highly depend on the specific movie as well as on the chosen network. Specifically, *Indiana jones* achieved the highest accuracy in 8 of 14 networks (SM, CogAC, EMOSF, eMDN, ER, VigAtt, MNS, eSAD), whereas *Inscapes* and *Circus* produced highest accuracies in two networks (*Inscapes*: Motor; *Circus*: ToM, Motor). RS, on the other hand, achieved the highest accuracies in 5 networks (AM, WM, ReW, Empathy, MNS). Notably, the connectivity profiles within the Motor network yielded low identification accuracies in comparison with the other networks across all stimuli. Lower-level cognitive structures such as the motor network show low variance between participants[49]. Furthermore, as the motor network was created solely based on fingertapping tasks, it seems reasonable to assume that activation was low in this network. Therefore, connectivity patterns are expected to be rather similar across participants. *Indiana Jones* was the stimulus that achieved the highest identification accuracy in the majority of networks. Previous studies have argued that the major driving factor for improvement of individual identifiability is the social content of a stimulus[46,47,50], which in the present study was most pronounced for *Indiana Jones*. In comparison, neither *Circus* nor *Inscapes* reach the level of social content depicted in *Indiana Jones*. *Circus'* complete lack of speech might have taken away from the social component whereas *Inscapes* does not depict any human interaction at all.

4.3 Identification accuracies for different network sizes

Since we observed an increase of identification accuracy with network size such that bigger networks tended to show higher accuracies, we investigated the influence of network size on identifiability in artificially created networks. The results show the same tendency that was observed in the meta-analytically defined networks, such that identification accuracy was highest for *Indiana Jones*, followed by RS, *Inscapes* and *Circus*. Confirming our observation, identification accuracy in artificial networks increased with network size, regardless of condition. Notably, all meta-analytical networks, except the motor network, outperformed artificial networks of the same size, supporting their biological validity. Following our previous line of argument, the motor network might not be suitable for subject identification based on FC, which might explain the underperformance compared to artificial networks.

4.3 Within- and between-subject correlations

To better understand the differences in identifiability across stimuli and networks, we investigated within- and between-subject correlations. Our results showed that in the majority of networks, intra- and inter-subject correlations were significantly altered during NV in comparison to RS. It is generally assumed that NV should increase between-subject similarity, given that all subjects are presented with the same stimuli, in comparison to no stimuli at all during RS [18,48,51]. On the other hand, it is unclear whether NV unique and reliable patterns across sessions, as measured by within-subject correlations. Vanderwal and colleagues investigated FC variability in NV and RS and showed that naturalistic paradigms increased within- and between-subject correlations on a whole brain level [20]. However, our results suggest that this effect is not unambiguously true for meta-analytical networks. Increased within-subject correlations were mainly observed in networks that are essential for perception and processing of action, behavior and emotions, namely EmoSF, Empathy, MNS and VigAtt. In other networks, NV resulted in more similar patterns between subjects (CogAC, eMDN, Rew and WM). Notably, multiple networks showed decreased within- and between-subject correlations during NV (AM, ER, eSAD, SM, ToM). We will discuss these three groups of networks subsequently.

4.3.1 Networks with higher within-subject correlations in movies

NV showed significantly higher within-subject correlations in networks that are essential for perception and processing of action, behavior and emotions (EmoSF, Empathy, MNS and VigAtt). In a recent publication by Finn et al[21] it was shown that NV outperformed RS in FC-based prediction of behavioral scores. In their study, movies with strong social content led to the more accurate predictions, regardless of whether the predicted score was social or cognitive. The authors hypothesize that social movies are not only more engaging, but also most likely to evoke divergent interpretations and reactions across participants. In agreement with this assumption, several studies have shown that social movies induce different neural responses across subjects [52–54] and that shared interpretation of a narrative or movie is associated with similariarity in neural responses [55,56]. Assuming that the social aspect of a movie stimulus induces stable individual connectivity patterns, it is reasonable to expect that this effect is more pronounced in networks that deal with the processing of social interactions. In the EmoSF network for example, which deals with the visual and emotional processing of faces or scenes [32], all three movie stimuli led to higher within-subject correlations compared to RS. Notably, the movie *Indiana Jones*, during which the emotional processing of faces is a key aspect, shows highest within-subject correlations. Here, differences in

the emotional assessment of the particular faces and scenes might have been the driving factor that evoked stable individual connectivity patterns during *Indiana Jones*.
In the Empathy network, which deals with the emotional cognition of moral behavior [27], within-subject correlations were increased during the movies *Circus* and *Indiana Jones*. During both movies, characters show varying emotions in response to different situations, which might have been experienced differently across subjects. *Inscapes* on the other hand performed similar to RS, likely because the depicted abstract shapes failed to engage the network.
In the MNS network, which is involved in the understanding of actions and their underlying intentions as well as the imitation of observed behavior, we observed an increase of individuality with increasingly complex stimuli[33]. Especially the two stimuli *Circus* and *Indiana Jones*, during which action and behavior of different characters are depicted, should engage the MNS network which in turn might have led to the increased within-subject correlations. The between-subject correlations were significantly stronger for *Circus* than for *RS*, but not different between the remaining conditions. Presumably, the movie *Circus* serves as the optimal stimulus for action observation since it shows moving characters, but (unlike *Indiana Jones*) does not include competing stimuli like speech.
The VigAtt network is involved in vigilant attention, i.e. the continued focus on intellectually un-challenging tasks[6]. Langner et al acknowledge a high overlap of the VigAtt network with the ventral attention network reviewed in Corbetta et al[57], which is associated with the stimulus-driven re-direction of attention. These authors suggest that potentially important stimuli such as alarms or sudden movements interrupt ongoing cognitive activity and attract attention. This underlying process might be reflected by higher within-subject correlations during *Indiana Jones* than during RS. In *Indiana Jones*, many action-packed scenes are depicted that might cause a stimulus-driven attention shift, thereby engaging the network during this movie. In addition, subjects showed more similar patterns during all three movies than during RS. Although it is of question whether NV belongs in the category of intellectually un-challenging tasks, this result can likely be attributed to the ongoing demand of keeping attention on the movie, in comparison to RS where the mind is free to wander off.

4.3.2 Networks with higher between-subject correlations in movies

NV showed significantly higher between-subject correlations in networks that are associated with executive functions and/or stimulus evaluation (CogAC, eMDN, EmoSF, MNS, Rew, VigAtt and WM). Here, NV synchronized the neuronal response across participants (i.e. higher-between subject correlation), but did not increase within-subject correlations. Several other studies have found NV to increase the similarity between subjects [17,18,20,58], which is likely caused by exposure to the same stimulus. Although these studies mostly agree that individual differences can exist on top of the shared response on a whole-brain level, they acknowledge two possible scenarios: On the one hand, the stimulus evoked synchrony across subjects might enable better observation of individual differences [20,21]. On the other hand, strongly increased similarity across subjects' neuronal response might blur individual features[16]. The same assumptions hold true from a network perspective, such that networks subjected to the same stimulus can either exhibit deviating patterns on top of the shared response, or highly similar patterns which conceal individual differences, depending on the specific network function.
Considering the main function of each respective network, none of the networks should be particularly engaged during RS or during any of the movies. The CogAC network is essential for the suppression of a predominant but inadequate response in favor of the contextually appropriate response[35]. The eMDN consists of core regions that are active during most processes which involve executive or higher cognitive functions and a set of more task-specific regions extending these core regions [34]. The Rew network is essential for reward-related decision making [31]. The WM network is

fundamental for the storage and manipulation of short-term memory[28]. Since individual differences are likely only enhanced in networks that are engaged during a certain condition, we assume that NV did not evoke stable individual connectivity patterns, as the processing of movies may not rely on the core network function. Therefore, subjects are less unique and more similar to themselves, increasing between-subject correlations especially in comparison with unconstrained RS where more heterogeneous responses are expected.

4.3.3 Networks with higher between- or within-subject correlations in RS

The vast majority of previous studies reported increased within- and between-subject correlations for NV in comparison with RS [17,18,20,58,59]. However, all of these studies employed analyses of whole brain connectivity, disregarding effects in single networks. While previous result patterns hold true in some networks, we also show that NV decreases within- and between-subject correlations in other networks (AM, ER, eSAD, SM and ToM).

The majority of these networks at least partially overlap with the default mode network, which is tied to intrinsically oriented functions, rather than the processing of external stimuli [18,60]. Therefore, it seems plausible that NV does not increase within- or between-subject correlations in these networks which are likely not engaged during movie watching. The AM network was the only network in which within-subject correlations for RS exceeded *Indiana Jones*. This network comprises brain regions engaged in processes concerning scene-construction and self-projection, or the ability to mentally project oneself from the present moment into another time, place, or perspective. Consequently we would expect the AM network to be more strongly activated during RS, when the mind is not occupied by the content of a movie. Our data indeed shows that participants during RS showed higher within-subject correlations than during the two narrative movie clips *Circus* and *Indiana Jones*, but not significantly different from the purely abstract animation *Inscapes*. Therefore, we conclude that in absence of a storyline, subjects divert to imagined situations instead of the external stimuli, thus engaging the AM network which leads to higher within-subject correlations for RS than for the narrative movies. We assume that the movie *Inscapes* is inbetween a narrative and the complete absence of a stimuli, thus it may fail to engage participants over a longer period of time, therefore letting the participant zone out eventually. In addition, RS and *Inscapes* also increased between-subject correlations in comparison to both narrative movies. Likely, increased between-subject correlations are driven by the joint activation of the AM network during RS and *Inscapes*. On the other hand, *Circus* and *Indiana Jones* likely engage the network to a lesser extent, thereby falling short of evoking coordinated activity which in turn reduces similarity between subjects.

The eSAD network was defined to comprise those brain regions that are part of the default mode network, but at the same time also involved in social or affective processing [5]. Thus, the network is engaged in socio-affective processing including emotional processes, cognition, reward, introception, memory and theory of mind functions. Although not exclusively a “task-negative” network, the eSAD network is highly overlapping with the default mode network and generally presumed to be more active when participants can let their thoughts run free[5]. RS showed higher within-subject correlations than *Circus* as well as higher between-subject correlations than *Indiana Jones*. In addition, *Inscapes*, which is arguably closer to RS than the other movies, also showed higher between-subject correlations as compared to *Circus* and *Indiana Jones*. Due to the default mode aspects of the eSAD network, it is perceivable that this network is more strongly engaged during RS and *Inscapes*. Thus, participants are more likely to express different connectivity patterns as compared to NV where the network is mostly unengaged. The movies *Circus* and *Indiana Jones* on the other hand might result in a less pronounced engagement of the network, thus failing to evoke similar patterns across participants.

The SM network is involved in retrieving semantic knowledge and is highly overlapping with the default mode network[7]. The authors argue that task-unrelated thoughts are inherently semantic, because they require the manipulation of stored knowledge[61]. Furthermore, semantic processing was reliably shown to be suppressed during demanding perceptual tasks[7], which is in accordance with our result pattern, showing increasingly complex stimuli to decrease within- and between-subject similarity (RS > *Inscapes* > *Circus* > *Indiana Jones*). We thus suggest that increasing complexity of the movie stimuli suppresses semantic processing and therefore leads to less engagement of the SM network. Presumably, due to a less pronounced engagement of the SM network during that *Circus* and *Indiana Jones*, participants show low between-subject correlations as well as low within-subject correlations.
The ToM network is fundamental for the understanding and contemplation of the behavior and intentions of others [27]. Within- and between-subject correlations in the ToM network were generally higher during RS than during the NV conditions. We assume that movies evoke different interpretations of the intentions of the depicted characters and thus may have led to diverging connectivity profiles, in turn increasing differences between subjects. On the other hand, these differences seem to be unstable across sessions, thus decreasing within-subject correlations during NV.

4.6 Limitations

While the current study sheds new light onto individual differences in, and stability of, brain states elicited by movie watching, it comes with some limitations. Firstly, individual outliers might have biased identification accuracies, due to the small sample size. However, previous studies on RS and NV reported similar identification accuracies as those achieved in this study [19,20]. Secondly, while we demonstrated enhanced individual difference and identifiability for certain stimulus-network combinations, our study did not include any phenotypes. Therefore this study is not suited to determine whether enhanced individual differences under NV can be used to more accurately predict phenotypes as compared to RS. Hence, future studies should investigate the interplay between increased identifiability and the accuracy of phenotype predictions. Thirdly, reliability of FC might at least partly be driven by structured noise such as vascular effects[62]. Although we applied a number of denoising strategies, results might thus be confounded by non-neuronal signals. Finally, it was not assessed whether participants had seen any of the movie clips prior to participating in the study. Knowing the film beforehand could affect engagement of the participant and thereby modulate the effect of NV. However, our results showed that connectivity patterns rather clustered according to stimulus than repetition, which suggests that the same movie stimulus can be used repeatedly to study FC of a subject across various time points. This also encourages the application of movie fMRI in clinical studies where it is necessary to monitor patients over a longer period of time.

4.7 Conclusions

NV has been suggested to show high potential for emphasizing individual differences, but effects have often been reported on a whole-brain level only. Our study extends the current knowledgen by characterizing the influence of NV on FC in meta-analytically derived functional networks. We show that NV increases identifiability of individuals based on functional connectivity in certain networks. However, there is not one naturalistic stimulus that will enhance individual differences across the brain. Therefore it is crucial to select the appropriate stimulus and networks for the research question at hand.

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Supplements

Network	Description
Autobiographical Memory (AM)	The AM network comprises a core network linked to self-projection and scene construction for remembering personal events from one's past (Spreng, Mar, & Kim, 2008). Inside that core network, an autobiographical memory network was identified, including the medial and lateral temporal cortices, precuneus, posterior cingulate cortex, retrosplenial cortex, temporo-parietal junction, lateral prefrontal and occipital cortices and medial prefrontal cortex. The network consists of a total of 22 nodes.
Cognitive attention control (CogAC)	The CogAC network (Cieslik, Mueller, Eickhoff, Langner, & Eickhoff, 2013) is essential for the suppression of a predominant but inadequate response in favor of the contextually appropriate one and consists of the anterior insula, inferior frontal gyrus, dorsolateral prefrontal cortex, dorsal premotor cortex, bilateral intraparietal sulcus and superior parietal lobe, right temporo-parietal junction, left inferior occipital gyrus, pre-supplementary motor area and anterior midcingulate cortex, as well as the right thalamus and right caudate nucleus. The network comprises 19 nodes.
Extended multiple demand network (eMDN)	The eMDN consists of a core network that is essential for executive functions, supplemented by additional subnetworks that are recruited for specific tasks. This eMDN consists of the bilateral inferior frontal gyrus, insula, supplementary motor area, intraparietal sulcus, middle frontal gyrus, dorsal pre-motor cortex, putamen, thalamus and the left inferior temporal gyrus (Camilleri et al., 2016). It comprises 17 nodes.
Emotional scene and face processing (EmoSF)	The EmoSF was defined based on a meta-analysis of studies investigating brain regions involved in the visual perception of emotional faces or scenes. The meta-analysis revealed consistent activation in the medial prefrontal cortex, bilateral inferior, middle and superior frontal gyrus, amygdala, parahippocampal gyrus, fusiform gyrus, medial prefrontal gyrus, orbitofrontal gyrus, lateral occipital cortex, thalamus, pulvinar, right middle temporal gyrus and right anterior cingulate cortex (Sabatinelli et al., 2011). The network consists of 24 nodes.
Empathy	Empathy is the adaption of someone else's emotional state (Singer & Lamm, 2009). A meta-analysis revealed an empathy network that comprises bilateral dorsomedial prefrontal cortex, anterior insula, inferior frontal gyrus, supplementary motor area, cingulate cortex, temporo-parietal junction, right amygdala, right middle temporal gyrus, right posterior superior temporal sulcus, left anterior thalamus, right posterior thalamus, right hippocampus, midbrain and right pallidum (Bzdok et al., 2012). The network includes 18 nodes.
Emotion regulation (ER)	The ER network is essential for cognitive reappraisal, which describes the ability to change one's interpretation of affective stimuli (Buhle et al., 2014). A meta-analysis identified the following brain regions as engaged during emotion regulation: the bilateral inferior frontal gyrus, middle frontal gyrus, superior parietal lobe, amygdala, right medial frontal gyrus, left anterior cingulate gyrus, left anterior insula, left superior temporal gyrus and left middle temporal gyrus (Buhle et al., 2014). The network comprises 14 nodes.
Extended socio-affective default network (eSAD)	The eSAD network is responsible for socio-affective processing, which includes emotional processes, cognition, reward, introception, memory and theory of mind functions. This network consists of the anterior cingulate cortex, bilateral amygdala and hippocampus, temporo-parietal junction, ventral basal ganglia, precuneus, subgenual cingulate cortex, ventromedial and dorsomedial prefrontal cortex and left middle temporal gyrus and sulcus (Amft et al., 2015). The network comprises 12 nodes.
Mirror neuron system (MNS)	The MNS network is essential for action observation and imitation tasks (Caspers, Zilles, Laird, & Eickhoff, 2016). A meta-analysis revealed an underlying network consisting of the bilateral inferior frontal gyrus, primary somatosensory cortex, lateral occipital lobe, right fusiform face and body area, left medial premotor cortex, left posterior middle temporal gyrus and right superior parietal lobe (Caspers et al., 2016). The network comprises 11 nodes.
Motor	The motor network was revealed during a meta-analysis on finger tapping tasks by Witt et al. (2008). The brain regions consistently engaged were the bilateral sensorimotor cortex, basal ganglia, anterior cerebellum, inferior parietal cortex, left ventral premotor cortex and supplementary motor area (Witt, Meyerand, & Laird, 2008). The network comprises nine nodes.
Reward (Rew)	The Rew network is essential for reward-related decision making. It consist of the bilateral insula, thalamus, brain stem, mid-orbitofrontal cortex, middle frontal gyrus, right nucleus accumbens, left pallidum, left dorsomedial prefrontal cortex, left medial orbitofrontal cortex, right amygdala, supplementary motor area, anterior and posterior cingulate cortex, left inferior parietal lobe, right angular gyrus, left frontal pole and left superior frontal gyrus (Liu, Hairston, Schrier, & Fan, 2011). The network comprises 23 nodes.
Semantic memory (SM)	The SM network is responsible for retrieving semantically stored knowledge (Binder, Desai, Graves, & Conant, 2009). A meta-analysis revealed that the angular and supramarginal gyrus, middle temporal gyrus, posterior inferior temporal gyrus, mid-fusiform gyrus, parahippocampus, dorsomedial, ventromedial and orbital prefrontal cortex, superior, middle and inferior frontal gyrus, posterior cingulate gyrus and ventral precuneus were involved during semantic memory tasks (Binder et al., 2009). The network comprises 23 nodes.
Theory of mind (ToM)	Along with the revelation of the Empathy network, the same meta-analysis revealed a network comprising theory of mind functions, which descrive the ability to contemplate another's thoughts, desires and behaviour (Premack and Woodruff, 1978; Frith and Frith, 2003). Brain regions involved in theory of mind were the ventromedial and dorsomedial prefrontal cortex, frontopolar cortex, precuneus, bilateral temporo-parietal junction, temporal pole, middle temporal gyrus, posterior superior temporal sulcus, inferior frontal gyrus and right visual area V5 (Bzdok et al., 2012). The network comprises 15 nodes.
Vigilant attention (VigAtt)	The VigAtt network is essential for the ability to maintain attention on repetitive and unengaging tasks for which not much cognitive effort is needed, so-called "Vigilant Attention" (Langner & Eickhoff, 2013). The network consists of the anterior paracentral lobe, right medial posterior superior frontal gyrus, dorsal midcingulate cortex, bilateral inferior frontal junction, anterior insula, thalamus, right inferior frontal sulcus, left precentral gyrus, left inferior occipital gyrus, right temporo-parietal junction, right middle occipital gyrus, right inferior parietal lobe and cerebellum (Langner & Eickhoff, 2013). It comprises 16 nodes.
Working memory (WM)	Working memory describes the ability to manipulate information over a short period of time. Brain regions commonly engaged during working memory tasks include the bilateral anterior insula, inferior frontal gyrus, caudal and rostral lateral prefrontal cortex, posterior superior frontal gyrus, thalamus, cerebellum, intraparietal sulcus, superior parietal lobe, left nucleus caudate and left globus pallidum (Rottschy et al., 2012). The network comprises 23 nodes.

Supplementary Table 1. Brief description of the 14 meta-analytic networks.

Within-Subject Correlations

Network	ANOVA	Post-Hoc Test							Network	ANOVA	Post-Hoc Test						
		group 1	*group 2*	*lower*	*upper*	*p_adj*	*significance*	*std.error*			*group 1*	*group 2*	*lower*	*upper*	*p_adj*	*significance*	*std.error*
		RS	Inscapes	-0.078	0.016	0.33	ns	0.007			RS	Inscapes	-0.028	0.077	0.62	ns	0.007
		RS	***Circus***	***-0.121***	***-0.028***	***p<0.0005***	*******	***0.007***			***RS***	***Circus***	***0.017***	***0.123***	***p<0.05***	******	***0.007***
AM	p<0.0005	***RS***	***Jones***	***-0.112***	***-0.018***	***p<0.05***	******	***0.007***	MNS	p<0.0005	***RS***	***Jones***	***0.057***	***0.162***	***p<0.0005***	********	***0.007***
		Inscapes	Circus	-0.091	0.003	0.08	ns	0.007			Inscapes	Circus	-0.007	0.098	0.12	ns	0.007
		Inscapes	Jones	-0.081	0.012	0.23	ns	0.007			***Inscapes***	***Jones***	***0.032***	***0.138***	***p<0.0005***	*******	***0.007***
		Circus	Jones	-0.037	0.056	0.95	ns	0.007			Circus	Jones	-0.013	0.092	0.21	ns	0.007
		RS	Inscapes	-0.045	0.038	p<0.05	ns	0.006			RS	Inscapes	-0.028	0.104	0.46	ns	0.009
		RS	Circus	-0.054	0.030	p<0.05	ns	0.006			RS	Circus	-0.084	0.048	0.89	ns	0.009
CogAC	0.317	RS	Jones	-0.024	0.059	0.06	ns	0.006	Motor	0.108	RS	Jones	-0.082	0.050	0.93	ns	0.009
		Inscapes	Circus	-0.050	0.033	p<0.05	ns	0.006			Inscapes	Circus	-0.122	0.010	0.13	ns	0.009
		Inscapes	Jones	-0.021	0.063	0.06	ns	0.006			Inscapes	Jones	-0.120	0.012	0.16	ns	0.009
		Circus	Jones	-0.012	0.071	0.07	ns	0.006			Circus	Jones	-0.064	0.069	1.00	ns	0.009
		RS	Inscapes	-0.032	0.046	0.97	ns	0.005			RS	Inscapes	-0.051	0.032	0.93	ns	0.006
		RS	***Circus***	***-0.080***	***-0.002***	***p<0.05***	***	***0.005***			RS	Circus	-0.050	0.033	0.96	ns	0.006
eMDN	p<0.05	RS	Jones	-0.041	0.038	1.00	ns	0.005	Rew	0.071	RS	Jones	-0.014	0.069	0.31	ns	0.006
		Inscapes	***Circus***	***-0.087***	***-0.009***	***p<0.05***	******	***0.005***			Inscapes	Circus	-0.040	0.043	1.00	ns	0.006
		Inscapes	Jones	-0.048	0.031	0.94	ns	0.005			Inscapes	Jones	-0.004	0.079	0.09	ns	0.006
		Circus	***Jones***	***0.000***	***0.079***	***p<0.05***	***	***0.005***			Circus	Jones	-0.005	0.078	0.11	ns	0.006
		RS	Inscapes	-0.003	0.075	0.08	ns	0.005			RS	Inscapes	-0.068	0.021	0.51	ns	0.006
		RS	Circus	-0.014	0.064	0.35	ns	0.005			***RS***	***Circus***	***-0.091***	***-0.002***	***p<0.05***	***	***0.006***
EmoSF	p<0.0005	***RS***	***Jones***	***0.026***	***0.104***	***p<0.0005***	*******	***0.005***	SM	p<0.05	RS	Jones	-0.089	0.000	0.05	ns	0.006
		Inscapes	Circus	-0.050	0.028	0.89	ns	0.005			Inscapes	Circus	-0.067	0.022	0.55	ns	0.006
		Inscapes	Jones	-0.010	0.068	0.21	ns	0.005			Inscapes	Jones	-0.065	0.024	0.65	ns	0.006
		Circus	***Jones***	***0.001***	***0.079***	***p<0.05***	***	***0.005***			Circus	Jones	-0.042	0.047	1.00	ns	0.006
		RS	Inscapes	-0.093	0.008	0.13	ns	0.007			***RS***	***Inscapes***	***-0.090***	***-0.003***	***p<0.05***	***	***0.006***
		RS	Circus	-0.043	0.058	0.98	ns	0.007			***RS***	***Circus***	***-0.127***	***-0.040***	***p<0.0005***	********	***0.006***
Empathy	p<0.0005	RS	Jones	-0.003	0.097	0.08	ns	0.007	ToM	p<0.0005	RS	Jones	-0.077	0.010	0.20	ns	0.006
		Inscapes	Circus	-0.001	0.100	0.05	ns	0.007			Inscapes	Circus	-0.080	0.007	0.14	ns	0.006
		Inscapes	***Jones***	***0.039***	***0.140***	***p<0.0005***	********	***0.007***			Inscapes	Jones	-0.030	0.057	0.85	ns	0.006
		Circus	Jones	-0.011	0.090	0.18	ns	0.007			***Circus***	***Jones***	***0.007***	***0.093***	***p<0.05***	***	***0.006***
		RS	Inscapes	-0.077	0.022	0.47	ns	0.007			RS	Inscapes	-0.025	0.060	0.71	ns	0.006
		RS	***Circus***	***-0.103***	***-0.005***	***p<0.05***	***	***0.007***			RS	Circus	-0.023	0.062	0.64	ns	0.006
ER	p<0.05	RS	Jones	-0.078	0.020	0.43	ns	0.007	VigAtt	p<0.05	***RS***	***Jones***	***0.013***	***0.098***	***p<0.05***	******	***0.006***
		Inscapes	Circus	-0.076	0.023	0.51	ns	0.007			Inscapes	Circus	-0.041	0.044	1.00	ns	0.006
		Inscapes	Jones	-0.051	0.048	1.00	ns	0.007			Inscapes	Jones	-0.004	0.080	0.10	ns	0.006
		Circus	Jones	-0.024	0.074	0.56	ns	0.007			Circus	Jones	-0.006	0.079	0.13	ns	0.006
		RS	Inscapes	-0.069	0.030	0.74	ns	0.007			RS	Inscapes	-0.051	0.024	0.79	ns	0.005
		RS	***Circus***	***-0.110***	***-0.010***	***p<0.05***	***	***0.007***			RS	Circus	-0.074	0.001	0.06	ns	0.005
eSAD	p<0.05	RS	Jones	-0.070	0.030	0.72	ns	0.007	WM	p<0.05	RS	Jones	-0.036	0.040	1.00	ns	0.005
		Inscapes	Circus	-0.090	0.009	0.16	ns	0.007			Inscapes	Circus	-0.061	0.015	0.40	ns	0.005
		Inscapes	Jones	-0.050	0.049	1.00	ns	0.007			Inscapes	Jones	-0.022	0.054	0.71	ns	0.005
		Circus	Jones	-0.010	0.090	0.16	ns	0.007			***Circus***	***Jones***	***0.001***	***0.076***	***p<0.05***	***	***0.005***

Supplementary Table 2. ANOVA and Tukey-Test results for differences between within-subject correlations for the different conditions in each network.

Between-Subject Correlations

Network	ANOVA	Post-Hoc Test							Network	ANOVA	Post-Hoc Test						
		group 1	group 2	lower	upper	p_adj	significance	std.error			group 1	group 2	lower	upper	p_adj	nifican	td.erro
		RS	Inscapes	-0.052	0.016	0.52	ns	0.005			RS	Inscapes	-0.022	0.081	0.46	ns	0.007
		RS	Circus	-0.111	-0.043	p<0.0005	****	0.005			RS	Circus	0.020	0.123	p<0.05	**	0.007
AM	p<0.0005	RS	Jones	-0.157	-0.090	p<0.0005	****	0.005	MNS	p<0.005	RS	Jones	-0.024	0.079	0.53	ns	0.007
		Inscapes	Circus	-0.093	-0.025	p<0.0005	****	0.005			Inscapes	Circus	-0.010	0.093	0.16	ns	0.007
		Inscapes	Jones	-0.139	-0.072	p<0.0005	****	0.005			Inscapes	Jones	-0.054	0.049	1.00	ns	0.007
		Circus	Jones	-0.081	-0.013	p<0.05	**	0.005			Circus	Jones	-0.096	0.008	0.12	ns	0.007
		RS	Inscapes	0.053	0.130	p<0.0005	****	0.006			RS	Inscapes	-0.022	0.081	0.46	ns	0.007
		RS	Circus	0.012	0.089	p<0.05	**	0.006			RS	Circus	-0.136	-0.033	p<0.0005	***	0.007
CogAC	p<0.0005	RS	Jones	0.048	0.126	p<0.0005	****	0.006	Motor	p<0.0005	RS	Jones	-0.075	0.028	0.63	ns	0.007
		Inscapes	Circus	-0.079	-0.002	p<0.05	*	0.006			Inscapes	Circus	-0.165	-0.062	p<0.0005	****	0.007
		Inscapes	Jones	-0.043	0.035	0.99	ns	0.006			Inscapes	Jones	-0.105	-0.001	p<0.05	*	0.007
		Circus	Jones	-0.002	0.075	0.07	ns	0.006			Circus	Jones	0.009	0.112	p<0.05	*	0.007
		RS	Inscapes	-0.004	0.064	0.11	ns	0.005			RS	Inscapes	0.058	0.121	p<0.0005	****	0.005
		RS	Circus	-0.025	0.043	0.90	ns	0.005			RS	Circus	0.072	0.135	p<0.0005	****	0.005
eMDN	p<0.0005	RS	Jones	0.025	0.093	p<0.0005	****	0.005	Rew	p<0.0005	RS	Jones	0.067	0.130	p<0.0005	****	0.005
		Inscapes	Circus	-0.055	0.013	0.39	ns	0.005			Inscapes	Circus	-0.017	0.046	0.65	ns	0.005
		Inscapes	Jones	-0.005	0.063	0.12	ns	0.005			Inscapes	Jones	-0.022	0.041	0.88	ns	0.005
		Circus	Jones	0.016	0.084	p<0.05	***	0.005			Circus	Jones	-0.037	0.026	0.98	ns	0.005
		RS	Inscapes	0.104	0.167	p<0.0005	****	0.005			RS	Inscapes	-0.063	0.006	0.14	ns	0.005
		RS	Circus	0.063	0.125	p<0.0005	****	0.005			RS	Circus	-0.112	-0.044	p<0.0005	****	0.005
EmoSF	p<0.0005	RS	Jones	0.050	0.112	p<0.0005	****	0.005	SM	p<0.0005	RS	Jones	-0.169	-0.100	p<0.0005	****	0.005
		Inscapes	Circus	-0.073	-0.010	p<0.05	**	0.005			Inscapes	Circus	-0.083	-0.015	p<0.05	**	0.005
		Inscapes	Jones	-0.086	-0.023	p<0.0005	****	0.005			Inscapes	Jones	-0.140	-0.071	p<0.0005	****	0.005
		Circus	Jones	-0.044	0.018	0.72	ns	0.005			Circus	Jones	-0.091	-0.022	p<0.0005	***	0.005
		RS	Inscapes	-0.054	0.028	0.85	ns	0.006			RS	Inscapes	-0.099	-0.007	p<0.05	*	0.007
		RS	Circus	-0.039	0.043	1.00	ns	0.006			RS	Circus	-0.210	-0.117	p<0.0005	****	0.007
Empathy	p<0.05	RS	Jones	-0.079	0.003	0.08	ns	0.006	ToM	p<0.0005	RS	Jones	-0.131	-0.039	p<0.0005	****	0.007
		Inscapes	Circus	-0.026	0.056	0.79	ns	0.006			Inscapes	Circus	-0.157	-0.064	p<0.0005	****	0.007
		Inscapes	Jones	-0.066	0.016	0.40	ns	0.006			Inscapes	Jones	-0.078	0.014	0.29	ns	0.007
		Circus	Jones	-0.081	0.001	0.06	ns	0.006			Circus	Jones	0.032	0.125	p<0.0005	****	0.007
		RS	Inscapes	-0.008	0.082	0.15	ns	0.006			RS	Inscapes	0.019	0.099	p<0.05	***	0.006
		RS	Circus	-0.051	0.039	0.98	ns	0.006			RS	Circus	0.013	0.093	p<0.05	**	0.006
ER	p<0.0005	RS	Jones	-0.082	0.007	0.14	ns	0.006	VigAtt	p<0.0005	RS	Jones	0.017	0.096	p<0.05	**	0.006
		Inscapes	Circus	-0.088	0.002	0.07	ns	0.006			Inscapes	Circus	-0.046	0.034	0.98	ns	0.006
		Inscapes	Jones	-0.119	-0.029	p<0.0005	***	0.006			Inscapes	Jones	-0.042	0.037	1.00	ns	0.006
		Circus	Jones	-0.076	0.014	0.28	ns	0.006			Circus	Jones	-0.036	0.043	1.00	ns	0.006
		RS	Inscapes	-0.013	0.090	0.22	ns	0.007			RS	Inscapes	0.002	0.072	p<0.05	*	0.005
		RS	Circus	-0.075	0.029	0.66	ns	0.007			RS	Circus	-0.017	0.053	0.54	ns	0.005
eSAD	p<0.0005	RS	Jones	-0.112	-0.009	p<0.05	*	0.007	WM	p<0.005	RS	Jones	0.017	0.086	p<0.05	***	0.005
		Inscapes	Circus	-0.113	-0.010	p<0.05	*	0.007			Inscapes	Circus	-0.054	0.016	0.49	ns	0.005
		Inscapes	Jones	-0.151	-0.047	p<0.0005	****	0.007			Inscapes	Jones	-0.020	0.049	0.71	ns	0.005
		Circus	Jones	-0.089	0.014	0.24	ns	0.007			Circus	Jones	-0.001	0.068	0.06	ns	0.005

Supplementary Table 3. ANOVA and Tukey-Test results for differences between within-subject correlations for the different conditions in each network.