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LANGUAGE EMERGENCE in Brains, Babies and Bygone Times

LIFE, COGNITION AND INTELLIGENCE. Lessons from

Emergence

BOOK REVIEW A Very Short

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Introduction to Comfexity.



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In science, a complex system is any system that is formed by many components interacting with each other to produce a whole that cannot simply be explained as the sum of its parts. It makes sense to view the brain as one such system. Among its 86 billion interconnected neurons, larger networks are built upon local networks and result in a complex and dynamic system that produces the higherorder emergent properties that are our behaviours, thoughts, and feelings. Thus, complexity science is being incorporated into the study of brain and cognitive science more and more in order to unearth some of the mysteries of the brain.

It is likely that many in our field see the word complexity and feel overwhelmed, afraid that they might have to deal with an obscure and intangible concept. However, studying something that is complex doesn't necessarily mean it is complicated. In fact, simplicity often lies on the other side of complexity. For example, when looking at the interconnectedness of species, if you want to predict the effect of one species on another, only focusing on their direct connection is likely have less predictive power than if you consider the entire network of species involved. In fact, the more you zoom out and embrace complexity, the more likely it is that you have a better prediction. This is because, by considering the whole complex system, you have a better chance of pinpointing the simple details that matter most.

In this issue of the ABC Journal, we wanted to untangle and dissolve some of the fears produced by the intimidating field of complexity. Therefore, along with two excellent research articles selected from the students of the Brain and Cognitive Sciences Master's at the University of Amsterdam, we have several original articles from our editors that are focused on complexity and emergence. The articles cover the topics of language emergence and emerging intelligence in robotics. Additionally, John Holland's book, 'Complexity: A Very Short Introduction', is reviewed.

Finally, we would like to thank our great team for all their hard work on this issue, as we have been digital members while away on internships abroad. The ABC Journal team now grows stronger with every issue and we believe this will continue for years to come.

On behalf of the editorial team,

Sammy Millard and Nikos Kolonis (a.k.a. digital members)

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From left to right: Feline de Wit, Sven Wientjes, Eylül Turan, Iris Bosch, Rose Nasrawi, Marianne de Heer Kloots (not pictured: Nikos Kolonis, Sammy Millard, Steven Voges, Christina Bruckmann)

Life, Cognition and Intelligence

Lessons from Emergence

by Sven Wientjes

iving a comprehensive definition of the concepts of 'intelligence' and 'cognition' is quite a challenge. Intelligence is often used in the context of IQ, describing individual differences in the ability to successfully engage in increasingly difficult abstract problem solving, and taken as a function of brain activity. However, while scientists are trying to solve these complicated problems, at the same time it turns out it is incredibly difficult for scientists and engineers to capture even 'simple' functions of brain activity, such as the mobility of an ant on a beach (Simon, 1996). This discrepancy between intelligence as complex reasoning and as simple behaviour is described by Stewart (1995) as a 'division of labour'. One definition captures one set of behaviours, while the other definition captures an entirely different set of behaviours.

One popular definition of cognition is the 'computational theory of mind', statingthat cognition and intelligent behaviour stem from the manipulation of symbolic represen-tations, following the rules of a formal syntax. This interpretation can help describe certain behaviours we tend to deem 'intelligent', such as playing chess, but feel out of place for more common-practice displays of intelligence such as navigating through difficult terrain. Is therea definition which could intuitively capture both these types of intelligence?

An alternative definition of cognition comes from the philosopher Humberto Maturana. While trying to find a unifying principle for how to define 'life', he decided that circular organization between an environment and an organism engaging in self-maintenance is a powerful description. This means that life = cognition, which can be absurd seeing that plants are also considered alive. This self-organization or 'autopoiesis' is best characterized as dynamical interaction between (parts of) the organism and its environment, also called an 'Ecological Niche'.

As we formalize all the interactions happening between e.g. light sources from the environment, the eye of an animal, the activity in its nervous system, and the motor output of the organism, such as in Figure 1, we can see there is a part of the animal considered the 'internal state', which is sealed off from the external world and interacts with it through sensation and action. This is required for the definition of an organism according to modern day interpretations of autopoiesis, especially the Free Energy Principle (FEP) (Kirchhoff etal., 2018). Such a partition between external and internal is also called a 'Markov Blanket', a term directly borrowed from Graph Theory. While these definitions make for a good fundamental description of cognition, it feels out of place for e.g. playing a game of chess. As one famous scientist, albeit from a different field, once said, 'What I cannot create, I do not understand'. While abstract notions of dynamical systems and Markov Blankets are insightful, trying to perfectly reconstruct the unified cognitive capabilities of a human might lead to a convincing general definition of intelligent cognition. While the field is currently far from reaching this point, in certain specific domains successes are being booked. Specialized systems can outperform humans in either Chess or Go, in recognizing dog breeds, or in arbitrary information retrieval. However, these machines are in a way always at the mercy of their human users. They require heaps of structured data to betrained and run as long as we provide them power.

According to Brooks (1991), a truly intelligent machine that might some day equate a human, will not be created this way. He states that first and foremost any intelligent creature knows how to appropriately and timely deal with a dynamic environment. This means it can deal with movement and complex surfaces, it can hold multiple goals and focus on the most appropriate one, and, importantly, it has a purpose in being. Brooks builds robots known as 'creatures' that adhere to these principles, and in doing so can completemany real-world tasks successfully. These



Figure 1. A Markov Blanket Partition of the external world and a human brain.

creatures can be described much in the spirit of the FEP and can actually be characterized as a collection of dynamical systems adaptively organized in Markov Blankets.

Perhaps the most famous creature today is the Roomba, the robot with the purpose of serving as a vacuum cleaner. These creatures are built radically different than the special systems that can outperform us in one abstract domain. They rely on a 'subsumption architecture', which means they have multiple independent but interacting subsystems implemented that are responsible for different behaviours, such as shown in Figure 2. For instance, the Roomba has a subsystem that keeps track of where it has been and incentivizes it tomove to unclean territory. However, it also has a subsystem for avoiding hitting obstacles. This subsystem will seize control over the movement of the creature when necessary. All these subsystems are deceptively simple, but the behaviour they create when combined is quite intelligent and adaptive. This is a beautiful example of emergence. Brooks compares the subsumption architecture to the original evolution of animal behaviour and cognition. In its basis a hierarchy of reflexes of increasing complexity, more and more complex reflexes can simply be added to the architecture, which is how Brooks actually developed his robots.

It all seems fine to start with a notion of a somewhat clever vacuum-cleaner, and abstractly claim that from developing these creatures according to evolutionary principles we can reach human-level intelligence, but how do we make this concrete? There are two gaps here: The first is how creatures originally came into existence in the first place, and the second is if through natural selection on a hierarchy of reflexive behaviour, cognitive capabilities can emerge that can reach levels we would call profoundly intelligent (note, it is not required they become better than the best chess engine to date!).

Considering the first question, pondering on the origin of life is always a difficult subject and any answer seems to be unsatisfying, as for now there simply is no way of knowing exactly where life came from. This does not stop people from trying to formalize their beliefs and intuitions though, and a powerful framework is again offered by the theories of Autopoiesis and the Free Energy Principle. As Friston



(2013) describes, in more mathematical detail than can be treated here, if an ergodic random dynamical system exists, Markov Blankets will form and maintain themselves. This sounds very abstract, so it requires clarification. A random dynamical system is any system of objects (say particles or cells), which can interact with each other, and do so rather unpredictably. If the system is ergodic, this means that over time, even though the system is random, states of the system are visited following a consistent probability distribution. This allows us to assign probabilities to the system being in a specific state when observed at random. If all these random interactions happen mainly locally, such as in electrochemical and nuclear forces, Markov Blankets form for long-range dependencies. In exactly such a model of a Primordial Soup, Friston (2013) sees very simple organisms emerge based on these rules.

To the second question, from Brooks (1991) it can be derived that the term 'intelligence' is difficult to capture. This is because it is not an innate or isolated property. Intelligence is an emergent property of certain complex systems, and typically directed toward something, essentially it is *adaptive goal-directed behaviour*. The famous quote that comes with this belief is that 'intelligence is in the eye of the beholder'. The fact that many successful real-world intelligent systems (i.e. robots) are based upon the subsumption architecture gives this definition of intelligence some force.

From a scientific perspective then, the frameworks of dynamical systems and behaviour-based robotics are complementary and provide many good tools not only for understanding, but also *creating* real-world intelligent behaviour. However, these frameworks still have lots to prove about scalability, as long as there are no WestWorld-style androids walking around. Dependent on the question being asked about the nature of life, cognition or intelligence, these frameworks may or may not provide useful answers. Other frameworks, such as neural networks or symbolic reasoning, definitely have their own strengths. Whether there is any preference for one of these frameworks from a philosophy-of-mind perspective, shall be left as an exercise for the reader.

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Figure 2. An example of the layout of a simple susumption architecture.



Hallucinations in schizophrenia; examination

of resting-state functional networks

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ABSTRACT

We investigate hallucinations, a highly impacting symptom occurring in several psychiatric disorders, using network and modularity measures while removing the confounding factor of overall pathology. We collected resting-state functional connectivity data of participants with and without hallucinations and used this data to measure coherence across brain regions. Using network measures we compared overall connectivity characteristics and found significant differences based on the absence or presence of hallucinations in participants. We examined within-community and between-community network measures of functional modular networks associated with salience, default mode and executive functioning, as well as connectivity between these networks and found significant differences based on absence or presence of hallucinations. Our findings imply that previous findings of general dys-connectivity in schizophrenia could be caused by hallucinations instead of being an effect of general pathology. Significant differences in network coherence localized both within salience, central executive and default mode cognitive networks, as well the functional connections between them, provide an argument for their involvement in hallucinations.

KEYWORDS

schizophrenia, hallucinations, symptomatology, functional connectivity, tripartite model, default-mode network, central executive network, salience network

INTRODUCTION

In subjects with schizophrenia auditory and visual hallucinations occur alongside other symptoms such as distortions in thinking, sense of self and behavior (Buckley et al., 2009). Functional connectivity between networks in the brain has been implicated as playing a role in this highly impacting symptom (Jardri et al., 2016; Alderson-Day et al., 2016; Curcic-Blake et al., 2016). However, the confounding effect of schizophrenia on brain connectivity presents a problem for research investigating the role of networks and connectivity in hallucinations (Stephan et al., 2009).

Modularity, the division of nodes into networks based on connectivity between them provides a way to compare cognitive networks. Activity from regions as measured by functional magnetic resonance imaging (fMRI) can be ordered into identifiable communities or modules, associated with specific cognitive functions such as vision, default-mode, attention, salience and motor control (Fox et al., 2005; Power et al., 2011; Bassett et al., 2013a). Dividing nodes into com- munities or modules is done by various algorithms in the realm of graph theory and network science (Blondel et al., 2008; Rubinov and Sporns, 2010). Modularity can be quantified through comparisons made by measurements of intra- and inter-module connectivity. Measures of modularity as applied to the brain have been found to be able to quantify theoretically anticipated differences in network development during adolescence (Gu et al., 2015) and in network disruptions in case of pathologies, including schizophrenia (Alexander-Bloch et al., 2010, 2012).

To examine schizophrenia in general and hallucinations in particular, patients have been compared to healthy subjects; a general decrease in connectivity has been found. Additionally, while large-scale modules of cognitive functionality such as the default mode network are robustly found, more localized module-specific differences in intra- and inter-connectedness in network modules are present (Stephan et al., 2009; Yu et al., 2012). Building on these findings, it is theorized that an imbalance in connectivity within and between specific, identifiable modules leads to the occurrence of psychiatric symptoms including hallucinations. Notable among these suspected involved modules are the central executive network, the default mode network and the salience network (Whitfield-Gabrieli et al., 2009; van Lutterveld et al., 2014; Lefebvre et al., 2016).

The identification of these modules as playing a role in hallucinations is congruent with the hypothesis that top-down regulation of sensory information is impaired in schizophrenia; insufficient control of the higher-order, cognitive networks could lead to a lack of filtering of signals from sensory modules, leading to hallucinations (Aleman et al., 2003; Gilbert and Sigman, 2007). The three functional networks and their interactions have been implicated in a variety of neurological and psychiatric diseases and symptoms and are referred together as the tripartite model (Menon, 2011).

Knowledge of the functional connectivity between and within large-scale brain networks suspected of being involved with hallucinations is limited. While research has been performed to examine the interaction of these modules (van Lutterveld et al., 2014; Lefebvre et al., 2016), modularity measures and associated network connectivity were not investigated. Additionally, since schizophrenia is associated with general dysconnectivity and changes in modularity, examination of the specific cognitive modules causing hallucinations was confounded by the effect on network connectivity of the overall pathology (Stephan et al., 2009; Jardri et al., 2016).

To alleviate this confounding effect we examined network measures of previously identified resting-state networks in subjects with schizophrenia but without hallucinations and compare these to subjects with schizophrenia and hallucinatory symptoms, while controlling for overall disease severity as determined by the Positive And Negative Syndrome Scale (PANSS) questionnaire (Kay et al., 1987). We hypothesized that subjects with schizophrenia and hallucinations have lower overall network connectivity compared to subjects with schizophrenia but without hallucinations. While we expected overall network division in cognitive modules to be similar across participants, we expected differences in specific module characteristics; we hypothesized that in subjects with hallucinations within-connectivity in modules associated with salience, the central executive network as well as the default-mode network were lower, and there furthermore would be lower connectivity between these modules. (Lawrie et al., 2002; Lefebvre et al., 2016; Stephan et al., 2009; van Lutterveld et al., 2014). The present study aims to increase knowledge of these specific network modules associated with hallucinatory symptoms, leading to a deeper understanding of this highly impacting symptom as well as possibly identifying targets for therapeutic intervention.

METHODS

Participants

Participants were drawn from a population of healthy controls and participants with schizophrenia who had taken part in various earlier studies in the University Medical Center Utrecht, The Netherlands (Sommer et al., 2010; Scheewe et al., 2012; Begemann et al., 2015; Abramovic et al., 2016). Eligible participants were rated on severity of psychosis symptoms using the PANSS questionnaire and had a previous clinical diagnosis of schizophrenia as confirmed using the Comprehensive Assessment of Symptoms and History (CASH) questionnaire; both were administered by trained clinical researchers (Andreasen et al., 1992). Subjects with schizophrenia where divided into groups without hallucinatory symptoms (SZ-) or with hallucinatory symptoms (SZ+) based on their score on item P3 of the PANSS scale ('hallucinatory symptoms') (Kay et al., 1987). Participants with a score of 3 ('mild') or higher on this 7-point item of the PANSS were assigned to the SZ+ group, while participants with score 2 or lower were assigned to SZ-. Healthy controls (HC) were selected from the pool used for the previous studies and were matched based on age, gender and handedness. Exclusion criteria for healthy controls were age > 60, any lifetime hallucinatory symptoms and any diagnosis on the schizo-affective spectrum. Using a measure of relative motion we excluded participants whose movement during the functional scan exceeded stringent standards (See MRI preprocessing).

Based on these criteria, from an initial selection of 415 we selected 30 participants with schizophrenia without hallucinatory symptoms (SZ-), 50 participants with schizophrenia with hallucinatory symptoms (SZ+) and 135 healthy participants as controls (HC) for a total of 215 participants. See table 2 for full participant information. All participants provided written informed consent before participation in the study. All studies were approved by the institutional review board of the University Medical Center Utrecht.

MRI acquisition

For all participants, MRI scans were collected on the same Philips Achieva 3 Tesla Clinical MRI scanner in the University Medical Center Utrecht (Philips Healthcare, Best, the Netherlands). 600 blood-oxygenation-level-dependent (BOLD) resting-state fMRI images were acquired using the following parameters settings: 40 (coronal) slices, repetition time (TR) 23 ms, echo time (TE) 33 ms, flip angle 27°, field-of-view (FOV) 224 x 256 x 160, matrix 64 x 64 x 40, voxelsize 4 mm isotropic.

This scan sequence achieves full brain coverage in 609 ms by combining a 3D-PRESTO pulse sequence with parallel imaging (SENSE) in two directions using a commercial 8-channel SENSE head coil (Neggers et al., 2008). Resting-state scans were acquired for 6 minutes, and participants were instructed to lie still with their eyes closed, not to think of anything in particular and not fall asleep. For a subset of 38 HCs, 18 SZ+ and 19 SZ- participants, 1000 images were acquired over 10 minutes instead of 600 over 6 minutes, with the same instructions (Scheewe et al., 2012). For these subjects, we selected the first 600 images and discarded the rest.

Additionally, a high-resolution anatomical scan was acquired for each participant for registration to standard space. Since we used previously collected data, scanning parameter differed across participants. 4 different studies were used with slight differences in voxel size, TR/TE time and Field of View (FOV). See table 1 for detailed scan information per study.

MRI preprocessing

Preprocessing of the fMRI data was performed using the FM-RIB Software Library (FSL v5.0.4, available at https://fsl.fmrib.ox.ac. uk) (Jenkinson et al., 2012). Structural and functional images were Table 1. High-resolution anatomical scan parameters

Participants selected	TR	TE	FOV	Slices	Voxel size
° 38HC,18SZ+19SZ-	10ms	4.6ms	240x240x160	200	0.8x0.8x0.8mm ³
^b 64HC	10ms	4.6ms	240x240x160	200	0.75x0.75x0.8mm ³
° 33HC,23SZ+	9.86ms	4.6ms	224x160x168	160	0.875x0.875x1mm ³
^d 9SZ+.11SZ-	11ms	4.6ms	240x240x160	200	0.8x0.8x0.8mm ³

Scanning parameters of the high-resolution anatomical scans per study from which participants where drawn. flip angle was the same for each high-resolution T1 anatomical scan at 8 °. Respective studies are: ^a: Scheeuwe et al., 2012; ^b: Abramovic et al., 2016; ^c: Sommer et al., 2010; d: Begemann et al., 2015.

skull-stripped using the BET soft- ware tool (Smith, 2002). Resting-state functional data was then realigned and co-registered to the structural high-resolution anatomical T1 scan for each participant using MCFLIRT and FEAT through an intermediate mean functional scan (Jenkinson et al., 2012). All resting-state data was re-sliced to the mean resting-state functional scan per participant, and then this mean functional scan was co-registered to the structural high-resolution scan.

On functional data, we used a high-pass filtering of 100 s to remove non-global frequency noise and applied a 5 mm spatial smoothing kernel. We linearly regressed out the signal of white matter and cerebrospinal fluid by constructing a mask using FSL FAST gray matter and taking the mean signal of white matter and cerebrospinal fluid and consequently including these values as nuisance regressors (Zhang et al., 2001).

Since head motion is known to have a strong effect on connectivity - and correspondingly, network and modularity measures - we used rigorous fMRI pre-processing steps to filter data for excessive motion (Friston et al., 1996; Power et al., 2012; Van Dijk et al., 2012; Power et al., 2014). For each timepoint compared to the previous timepoint for each participant, rigid body head motion was estimated using FSL's MCFLIRT routine. The resulting three translation parameters and three rotation parameters can be condensed to a single vector representing the root mean squared volume-to-volume displacement of all brain voxels (Jenkinson et al., 2002, 2012). From this one-dimensional motion vector for each volume relative to each preceding volume for the total timeseries we calculated mean relative motion displacement for each participant by averaging over the number of volumes(Satterthwaite et al., 2013). We excluded participants if their functional data showed a relative mean displacement larger than 0.2 mm, as well as participants who had 20 or more volumes with a relative displacement of 0.25 mm or higher (Gu et al., 2015).

To control further for spurious connectivity between brain regions induced by motion, we used the ICA-AROMA approach to remove motion-related signals that are identified with single-participant independent-component analysis, derived from the functional data for each participant (Pruim et al., 2015). Finally, functional timeseries were filtered using wavelets to retain frequencies between 0.05 - 1 Hz.

Coherence matrices

Per participant mean BOLD timeseries from 264 previously defined regions of interest (ROI) were selected, using an atlas specifically constructed for analysis of functional MRI data (Power et al., 2011) An overview of the locations of the ROIs is shown in figure 1. A wavelet-based algorithm decomposition was applied to extract information from the raw timeseries in the 0.05 - 0.1 Hz range (Percival and Walden, 2006). Compared to a direct Pearson's correlation between two ROI timeseries, wavelet coherence additionally makes use of the power spectrum of the signals between two regions using a Fourier transform. This method yields an invariant measure of how much activity between two corresponding regions is connected. Wavelet-based decomposition is especially suited for deriving brain connectivity because of the long-term effects of transient short-term increased activity ('memory') characteristically present in brain measurements, as well as ease of de-noising the signal and inherent robustness to outliers (Achard and Bullmore, 2007; Bassett et al., 2008, 2013a; Gu et al., 2015).

Using this wavelet-based decomposition technique, estimations of functional coherence Aij between any ROI i to any other ROI j was determined; this was repeated for all 264 ROIs in the predetermined atlas. This resulted in a 264 x 264 undirected coherence matrix, with each field Aij having a weighted value between 0 and 1. Here, 0 reflects a total absence of coherence, and 1 reflects perfect coherence between ROIs. No directional causality can be derived from this value; coherence from i to j is exactly the same as from j to i, and is as such undirected. The resulting coherence matrix represents the full functional coherence between all 264 ROIs for a participant (Gu et al., 2015; Zhang et al., 2016; Bassett et al., 2013b). The procedure was repeated for each participant in our 3 groups; group-averaged coherence matrices are shown in figure 3.



Figure 1. Location and division of 264 nodes into 14 putative functional net- works in the human brain, following Power et al., 2011; different colors denote different cognitive net-works found and validated in resting-state fMRI data. Image generated using BrainNet-Viewer (Xia et al., 2013).

Overall connectivity measures

From the coherence matrices various network measures can be derived. These can serve to give brain-wide measures of differences in connectivity. To examine these overall connectivity measures for significant effects based on the presence of absence of hallucinations, we calculated mean coherence and variance thereof. To examine the overall strength of brain connectivity, we calculated overall network coherence. For this measure, all coherency values Aij in the 264*264 coherence matrix A are summed and then divided by the total number of nodes in A, leading to the mean coherence strength of the matrix. In our study, coherence between 264 ROIs was taken and averaged; this procedure was repeated for each individual connectivity matrix. The resulting coherence coefficient per participant is indicative of network strength (Zhang et al., 2016). To compare groups, we performed a one-way ANOVA.

Similarly, the range of values Aij present in a coherence matrix A can be used to derive the variance in coherency values between nodes. This variance serves as a measure of uniformity among ROI coherence. Increased variance is interpreted as an increase in how well-defined networks are from the total ROIs are (Bassett et al., 2013a). We calculated the variance across all coherence values for each participant, and compared groups using a one-way ANOVA.

For significant findings we examined whether a trend exists between the three groups using a Jonckheere trend test to establish whether or not a gradient exists between groups.

Network division using modularity algorithm

To examine whether our groups coherence matrices show similar divisions of nodes in cognitive networks, we aimed to compare our coherence matrices to a previously found and validated division (Power et al., 2011). We created a functional network division for each participants unique coherence matrix using modularity algorithms, as used in graph and network science (Blondel et al., 2008; Gu et al., 2015). Modularity algorithms aim to divide nodes (in this case, the 264 ROIs) into communities with stronger connections (edges, in this case coherence Aij between any brain regions i and j) within members in the group compared to other nodes, thus detecting groups where connectivity is significantly correlated - putative cognitive modules. These modules can be visualized as areas of high coherences along the identity line in connectivity and coherence matrices if ordered per division (see figure 3). To implement this, we used a modularity-based greedy Louvain-algorithm, originally developed in the field of network science, implemented in MATLAB (Blondel et al., 2008; Jutla et al., 2011).

Suppose a network G = (V, A, C) where V = $(v_1, ..., v_n)$ is the set of nodes, A is the weighted adjacency matrix, and C = $\{C_1, ..., C_k\}$ is a partition of nodes into modules or communities $C_i \in C$. To identify an optimal partition of nodes into communities, we search for a partition C that maximized the following modularity quality function:

$$Q(C) = \sum_{ij} (A_{ij} - \gamma * \frac{P_i P_j}{2M}) \sigma_c(i, j)$$

where $2m = \sum_{ij} A_{ij}$, P is $(p_1, ..., p_n)^T$, $p_j = \sum_i A_{ij}$, γ is a structural resolu-

tion parameter, and $\sigma_c(i,j) = 1$ if v_i and v_j are in the same community and $\sigma_c(i,j) = 0$ otherwise. The structural resolution parameter γ has a strong effect on the total number of divisions into which the algorithm will divide the ROIs. We used a value of 1.00, as this is the most commonly used value in previous research (Gu et al., 2015). Following Lerman et al. (2016), we sparsified the coherence matrices to the strongest 10% of coherence values and then used the Louvain algorithm to divide the 264 ROIs into network modules. Because of the inherent non-deterministic nature of the algorithm, we repeat the procedure 100 times per participant, then select the network with the highest Q and its associated community division for further analysis.

Comparisons of network divisions can be guantified by calculating the z-score of the Rand coefficient measure of network similarity. This measure calculates the similarity of a division of nodes in communities to another division. To quantify and compare this per-network division, we calculate for the division with the highest Q per participant the z-score compared to a previously found and validated division (Power et al., 2011). The resulting value gives a quantification of network division similarity for each of the participants in our three groups HC, SZ- and SZ+. These groups can be compared to test whether differences in modularity assignment are present using a one-way ANOVA. We expect a non-significant difference in overall partitioning between groups, since although previous research has found differences in brain-wide dysconnectivity as well as changes in connectivity in specific cognitive networks, overall cognitive networks have been shown to be robust even in cases of psychiatric disorders such as schizophrenia. A similar modularity division across groups is an argument for the use of a previously determined network division for further examination of network connectivity (Lerman-Sinkoff and Barch, 2016).

Within and Between connectivity

To examine the connections between the salience, central executive and default mode networks, we calculated within-network connectivity as well as between-network connectivity. These networks of the tripartite model have been identified as playing a possible role in psychiatric disorders (Menon, 2011) and hallucinations in particular (Lefebvre et al., 2016). To define these networks in our participants, we made use of a previously found and validated division of our 264 regions of interest in 14 previously defined putative functional networks (Power et al., 2011). Using this division we measured within- and between connectivity for these networks for each of our participants (Gu et al., 2015). The mean connectivity of all connections between nodes in the community that makes up a functional network as well as the mean connectivity of all connections from nodes in a community to nodes not in the community were selected. This procedure was repeated for the 3 previously identified functional communities in the tripartite model for each participant - the default mode network, the central executive network and the salience network - and was then repeated for each participant in each of the groups. Comparisons between the SZ- and SZ+ groups was performed using students T-test for independent samples; since multiple networks were tested for significance, results were corrected for multiple comparisons using a bootstrapped random permutation test (Phipson et al., 2010).

Connectivity between modules of the tripartite model

To further examine network connectivity in the tripartite model, we narrowed down between-network connectivity. Rather than looking at the outgoing coherency from one network to all other networks, it is also possible to select specific coherence values between nodes in one network to specific other defined cognitive nodes. When repeated for all nodes in the two identified and averaged over the number of connections, the resulting value measures functional coher- ence between the two networks. We applied this procedure for the connections of the 3 networks identified in the tripartite model, taking all connections between the nodes in the salience, central executive and default mode networks. To test whether these networks identified in the tripartite mode is significantly different as a correlate of the presence or absence of hallucinatory symptoms, we compared the SZ- and SZ+ participant groups using a students T-test for independent samples.

RESULTS

Demographics

After initial selection based on availability of functional and structural MRI scans as well as availability of clinical measures (N = 415), we excluded participants based on excessive motion as defined by mean relative motion between frames of greater than 0.2 mm or more than 20 frames in the functional scan with larger frame-wise displacement that 0.025 mm (N = 88), failures in the automated MRI registration pipeline (N = 110) and past intra-cranial infarcts (N=1). After dividing participants with schizophrenia in SZ- and SZ+ groups, healthy controls were matched to clinical participants based on age and gender, creating 3 participant groups used further in analysis: SZ+ (N = 50), SZ- (N = 30) and HC (N = 135).

Detailed demographic information is shown in table 2. The PANSS total score was marginally significant between SZ+ and SZ-(T(78) = 2.037, P = 0.045); however, by splitting up the various items we found the main driver of this significance to be the positive items on the symptom scale - among which is the item on which the

Table 2. Demographics and clinical measures

groups were divided. No significant difference was found for negative or general items on the symptom scale. Neither age, gender, use of antipsychotic medication in the month before the scan or handedness significantly differed between HC, SZ+ and SZ-, as is presented in table 2.

Overall connectivity measures

Following (Zhang et al., 2016), we calculated the mean coherence coefficient for each individual coherence matrix as well as the variation of coherence thereof and compared these measures across groups by using a one-way ANOVA. We found a small but significant effect of mean coherence coherence coefficient among groups, (F(2,212) = 4.08, p = 0.018). Using post-hoc Tukey tests, when comparing HC to SZ-, we found no significant difference in mean coherence coefficient, Tukey's P = 0.628. A significant difference was found between HC and SZ+, P = 0.039 as well as between SZ+ and SZ-, P = 0.029. For details, see figure 2.

For variance of the coherence coefficient we found a similar pattern; one- way ANOVA, (F(2,212) = 4.294, p = 0.015). Using posthoc Tukey tests, the difference between HC and SZ- was not significant, P = 0.810, while there was a significant difference between the two groups without hallucinations compared to the SZ+ group (P = 0.022 and P = 0.039 for HC vs SZ- and SZ- vs SZ+, respectively).

To establish whether a gradient exists between the groups, we performed a Jonckheere trend test on these overall coherence measures. Results were significant at the a < 0.05 significance level; both coherence coefficient (z = 2.496, one-sided p = 0.006) as variance in coherence coefficient (z = 2.426, one-sided p = 0.007) showed a trend from HC via SZ- to SZ+.

Network division using modularity algorithm

Using individual networks sparsified to the 10% strongest connections, divisions were created using the Louvain algorithm. The resulting divisions of 264 nodes into putative networks were compared against the standard division from Power et al. (2011). The resulting z-score of the Rand coefficient for each network were tested across groups using a one-way ANOVA. The result was not significant, F(2,212) = 0.091, P = 0.913, indicating that the 264 were partitioned in roughly similar networks across participant groups

Group	HC (N = 135) mean (SD)	SZ- (N = 30) mean (SD)	SZ+ (N = 50) mean (SD)	Stats ^a
Age (years)	32.10 (10.35)	28.00 (6.79)	30.50 (9.895)	F = 2.590, P = 0.077
Gender(M:F)	82: 53	24: 6	32: 18	Chi-Square,P=0.138
Handedness(L:R)	25: 110	5: 25	3: 47	Chi-Square,P=0.106
Antipsychotics use (Y : N)	-	28: 2	43: 7	Chi-Square,P=0.315
PANSS score				
total score	-	58.23(11.74)	64.17 (12.97)	T = 2.037, P = 0.045
general symptoms	-	29.93 (6.02)	31.77 (6.88)	T = 1.202, P = 0.233
positive symptoms	-	13.00 (3,07)	16.71 (4.28)	T = 4.142, P < 0.001
negative symptoms	-	15.30 (5.34)	15.86 (4.94)	T = 0.476, P = 0.635

Detailed demographic and clinical information of the participants, divided into HC, SZ- and SZ+ groups. PANSS = Positive and Negative Symptom Scale. ^aAge across 3 groups was compared using a one-way ANOVA, binary variables including gender and handedness were compared using Pearsons exact Chi-square test and PANSS scores were compared using a t-test for independent samples.



Figure 2. Top: Mean coherence coefficients across groups. Boxes bars represent 1 SD; lines represents the median. A significant result was detected using a one- way ANOVA (F(2,212) = 4.08, p = 0.018). Tukey post-hoc tests were performed to examine differences between groups. HC vs SZ- was not significant, P = 0.628. HC vs SZ+ was significant, P = 0.039, as well as SZ+ vs SZ-, P = 0.029. Bottom: Variance in mean coherence coefficients displays a similar pattern. One-way ANOVA was significant (F(2,212) = 4.294, p = 0.015). Post- hoc testing showed HC vs SZ- was not significant, P = 0.815. HC vs SZ+ was significant, P = 0.0215, as was SZ+ vs SZ-, P = 0.039.

compared to the standard Power et al. division.

Within and Between connectivity

We measured within- and between connectivity for 14 previously found functional networks for each of our participants (Gu et al., 2015). The mean connectivity of all connections between nodes within the community that makes up a functional network as well as the mean connectivity of all connections from nodes in a community to nodes not in the community were selected. This procedure was repeated for each of the previously identified functional communities of interest per participant, and was then repeated for each participant in each of the groups.

Healthy Controls versus SZ- and SZ+



Figure 3. Mean coherence adjacency matrices, averaged over groups. From top to bottom, HC, SZ- and SZ+. Note the clusters of high coherence across the identity line, indicating putative modular networks. Mean coherence averaged over groups was highest for HC+ and lowest for SZ+.

3.4, P = 0.035) connectivity. In all mean connectivity measures of networks HC had the highest and SZ+ the lowest mean connectivity. Using post-hoc Tukey's testing, we found that mean connectivity between HC and SZ- did not differ significantly for these networks.

SZ- versus SZ+ groups

To further analyze specific network characteristics based on the presence or absence of hallucinations, we compared within and between mean connectivity per functional network using a students T-test. We report a significant difference for connections between nodes in the 'salience' network (T = 2.343, P = 0.022) when comparing the SZ- and the SZ+ groups, with the SZ- having higher average connectivity within this network. To correct for the possibility of false positives arising from multiple comparisons, we used used a random permutation test with 50.000 iterations to our finding of within-connectivity of the salience network. This resulted in a corrected Table 3. Within and between connectivity for functional network modules

Group	SZ-	SZ+	Stats ^ª
Default Mode within	0.3026	0.2796	T=1.976,P=0.052
Default Mode between	0.2994	0.2753	T=1.286,P=0.202
Central executive within	0.3086	0.2938	T=1.024,P=0.309
Central executive between	0.2716	0.2526	T=0.942,P=0.349
Salience within	0.3847	0.3367	T = 2.343, P = 0.021*
Salience between	0.2983	0.2595	T = 1.547, P = 0.126

^aVariables were compared using the Students T-test * = Significant at the p= 0.05 significance level. When correcting for multiple comparisons, this P-value was adjusted to P = 0.022, indicating a significant difference in the within-connectivity measure of the salience network between the SZ- and SZ+ groups.

P-value of 0.022; see table 3 for details.

Connectivity between modules of the tripartite model

We examined coherence between specific modules earlier identified in the tripartite model by selecting mean coherence values between the default mode, central-executive network and the salience network for each participant, yielding mean coherence across modules of the tripartite model. To compare SZ- and SZ+ coherence, we performed a students T-test for independent samples. The test showed a significant effect, T(78) = 2.268, p = 0.026. Connectivity between these previously identified network modules thus shows a significant difference across clinical groups divided using the presence or absence of hallucinations.

DISCUSSION

We examined functional connectivity and network measures of participants with schizophrenia with or without hallucinations compared to healthy controls. A comparison between patients with schizophrenia with and without hallucina- tions allowed us to disentangle symptom specific effects (e.g. hallucinations) from disease specific effects (e.g. effects due to the illness schizophrenia).



Figure 4. Location of nodes assigned to large-scale functional networks in the tripartite model, as defined by the standard atlas (Power et al., 2011). Red: central-executive network, green: salience network, blue: default mode network. Picture generated using Brain-NetViewer, (Xia et al., 2013).

Differences in overall connectivity

We found a significant difference in mean coherence coefficient between the SZ- and SZ+ groups; this measure reflects the averaged brain-wide connectivity over all regions. Using this measure we found that overall connectivity is stronger in the group without hallucinations compared to the group of participants with hallucinations. Thus, the presence of hallucinatory symptoms is associated with significantly lower overall coherency on brain-wide measures of connectivity. Previous research has shown that, when comparing a participants with SZ - without regard to the presence of hallucinations or not - have less over- all connectivity compared to HC (Lynall et al., 2010); we replicate this finding of significant less overall connectivity between HC and SZ+, but no significant difference between HC and SZ-.

The variance of the overall connectivity showed a similar significant difference between groups. The variance shows the range of coherence present between all nodes. In participants with schizophrenia, we found that, on average, the variance of overall connectivity is significantly smaller than the variance present in individual networks of healthy participants and participants with schizophrenia but no hallucinatory symptoms. This can be interpreted as nodes being less differentiated from each other in participants with schizophrenia, and in turn suggests that modules composed of these nodes are less-well defined.

Our findings suggest that the previously found decrease in overall connectivity between healthy controls and subjects with schizophrenia was mainly driven by the difference between the HC and SZ+ groups - in effect by the presence of hallucinatory symptoms, instead of an overall effect of schizophrenia. By disentangling participants with schizophrenia into SZ- and SZ+ groups we show a significant trend from HC to SZ- to SZ+ for both measures. Thus, simple graph metrics, in this case the mean coherence coefficients and the variance thereof, show significant differences based on the absence or presence of hallucinatory symptoms in a clinical population, arguing for the importance of symptomatology in interpreting functional data from participants with schizophrenia.

Network division using modularity algorithm

Our use of the Louvain algorithm to divide networks based on inherent coherence values using the z-score of the Rand coefficient showed a non-significant result. This was as hypothesized, since the modular cognitive networks are robustly found across various disorders, including schizophrenia (Lerman-Sinkoff and Barch, 2016). The non-significant findings served in this case as a validation of the choice to select previously identified specific functional modules. Since the z-score did not differ significantly across the HC, SZ- and SZ+ groups, selecting previously identified networks did not introduce a difference in modularity selection across groups. This provides an argument that further examination of cognitive modules was not biased by network modularity differences between groups as compared to the Power standard division (Power et al., 2011); this is especially important since we used this previously division to select our func- tional network modules.

Coherence between specific functional networks

To narrow down the functional networks responsible for specific symptoms we aimed to investigate within and between-network connectivity of modules, focusing on the tripartite model - the default mode, central executive and salience modules (Power et al., 2011). These modules have been associated with psychiatric disorders and hallucinatory symptoms in particular (Lefebvre et al., 2016; Alexander-Bloch et al., 2012). Our results showed that the mean coherence between the default mode, salience and central executive modules was significantly different between the two groups of participants with schizophrenia. This difference between patients with or without hallucinations indicates that alterations of connectivity between modules in the tripartite models are involved in hallucinatory symptoms; this argues for a paradigm of hallucinations where dys-connectivity in cognitive networks leads to hallucinations, instead of the alternate view where dys-connectivity within sensory networks such as the auditory cortex causes the symptom (Whitfield-Gabrieli et al., 2009). Higher- order cognitive networks could have too little activity in suppressing or filtering of signals coming from sensory areas, leading to perceiving stimuli that are not actually present - hallucinations. Since the 3 functional networks which showed a significant effect in our analysis are higher-order, non-sensory cognitive networks, our research supports the importance of higher-order networks in the occurrence of hallucinatory symptoms (Aleman et al., 2003; Gilbert and Sigman, 2007).

When looking at specific modules within this framework, we found an effect in the within-connectivity of the resting-state functional network previously identified as the 'salience' network (Power et al., 2011). For this network, we found that the presence of hallucinatory behavior was associated with a lower measure of within-community, reflecting a weaker coherency in this functional network. This effect persisted after correcting for multiple comparisons. The salience network has been proposed to play a central role in psychosis (Palaniyappan and Liddle, 2012); our findings show an involvement with one particular symptom of schizophrenia, possibly narrowing down the role it plays. The combination of a significant effect of this network, combined with the differences found in coherence between the modules of the tripartite model are thus supportive of the literature in regards to the proposed importance of these networks for psychiatric symptoms and disorders.

Difference in PANSS score between groups

When examining participant groups for clinical measures, we found a significant difference between the SZ- and SZ+ groups in regard to total PANSS score. Any further analysis using these differing groups could be due to innate differences in group due to severity of disorder (Lynall et al., 2010). Specifically, the PANSS score is used as a measure of disease severity (Kay et al., 1987); to further examine this difference we investigated our groups with regard to PANSS scores divided in the 3 major subdivisions, namely negative, positive and general scale items, reflecting symptoms in these categories. In this analysis, we found no significant difference for the negative or the general part of the scoring system. The positive measures, which include item P3 - which rates participants for hallucinatory symptoms - was found to be significantly different.

Since we explicitly used this item to divide participants and there were no significant differences between the other groups, we argue that this difference between groups is not a confounding factor of disease severity, but rather reflects the presence of hallucinations. We cannot exclude a partial effect of other positive symptoms measured by the PANSS, such as delusions or conceptual disorganization, on our results.

Strength and weaknesses of the research

These finding are, to our knowledge, the first trait-based connectivity analysis that reflects the proclivity to have hallucinatory symptoms around the time of the functional brain scan. The large number of participants, both for people with schizophrenia and for healthy controls is an indication of the robustness of our findings. Our HC sample is ecologically plausible, with incidental presence of depression, anxiety or (ab)use of drugs.

There was no significant difference between anti-psychotic medication us- age for the SZ- and SZ+ groups; this is of importance because anti-psychotic medication has a proven effect on connectivity (Hadley et al., 2014). The non-significance of medicine use between our groups thus argues against our findings being affected by change in connectivity associated by medicine use.

The current research used a parcellation of cortical and some sub-cortical regions previously defined in the literature for examination of resting-state networks (Power et al., 2011). Some recent studies include specific sub-cortical regions of interest as nodes in addition to the nodes defined in the Powers atlas, or use only self-defined regions of interest (Lerman-Sinkoff and Barch, 2016; Lefebvre et al., 2016). While we followed previous research in our choice of atlases, results might slightly differ with other node definitions.

A large subset (N=20 out of a total group of 30) of the non-hallucinating participants with schizophrenia had experienced hallucinations at any time in their lifetime prior to their inclusion; the PANSS questionnaire we used to divide our groups only rates hallucinatory symptoms in the past 2 weeks. Data regarding lifetime experiences of hallucinations was not available; the experiences might have been several years before the current research, or induced by drug use, but they might have also been more recent and caused by schizophrenia, but recently diminished. We assume this does not confound the network connectivity for our division of groups; but this is an assumption that is unproven. Further research, based on frequency, severity, type as well causality regarding these lifetime hallucinations might provide additional strength and specificity to net- work measures involved in hallucinations because of a more stringent selection of participants. Division of participants based on the modality of auditory or visual hallucinatory symptoms might also increase specificity of analysis.

A potential effect we did not examine is the difference between state- and trait-based hallucinatory symptoms. Some previous research has used explicit reporting of hallucinations during scanning (Lefebvre et al., 2016; Jardri et al., 2016) while we used the PANSS rating scale as a division of functional data of participants; the difference in measuring a propensity to hallucinate compared to the knowledge and timing of specific hallucinations will have a different effect in the associated network connectivity. The 2-week duration of the PANSS rating items limit these effects somewhat, but the potential difference between a propensity or trait to hallucinate versus actual hallucinations during the scan remains.

Clinical relevance and future research

Hallucinations are a commonly-occurring symptom of various psychiatric disorders including schizophrenia and often have a large impact on subjects. Certain functional networks have been implicated and interaction between multiple large functional networks has been suspected; but much remains unknown. The current research aimed to contribute to knowledge regarding hallucinatory symptoms (Shergill et al., 2003; Lerman-Sinkoff and Barch, 2016; Allen et al., 2008).

The significant effect of hallucinatory symptoms on mean coherence, the variance thereof and within-connectivity of modules making up the tripartite model, dependent on the presence of hallucinatory symptoms is a novel finding that in the clinical context might lead to improved understanding of the heterogeneous nature of schizophrenia and its symptoms.

Previous findings of lower mean connectivity correlations in participants with schizophrenia compared to healthy controls will have to be reinterpreted as our findings support the theory that dys-connectivity might not be due to the disorder of schizophrenia, but might instead be a correlate of specific symptoms (Lynall et al., 2010).

Future research could repeat the present research with the addition of a group of healthy voice-hearers to see if we can find a more expressed gradient in network dysfunction, with as added benefit the medication naivety of this population (Sommer et al., 2010). Participants with other diagnosis and hallucinatory symptoms could be included as well to further find cross-diagnosis evidence of a single underlying cause for hallucinatory symptoms, or to identify differing mechanisms whereby hallucinations can occur. Inducing hallucinations by administering drugs and examining the resulting changes in connectivity could potentially exclude interference of pathology altogether, although this would introduce large-scale effects of the administered drugs on brain networks (Carhart-Harris et al., 2016).

Concluding, our research has shown that hallucinatory symptoms have a significant effect on brain connectivity data. Narrowing down this effect to connectivity between previously found networks by comparing participants with and without hallucinations makes possible removing one of the main confounding factors, the general dys-connectivity associated with schizophrenia. Greater understanding of both the heterogeneity of schizophrenia and effects of specific symptoms on large-scale functional networks will hopefully increase our ability to, in the future, improve our treatment for specific symptoms as well as the general disorder.

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Language emergence in brains, obc babies & bygone times

by Marianne de Heer Kloots & Feline de Wit

anguage is all around us, permeating every aspect of everyday human life. But to an alien from outer space, a non-human animal, or even another human from a different part of the world, the sounds and signs that you use to communicate with will seem completely obscure. At some point in linguistic communication, meaningful concepts emerge from arbitrary physical signals. In this piece we look at language emergence on three different levels. First, how does our brain create representations of speech sounds, words and sentences? Second, what stages do initially incompetent babies go through when acquiring their native language? And, finally, how did our species end up with such a complicated communication system in the first place? We probe into these questions through a few glimpses of findings and questions in the literature around these different topics, and also consider how these processes might shape the ways our languages work¹.

BRAINS

Language only exists through our brains, as this is where we map a physical signal, such as a sound wave in spoken language or a movement pattern in sign language, to meaning (or the other way around). The sound waves themselves are not neatly divided into separate entities such as words or sentences, but instead they form a continuous stream of sounds. This means that you cannot hear silences between words in the same way that you can, for example, see the spaces between the words in this text. Yet somehow, our brains are able to connect these continuous speech signals to cognitive representations of concepts, thereby creating meaning. How do our brains do this? That is one of the central questions that neurolinguists try to answer.

Early neurolinguistic approaches started by trying to find out where in our brains language is localized. Much of this knowledge comes from fMRI experiments and studies of people with lesions in their brains that affected their language abilities. Such research postulated for example that Broca's area would be associated with the regulation of grammatical structures for language production, and that Wernicke's area plays a role in storing the word meanings for language understanding. However, a more recent casestudy showed that after surgery the plasticity of the brain enables other regions to take over at least some of the language functions that Broca's area regulates². Additionally, other regions in the brain have been identified that are sensitive to language^{3,4}. It is clear that language is a distributed function rather than contained within one specific brain region.

The question of *how* language is processed is however not entirely answered by finding out *where* the processing happens. Another dimension of neurolinguistic research investigates the oscillatory dynamics of neural populations associated with temporal aspects in language processing. In EEG studies, well-known ERP effects like the Mismatch Negativity or the N400 response are measured to investigate whether people for example predict specific upcoming words in discourse⁵. On the parsing of structured units from a continuous signal, some relatively new work is investigating the neural tracking of abstract linguistic structures: while participants listen to speech, their cortical response spectrum has peaks at the syllable, phrase and sentence levels, indicating that hierarchical linguistic structures are somehow reflected in the brain signal⁶.

¹ Although we discuss different and separate literatures in the three different sections of this piece, the idea of connecting the three timescales draws from work nicely brought together in this book: Christiansen & Chater (2016). *Creating language. Integrating evolution, acquisition and processing.* MIT press.

² Plaza, M., Gatignol, P., Leroy, M., & Duffau, H. (2009). Speaking without Broca's area after tumor resection. Neurocase, 15(4), 294-310.

³ Chang, E. F.MD, Raygor, K. P.AB, & Berger, M. S.MD. (2015). Contemporary model of language organization: an overview for neurosurgeons, *Journal of Neurosurgery JNS*, 122(2), 250-261.

⁴ Fedorenko, E., Behr, M. K., & Kanwisher, N. (2011). Functional specificity for high-level linguistic processing in the human brain. *Proceedings* of the National Academy of Sciences, 108(39), 16428-16433.

⁵ Van Berkum, J. J., Brown, C. M., Zwitserlood, P., Kooijman, V., & Hagoort, P. (2005). Anticipating upcoming words in discourse: evidence from ERPs and reading times. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 31*(3), 443.

⁶ Ding, N., Melloni, L., Zhang, H., Tian, X., & Poeppel, D. (2016). Cortical tracking of hierarchical linguistic structures in connected speech. *Nature Neuroscience*, *19*(1), 158–164.

BABIES

As described above, the physical channels through which language is transmitted are not clearly divided into ready-made units for the brain to store. However, babies are able to learn their mother tongue fairly quickly. How are babies able to do this? Babies already start learning the prosodic structure or contour of language when they are in the womb^{7,8}. Very young babies are already able to distinguish phonemes (sounds that can make a difference in meaning, such as the *b* and *c* sounds in bat and cat), and they quickly become sensitive to the sounds used in their own language. While newborn babies can distinguish phonemes from both their mother's language and a foreign language, slightly older infants already lose this ability to some extent⁹, and are able to recognize the phonemes in their mother tongue better than phonemes of a foreign language¹⁰. In this way, the baby's brain perceptually tunes to the language it is trying to learn. In this stream of familiar sounds, babies pick up statistical regularities. Some sounds very frequently occur in combination with other sounds, and in combination with certain people or objects. By recognizing this, babies can divide the speech stream into chunks, which can be mapped to a certain concept (for example, "mama" is mapped to their mother).

The acquisition of the language is not a linear increase: at certain points during development, sudden 'jumps' in acquisition occur. For example, in many children, the amount of words they know increases suddenly around two years of age¹¹. Although children are seemingly able to pick up a language much easier than adults, acquisition does not really end. Adults learn new words, phrases, and even new grammatical structures, for example in second languages, but also in their own. And it's a good thing that we never really stop acquiring language: languages need to be flexible and constantly evolve, so we can continue to describe the world around us and communicate about it. Without continued acquisition, our language would rapidly become out of date.

BYGONE TIMES

The third and largest timescale for language emergence is that of our entire species: when did humans first start using language? How did some simpler *protolanguage* develop into a more complex grammatical system that we would recognize as language today? What did this protolanguage consist of anyway? These questions are definitely hard to answer empirically: since language itself does not fossilize, we mostly rely on indirect archaeological evidence for identifying at what time point it would be reasonable to assume that human language first came into existence. It is generally agreed upon that it must have been sometime after the point that the human lineage split from the lineage of chimpanzees (about 2.3 million years ago), and before the earliest evidence of behavioural modernity such as tool use and cave art (about 50.000 years ago). Obviously, this still leaves open a huge time range for archaeologists and geneticists working out the behavioural and biological correlates of language and, for example, whether any of the other hominid species had them.

Another question is how language came to be - did language emerge in our species all at once or was there some gradual transition from an earlier nonlinguistic form of communication? For this question it's useful to decide what actually distinguishes human languages from other animal communication systems. One element that is thought to be unique about human languages is that we can produce an infinite amount of meanings, and that we do this in a specific way: by first combining discrete but meaningless speech sounds (or hand shapes, for sign languages) in a variety of ways to form different meaningful words, and then by combining those words in another variety of ways to form different sentences meaning different things¹². An important switch or transition is then between a communication system having a set of signals that only have referential function (pointing to something in the direct environment), and a communication system that can productively combine signals to form new meanings. In this respect, it is important to note that the emergence of these kind of systems is all but bygone, despite the title of this section. A classic example of a new language emerging in recent times is that of Nicaraguan Sign Language, which developed when a group of previously isolated deaf children were brought together in a new school for deaf education¹³. The children had no previous model of any spoken, signed or written language before going to school together, but started developing conventions and eventually grammatical rules in their signing, creating their language as they were in-

 ⁷ Nazzi, T., Floccia, C., & Bertoncini, J. (1998). Discrimination of pitch contours by neonates. *Infant Behavior and Development*, 21(4), 779–784.
 ⁸ Mampe, B., Friederici, A. D., Christophe, A., & Wermke, K. (2009). Newborns' Cry Melody Is Shaped by Their Native Language. *Current Biology*, 19(23), 1994–1997.

⁹ Werker, J., & Tees, R. (2002). Cross-language speech perception: Evidence for perceptual reorganization during the first year of life. *Infant Behavior and Development*, 25(1), 121–133.

¹⁰ Kuhl, P. K., Stevens, E., Hayashi, A., Deguchi, T., Kiritani, S. & Iverson, P. (2006). Infants show a facilitation effect for native language phonetic perception between 6 and 12 months. *Developmental Science*, *9*, F13-F21.

¹¹ Goldfield, B. A., & Reznick, J. S. (1990). Early lexical acquisition: Rate, content, and the vocabulary spurt. *Journal of child language*, 17(1), 171-183.

¹² Of course, there are more things thought to distinguish human language from animal communication. Some famous design features of human language are listed by Hockett, C. F. (1959). Animal 'languages' and human language. *Human Biology*, *31*(1), 32-39.

¹³ Senghas, A., & Coppola, M. (2001). Children creating language: How Nicaraguan Sign Language acquired a spatial grammar. *Psychological science*, 12(4), 323-328.

teracting with each other. Many other examples of similar community sign languages exist, and studying the emergence of these systems is probably the most promising way of studying how language first came to be using currently available data.

CONNECTING TIMESCALES

We discussed three levels of language emerging, each applying to different timescales. Firstly, within the individual during language processing, we have seen that it is hard to localize a specific 'language area' in the brain. In fact, it might not really be sensible on the neural level to even make hard distinctions between the processing of meaning and the processing of sentence structure, or even between language production and language understanding. Secondly, still on the individual level but over the time course of development, we saw that babies perceptually tune to the language they are learning in order to start recognizing words and eventually form complex sentences. But we also noted that our language use actually stays flexible and still develops in adulthood, such that it is a hard question what really constitutes the endpoint of language acquisition. Finally, on the species level over the timescale of evolution, we find that there are many open questions that will be hard to answer, but also that the emergence of language within a community can actually still be observed in the present.

So why do human languages work the way they do? One account stresses how languages themselves depend on the community of people using them. Potential elements of a language, which cannot be easily processed in real-time by all members of a community, will have a lower chance of persisting throughout that language. Similarly, grammatical structures that are hard to learn for children will be less likely to be passed on to the next generation. In this perspective, the different levels we discussed above come together: languages themselves will adapt to existing human cognitive biases. Since languages are formed through communicative interaction, and through being repeatedly acquired by new learners, they will become easier to learn and use: humans adopt those words and grammatical structures that were easily learned by the humans before them, and those words and structures form the language¹⁴. To what extent this account can actually explain all the intricate grammatical differences between languages is of course still to be further examined, but it is a nice insight into the complex multilevel interactions behind language emergence.

¹⁴ This account is outlined in Christiansen, M. H., & Chater, N. (2008). Language as shaped by the brain. *Behavioral and brain sciences*, 31(5), 489-509. -- and also further discussed in the book mentioned in footnote 1.



How do physiological responses change when people deliberately choose to view negative stimuli?

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ABSTRACT

Many argue that people are prone to seek out positive experiences and knowledge whilst avoiding negative information. However, there are plenty of examples wherethis does not always hold true. Hence, if a person deliberately approaches negative stimuli will their defensive system engage differently? In the present study, we investigated the notion that approach behaviors towards negative stimuli may impact physiological responding. We hypothesized that approaching negative stimuli would down-regulate startle responses. A previously published paradigm was used which employed fEMG to the orbicularis oculi muscle as a measure of the startle response and consisted of a task which tested participants' morbid curiosity behaviorally while eliciting startle probes to investigate the startle modulation response. Using this task, we were able to observe a clear startle modulation response; however, the effect of choosing to approach negative stimuli had an effect opposite to what we expected. This could be due to systematic errors in the paradigm, a range of confounds or excitation transfer phenomena. It could also be that the effect intended and expected is not there. Nevertheless, the fact that our results were inconclusive leaves the door open for further questions, manipulations, and improvements to better understand the effect of choice and approach towards negative stimuli.

Everyone has experienced jumpscares at some point, whether it is because of a scary movie or a startling sound, the feeling is familiar. It only takes a sudden loud bang for your body to react, your heart races and your palms sweat. This study particularly looked at such bodily responses elicited after a startling sound was presented during deliberate pursuit and exposure to negative stimuli. Many argue that people are prone to seek out positive experiences and knowledge whilst avoiding negative information (see Krypotos et al., 2015; Servatius, 2016). Nevertheless, there are plenty of examples that this does not always hold true. Familiar examples of this incongruence are seen in people's attraction of horror movies and crime shows; rubbernecking (i.e. slowing down in a highway to look at an accident's aftermath) and dark tourism (i.e. visiting sites known due to their negative associations). The incidence of these commonplace behaviors demonstrates the pervasiveness of approach behaviors towards aversive stimuli in life.

Classic theories of emotion tend to emphasize a bivariate approach to emotion with valence and arousal as its dimensions and disregard motivational approach. However, as early as 1963, there were already discussions regarding the idea of a motivational system in terms of eithering or defensive approach (Sokolov, 1963). More recently, there has been a renewed interest in this third dimension to characterize emotions.

Bradley and colleagues (Bradley et al., 2001) are proponents of a motivational approach by which there are two competing systems: an appetitive and an aversive system. These two systems summate for each stimulus encountered and give rise to the motivational intention each emotion has regardingthat stimulus. It is commonly assumed that stimuli that have a negative valence will result in avoidance behaviors and engage a person's defensive system (Phaf et al., 2014). It is an open question what whether the defensive system will engage differently when a person deliberately approaches negative stimuli.

A common way of testing motivational engagement in relation to affective stimuli is through the startle reflex (Bradley et al., 2001). As the name implies, the startle reflex is a response to external sudden stimulation, often presented aurally in the lab. The startle reflex comprises the whole body but is most commonly measured via activity on the orbicularis oculi muscle which surrounds the eye (Jones & Kennedy, 1951; Bradley et al., 2001; Blumenthal, 2005). The physiological activity in this muscle in response to the startle probe has been previously shown to be modulated by the presentation of affective images (Vrana et al., 1988; Lang, Bradley, & Cuthbert, 1990) and therefore serves as a tool for understanding physiological responses towards differently valenced stimuli. This modulation is such that when people hear a short burst of white noise in combination with a negative stimulus (e.g. an image of a weapon) they show a stronger startle reflex than when they to hear a burst of white noise in combination with a neutral or positive stimulus (Vrana et al., 1988). Similarly, it has been shown that a high startle reflex was elicited by highly aversive and arousing content (Bradley et al., 2001).

Using a startle modulation paradigm, we seek to better understand the desire to pursue negative information, also called morbid curiosity (Oosterwijk et al., 2015; Oosterwijk, 2017). In particular, we will study how a deliberate approach of negative information might influence bodily reactions towards the negative stimulus. Morbid curiosity is defined as a curiosity for information involving death, violence or physical harm (Oosterwijk, 2017). This paradoxical state combines the desire to fill an information disparity between what one knows and what one wants to know (Loewenstein, 1994; Golman & Loewenstein, 2015) with a specific intention to expose oneself towards negative stimuli. Differences in response to usually aversive stimuli have been recently documented in the literature and have been related to individual differences. People with higher sensation seeking seem to engage more in approach motivational behaviors when presented with negative stimuli and have dampened fear-potentiated startle and skin conductance responses to stimuli compared to their low sensation seeking counterparts (Lissek & Powers, 2003; Lissek et al., 2005).

The response modulation towards negative stimuli has been interpreted in several ways. There is evidence that physiological markers for arousal change according to the participant's interest in the stimuli presented (Bradley et al., 2001; Lissek et al., 2005). Conversely, Lissek and colleagues have shown that people with high sensation seeking have lower anxious reactivity; namely, people that seek stimuli have dampened arousal responses to them (Lissek & Powers, 2003; Lissek et al., 2005). Altogether, these findings seem to suggest that participants often respond appetitively to negative stimuli and in doing so their physiological responses towards negative stimuli change.

Present Study

The current study sought to investigate the relationship between morbid curiosity and the physiological state of the body. More specifically, we tested whether intentional viewing during negative image presentation will down-regulate a person's startle response as was previously observed by Lissek and colleagues regarding sensation seeking (Lissek & Powers, 2003; Lissek et al., 2005). This study also aimed to observe if there was a difference between high and low morbid curiosity individuals in their internal processing of stimuli as seen in their startle modulation. For this, facial electromyography was used as our primary dependent measure to record and analyze the startle reflex and modulation response (fEMG). Additionally, skin conductance response was also recorded as an exploratory measure to better characterize morbid curiosity's physiological signature.

In order to assess the effects, a previously published paradigm will be used (see Oosterwijk, 2017). In this paradigm, half of the participants were presented with a choice to view a neutral or a negative image under uncertain conditions (voluntary choice condition). The other half of the participants were presented with the exact same trial setup but did not have any choice; their images were selected by the system (computer condition). This distinction allowed us to directly observe the differences between choosing and being assigned a negative image to view. Hence, these two conditions were used as an independent factor which varied between participants. Moreover, curiosity was evoked by presenting participants with a series of choices in which the participant had to indicate whether they wanted to view a negative or a neutrally valenced image. Morbid curiosity was indicated by the number of times the participant chose to view the negative alternative (see further Oosterwijk, 2017). Through this operationalization, a person with a higher morbid curiosity would more often choose to view negative images whereas a person with low morbid curiosity would more often choose to view the neutral images. Based on this definition, this behavioral measure of morbid curiosity was treated as an independent variable in order to assess individual differences in responses to stimuli.

The present paradigm allowed participants to choose which stimuli they wanted to view, however, this posed methodological issues that needed to be addressed. Because morbid curiosity shows strong individual differences (Oosterwijk, 2017), the choice task could result in an unbalanced number of viewed negative and neutral images if the participants were always allowed to view what they chose. Not only would this have hindered our ability for sound statistical comparisons but also would have affected the startle response itself due to habituation. Because the startle reflex is particularly sensitive to habituation (Bradley, Lang, Cuthbert, 1993), we implemented an additional manipulation to ensure that participants all saw an equal number of negative and neutral images. This last manipulation involved the probability that the image presented would be the one selected, either by the system (computer condition) or the participant (voluntary choice condition). More specifically, chance was introduced in the form of an 80:20 probability of showing participants the image that was selected or the one that was not. As an added benefit, uncertain conditions have previously been shown to be the most effective to elicit curiosity towards negative stimuli (Hsee & Ruan, 2016). Thus, uncertainty was an independent variable varied within participants which improved the chances of eliciting morbid curiosity as well as balanced the participants' exposure to negative and neutral images to avoid habituation effects and allow for sound statistical comparisons.

Due to the multiple variables and manipulations used in this study to make sure that people viewed an equal number of neutral and negative images, the design and the analysis used were intricate. We decided to test our research question in three different ways, comparing different relevant conditions. The first analysis examined the general effect of choosing vs. not choosing irrespective of how often people chose negative images. We hypothesized that the startle modulation effect would be stronger in the non-choosing condition (computer) than in the choosing condition (voluntary choice) (H1). The second analysis compared the startle modulation effect between people who often choose negative images (high morbid curiosity) and those who did not (low morbid curiosity). This analysis was performed within the voluntary choice condition since there was not a way to discriminate between high and low morbid curiosity in the computer condition. We hypothesized that the startle modulation effect would be larger among participants with low morbid curiosity as compared to participants with high morbid curiosity (H2). Note, however, that in this analysis, high morbid curiosity individuals viewed negative images that they chose, whereas low morbid curiosity individuals were confronted with negative images that they explicitly did not choose. Thus, in this comparison, the effect may be driven by the fact that people saw a negative stimulus that they explicitly noted that they did not want to see (and not by the fact that people saw a negative stimulus that they explicitly noted that they wanted to see). Because of the aforementioned ambiguity, we performed a final analysis in which we compared startle amplitude between high morbid curiosity individuals and participants in the computer condition. More specifically, we hypothesized that the startle amplitude during negative images in the high chance condition for high morbid curiosity individuals is higher compared to the startle amplitude for negative images in the high chance condition for participants in the computer condition (H3). This analysis provided the most straightforward test of whether choosing negative images per se down-regulates physiological reactions.

METHODS AND MATERIALS

Participants

In total, 110 subjects took part in this experiment. The sample had an average age of 24.63 (SD=8.91; due to missing data these descriptive measures only represent n=93) and was composed of 72.2% women. One participant was excluded due to missing data and another due to recording issues; analyses are performed on the remaining 108 participants. Recruitment took place over two iterations of the study. The first data collection iteration took place in 2013 and included 46 participants. Data from this iteration had not been analyzed before. The second iteration was during 2018 when 64 participants were recruited. In total, there were less participantsin the non-choosing condition (computer, n=48) than in the choosing condition (voluntary choice, n=60). This is due to the first iteration of data collection having an increased number of people in the voluntary choice condition. Furthermore, the unequal group sizes were not corrected because they were useful for our analysis. Our second and third hypotheses call for a median split of the choosing condition and therefore a larger sample size for this condition would retain power for analyses. All participants were recruited via the University of Amsterdam online system and either participated for course credit or financial compensation.

Study Design

This study had a 2 (agency; voluntary choice vs. computer; varied between participants) x 2 (chance; 20-80 vs. 80-20; varied within participants) x 2 (viewed stimulus; negative vs. neutral; varied within participants) mixed design. Agency and chance were manipulated to determine viewed stimulus. Agency was a two-level between-subjects variable and described whether the participants could choose which image they wanted to see (voluntary choice condition) or whether the computer chose the images for them (computer condition). Chance was a two-level within subjects' variable which varied in whether participants had an 80% or a 20% chance to see what they chose (in the voluntary choice condition), or whether participants had an 80% chance or a 20% chance to see the negative option (in the computer condition). This variable was implemented in the design to balance exposure to negative and neutral stimuli, irrespective of the choices people make. Finally, the viewed stimulus is a within-subjects variable that reflects whether participants saw a negative or a neutral image in each trial based on their viewing history, selected choice, and a chance for a given trial. The dependent variables measured are the proportion chosen negative images as well as the physiological response (i.e. skin conductance and facial electromyography) to the startle probe elicited during image viewing.

Procedure

Data were collected at the Universiteit van Amsterdam where participants were recruited and screened. Participants signed up for lab sessions based on a brief description of the experiment and what it entailed. Before their arrival at the lab, participants were assigned to a condition (computer or voluntary choice) and the appropriate programs were loaded onto the computer. Once participants arrived at the lab, they were informed of the task, its instructions, as well as warned about the sensitive content of the stimuli. If they consented to the experiment, participants completed the task during which facial EMG and skin conductance was recorded concurrently with their choice behavior. Finally, they were compensated for their time and participation in the form of research credits or cash before they left.

Task

The experimental task was presented using Presentation® software (Version 18.0, Neurobehavioral Systems, Inc., Berkeley, CA, www.neurobs.com) to participants. Data was recorded using VSR-RP (UvA TOP). Each trial for the experimental task consisted of the following. A fixation cross was presented for 500ms, followed by the written description of a neutral and a negative image on either the left orthe right side of the screen. The written description of the images was shown for 6 seconds after which an image needed to be selected. Next, participants in the voluntary choice condition could choose which image they preferred by pressing on either the left or right arrow key whereas participants in the computer condition were shown a screen saying,"The computer is choosing...". After an image was selected, a pie chart was shown to the participants for 2 seconds depicting the chances of the selected image being presented to them. The probability of viewing the image selected could be 80% or 20%. The probability displayed was based on the participant's individual viewing history up to that point and the selection made for that trial. Hence, we could ensure an equal number of viewings for negative and neutral images for all participants. Based on the choice made for that trial and the probability of a particular image, the participants were shown either a negative or a neutral image for 6 seconds. The image presented would be in a large format and occupy most of the screen. Whilst the stimuli image was displayed, a startle probe was played aurally at 104db for all participants. The startle probe was elicited at a jittered time (3, 4 or 5 seconds) and consisted of a 400Hz white noise burst lasting 500ms. Finally, the trial ended with a 2-second inter-trial interval (see Figure 1). The experimental task consisted of 80 trials where the startle probe was presented and 10 in which it was not. Out of the trials where the startle probe was present, 40 of them resulted in the participant viewing negative images and the other 40 in the participant viewing neutral images. Location of descriptions (left or right side of the screen) for negative and neutral image descriptions would be counterbalanced across trials.

Stimuli

Δ

The study used images of either negative (e.g. 'Man carries a dead baby') or neutral (e.g. 'Man carries a laughing baby') valence. Parts of the negative and neutral stimuli were selected from the International Affective Picture System (IAPS; Lang, Bradley & Cuthbert, 1997) and the Nencki Affective Picture System (NAPS; Marchewka, Zurawski, Jednorog, & Gradowska, 2013) which are commonly used in research in emotion science. In addition, images found on the internet were used to generate a sample of images that are large enough to carry out the relevant research. These images were mainly from news sites and have a similar, socially-negative, or socially neutral content as the images from the IAPS and NAPS dataset. The startle was elicited during stimuli presentation consisted of a 400Hz white noise burst lasting 500ms and presented through headphones at 104db. Based on the previous literature, the response window was determined to be 21-200msec after stimulus onset (Berg & Balaban, 1999; Blumenthal, 2005). Startle responses are often analyzed in terms of percentage-based or standardized potentiation, however, there is evidence that this method is highly affected by artifacts and that standardized potentiation could skew the data (Bradford et al., 2015). Hence, we opted for analyzing the activity from the specified time window in terms of its raw potentiation as has been previously suggested (Bradford et al., 2015). We also determined that the baseline activity with which to compare the startle response measured would be the preceding 50msec to stimulus onset as suggested by van Boxtel (2010).

Pre-processing

All analyses were performed on the facial electromyographic (fEMG) amplitude of the startle response elicited. Raw fEMG traceswere processed before data analysis took place using in-house software (VSRRP). To prevent aliasing, the sampling rate of the recordings was 1000Hz as suggested by Blumenthal and colleagues (2005). Amplification took place first within the in-situ amplifier. Next, the data collected was filtered using a notch filter at 50Hz which minimized noise from powerline and extraneous noise sources. Following filtering, the signal was rectified to avoid positive and negative components of the signal canceling each other out. Rectification involves summing the absolute values of the trace into a single positive waveform. Huang et al. (2005) suggest a full wave rectifier for this process which was implemented on VSRRP.

Outlier and Exclusion Criteria

After pre-processing, data points in which no startle response was present were recoded into zeros. A lack of a startle response was characterized as the minimum detectable response of the equipment used and therefore we heeded to what is suggested by Blumenthal and colleagues (2005) and marked non-response trials with a value of 0. Secondly, values for each participant were normalized to z-scores in order to detect outliers. Each value that dif-



Startle Probe and Identification

Figure 1. Diagram of the task for participants in the voluntary choice condition (A) and in the computer condition (B).

fered more 3 standard deviations from the individual's mean startle response was marked as an empty cell and excluded from further analysis. In a third step, the mean response of each participant was calculated and transformed to z-scores based on the sample mean and standard deviation. Participants were considered outliers and excluded from further analysis if their individual mean response overall deviated more than 3 standard deviations from the entire sample's mean per condition and overall. Finally, as per the suggestion of Blumenthal and colleagues (2005), participants who showed no startle responses in more than two-thirds of the trials were categorized as non-responders and excluded from further analysis (see also Mallan & Lipp, 2007).

Data Analysis & Hypothesis Testing

Three different hypotheses were tested in the present study. The first analysis examined the general effect of choosing vs. not choosing irrespective of how often people chose negative images. We hypothesized that the startle modulation effect will be stronger in the non-choosing condition (computer) than in the choosing condition (voluntary choice) (H1). This hypothesis was tested with a 2x2 mixed ANOVA with independent variables viewed stimuli (within) and condition (between). The second analysis compared the startle modulation effect between people who often chose negative images (high morbid curiosity) and those who did not (low morbid curiosity). This analysis was performed within the voluntary choice condition. We hypothesized that the startle modulation effect would be larger among participants with low morbid curiosity compared to participants with high morbid curiosity (H2). To test this hypothesis, we performed a median split within the voluntary choice condition whereby participants who chose more negative images than the median were classified as having high morbid curiosity whereas those that chose less than the median were classified as having a low morbid curiosity. Then, we conducted a 2x2 mixed ANOVA comparing high and low morbid curiosity individuals' mean peak startle responses across negative and neutral viewed image trials. Finally, we compared startle amplitude between high morbid curiosity individuals and participants in the computer condition. We hypothesized that the startle amplitude during negative images in the high chance condition for high morbid curiosity individuals was higher as compared to the startle amplitude for negative images in the high chance condition for participants in the computer condition (H3). This analysis utilized the median split variable mentioned previously. An independent samples t-test was used to compare the mean startle amplitudes in the appropriate groups. In order to account for unequal groups' sizes, we tested the assumption of homogeneity of variances using Levene's test and corrected accordingly.

RESULTS

Sample

Data were analyzed for a total of 107 participants, due to three participant exclusions. Two participants were excluded due to data collection errors whereas the third was deemed an outlier when compared to all the other participants mean startle responses (|Z-scores|>3). All participants had a measurable startle response in over two-thirds of the trials and therefore no participants were excluded due to non-responsiveness. All data analysis was conducted on SPSS 24 (IBM). The data was checked for assumptions of normality which were violated (W-S Test, p<0.001).

Choice Behaviour

Participants chose the negative image an average of 27.38 times (SD= 22.69) out of 80 trials. It is noteworthy that the range for choosing to view the negative image spanned over almost the entirety of the possible range given by the task. The hypothetical number of times a participant could choose the negative was between and including 0 to 80 whereas the recorded range of choosing negative images across participants (n=60) was between and including 0 to 79.

Statistical Analysis

The first analysis examined the general effect of choosing versus not choosing irrespective of how often people actually chose negative images. It was hypothesized that the startle modulation effect would be stronger in the non-choosing condition (computer, n=47) than in the choosing condition (voluntary choice, n=60) (H1). This hypothesis was tested using a 2x2 mixed ANOVA with independent variables viewed image (within) and condition (between) on the mean startle peak amplitude. Assumption testing was conducted, and it was found that the data met the assumptions of homogeneity of covariance (Box's Test, p=0.541) and of equality of Error Variances (Levene's Test, Negative: p=0.957, Neutral: p=0.977). There was a significant main effect of image viewed (F (1,105) = 14.82, p<0.001, η_{n}^{2} =0.124) in which negative stimuli (M=271.40; SE=23.37) had a larger amplitude than neutral stimuli (M=250.53; SE=22.43). On the other hand, there was no significant main effect of condition (F (1,105) = 0.281, p=0.597, $\eta_{2}^{2} = 0.003$), as observed in mean startle peak amplitude between the computer (M=273.03; SE=34.06) and the voluntary choice condition (M=248.90; SE=30.15). Finally, there was also no interaction between the valence of the stimuli presented and the condition assigned to each participant (F (1,105) =0.468, p=0.495, η²=0.004).

The second analysis compared the startle modulation effect between people who often chose negative images and those who did not. This analysis was performed within the voluntary choice condition only and used a proxy measure of morbid curiosity. Morbid curiosity was operationalized as the number of times participants chose to view negative images. A median split was used to classify participants into high or low morbid curiosity groups based on their choice behavior. Participants who chose the negative option more often were labeled as having a high morbid curiosity (n=30) and those who chose it less often was labeled as having a low morbid curiosity (n=30). We hypothesized that the startle modulation effect would be larger among participants with lower morbid curiosity as compared to participants with higher morbid curiosity (H2). In order to test this hypothesis, a 2x2 mixed ANOVA was conducted with variables viewed image (within) and morbid curiosity level (between).



Figure 2. Mean peak startle amplitude between choosing conditions comparing startles that took place when the participants were viewing negative of neutral images. Error bars show +/-SE.

Assumption testing was conducted before testing and it was found that the data did not meet the assumptions of homogeneity of covariance (Box's Test, p<0.001) nor of equality of error variances (Levene's Test, Negative: p=0.008, Neutral: p=0.004). Regardless, with equal group sizes, an ANOVA is generally robust against homogeneity violations, so it was conducted. After conducting the aforementioned 2x2 mixed ANOVA, it was found that there was a significant main effect of image viewed on mean startle peak response (F(1,58) =5.01, p=0.029, η_n^2 =0.08) in which negative stimuli (M=257.48, SE=30.46) resulted in a larger startle amplitude than neutral stimuli (M=240.32, SE=29.55). On the other hand, there was no significant main effect of morbid curiosity level (F(1,58) =69.94, p=0.195, η_2^2 =0.029). This main effect showed, albeit non-significantly, that participants with a high morbid curiosity (M=287.89, SE=42.09) had a stronger startle response than participants with a low morbid curiosity (M=209.92, SE=42.09). Similarly, the interaction between valence and morbid curiosity was not significant (F(1,58) =0.379, p=0.54, η_n^2 =0.006).

Because of the ambiguity between shown and chosen images, we performed a final analysis in which we tested whether startle amplitude during trials in which negative images were presented was higher for people that chose to view negative images compared to those who were assigned to view negative images. This analysis provides the most straightforward test of whether choosing negative images down-regulates physiological reactions. This analysis draws on the median split mentioned previously which divided participants into high and low morbid curiosity groups. We expected that startle amplitude for negative images would be decreased for people who

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Figure 3. Mean peak startle amplitude between participants in the Low and High morbid curiosity (MC) groups comparing their mean peak startle responses when presented with negative or neutral stimuli. Error bars show +/-SE.

often chose to view and saw said images (n=30) compared to people confronted with negative stimuli outside of their control (n=48). This hypothesis was tested using an independent samples t-test. Assumption testing was conducted beforehand, and it was found that the data did not meet the assumption of equality of error variances (Levene's Test, p<0.001). Therefore, the t-test conducted was corrected and showed a marginally significant effect of choosing to view negative images as opposed to being merely assigned to them (tcorr(30.27) =-1.79, p=0.083). Anecdotally, the means seemed to show that participants who chose to view the negative stimuli (n=30, M=484.15, SE=42.09) had a higher startle response than those that were assigned to negative stimuli (n=48, M=407.99, SE=6.21).

DISCUSSION

All in all, our findings are inconclusive with regards to the hypotheses being tested. In the first test, when comparing between conditions (voluntary choice vs. computer) irrespective of actual choice we found no significant effect of condition on the mean startle amplitude and a significant effect of startle modulation between what images presented. On the second test, we compared high and low morbid curiosity participants and found that they had no significant differences between each other as well as a significant difference in startle modulation. Finally, on the third test, we found a marginally



Assigned Negative Chose Negative Figure 4. Mean peak startle amplitude while viewing negative images between participants who had a high chance of viewing a negative image in the computer condition (Assigned Negative) compared to those with a high morbid curiosity who chose to view negative images and had a high chance of being presented with a negative image (Chose Negative). Error bars show +/-SE.

significant effect of choosing or being assigned to negative stimuli when looking at trials where only the negative stimulus was presented

These findings clearly show an effect of startle modulation which matches the effect described previously by Vrana and colleagues (1988). This is important as it constitutes a manipulation check on the protocol used. By observing this very strong effect of the image presented on the startle modulation, we can see that the program and measures used are capturing a startle modulation effect consistent with previous findings. This, in turn, allows us to focus on the differences elicited by choosing. In this case, the effects of choosing are a lot less clear since they are for the most part (2 out of 3 tests showed no main effects of choosing nor interactions) non-significant.

Even from the non-significant results, we can derive knowledge. From our first analysis we can observe that there is no effect of condition on startle response, hence there is no indication that choosing to view stimuli as opposed to being confronted with stimuli down-regulates the startle response. Moreover, the second analysis indicates that the effect of choosing does not change the startle response significantly when accounting for the individual choice patterns of participants themselves (i.e. High and Low Morbid curiosity participants). Finally, in the third analysis, we can observe that there is a marginally significant effect of choosing to view negative stimuli as opposed to being assigned to them (p=0.08). This effect could prove to be interesting for future directions and warrants a closer look.

The fact that our results are not consistent with the work by Lissek and colleagues (2003 & 2005) is puzzling. We based our hypotheses on the assumption that we would be able to show similar trends to those shown by Lissek and colleagues, based on the assumption that morbid curiosity is related to sensation seeking. One possible explanation for the different findings is that Lissek and colleagues used a self-report questionnaire measured in order to determine sensation seeking scores and levels (Lissek & Powers, 2003; Lissek et al., 2005). Our failure to mimic their findings could also stem from the fact that our measure of morbid curiosity was based on the participant's behavior during the task itself rather than a self-report questionnaire. This would point towards a difference in processing in the spur of the moment as opposed to when filling out the questionnaire. Due to this conflicting information, it is also impossible to determine which of them provides a more accurate portrayal of the information processing of negative information in terms of startle modulation responses. Therefore, studies using behavioral measures of sensation seeking or a questionnaire to quantify morbid curiosity could be useful in comparing these two methodologies and better understand the system at play and where could these differences stem from.

Additionally, we need to consider that our hypotheses were wrong, and that a state of curiosity may very well enhance the startle response. First, the experience of curiosity itself may be an experience with some degree of arousal due to curiosity relief (Van Lieshoutet al., 2018). Second, participants may have experienced a build-up of anticipation or uncertainty regarding the viewing of the negative stimuli that they chose. There is evidence that anticipation and uncertainty are highly arousing states. For example, both uncertainty, empathy and emotional feelings engage the anterior cingulate cortex and the insula, brain regions associated with generating and representing arousal in the body (Singer et al., 2009). Taken together, these two sources of arousal may have spilled over to the time window in which the startle probe was encountered, through a phenomenon called excitation transfer (Zillmann et al., 1972; see also Oosterwijk et al., 2010). Excitation transfer refers to when an increased arousal or excited state from one action or task can be reflected on the subsequent action or task. Hence, it is not far-fetched to think that the excitement created by the choice to view a negative stimulus could have affected the subsequent events, namely, the viewing of the negative image, the startle probe, and the ensuing reflex. This excitation transfer may explain why our results are the opposite of what was expected and why mean peak startle amplitude is highest for participants in the voluntary choice condition who

had a personal stake in choosing and were waiting to see if they got what they wanted.

Finally, it is worth pointing out that confounds could arise from the task that we used. First, tiredness was sometimes mentioned by the participants as they departed. This is understandable as the experiment took approximately an hour and in the case of the computer condition they did not have to engage with the task at all. Additionally, due to the task's coding, stimulus identity could not be accounted for in each trial. This means that it was not possible to determine if there were stimuli that were driving the effects observed or lack thereof. Likewise, without stimuli identity, it was also not possible to organize events chronologically and therefore we were unable to account for any habituation that could have been taken place in the latter parts of the experimental task.

Luckily many of the issues mentioned before can be solved or at least further investigated to varying degrees. To account for excitation, transfer due to uncertainty after their choice, it would be useful to include trials were certainty is taken out of the question. This could be done implemented in the task in the form of 100% chances of viewing a negative or a neutral stimulus per trial, this way a control for anticipation could be included in the task itself and further used for analysis purposes. In terms of fatigue, it is harder to account for it. An option would be to decrease the number of trials in the experiment or to divide it into multiple sessions or blocks. Decreasing the number of trials would decrease power and dividing it up into sessions could increase the attrition rate of participants. An alternative, albeit arguably it could have its own issues, is through a self-report exit questionnaire. This way potential confounds, such as perceived and subjective fatigue, can at least be quantified and consideredin the analysis and interpretation of the data. In order to address the boredom and monotony facing participants particularly those in the computer condition, it might prove useful to include a filler task to keep them engaged with the experimental task. This could be as simple as a basic search task where they would have to press left or right arrow key depending on which side of the screen the object is presented. This would enable the participants in the computer condition to engage with a task that is likely to need minimal cognitive memory resources and use a similar movement pattern than participants in the voluntary choice condition. Finally, it would be interesting to analyze the skin conductance responses obtained as exploratory measures to better assess whether curiosity itself is an arousing state that sharpens people's physiological responses.

There is much to be learned from the questions that arise from this study, even if we were not able to conclusively observe the physiological differences between being deliberate and assigned exposure to negative stimuli. The results obtained were the opposite of what was expected based on previous findings which beg the question as to why. Furthermore, the results could be due to methodological confounds embedded in the paradigm. It may very well be the case that there are no startle response differences present due to choosing and a different measure or method is needed. Nevertheless, all these questions and issues were identified through this experiment which was able to shed light on the complexity of understanding the mental state of curiosity and its physiological consequences.

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Complexity: A Very Short Introduction

Review by Sammy Millard

BOOK REVIEW

he late John H. Holland (February 2nd, 1929 – August 9th, 2015) was a professor of psychology as well as a professor of electrical engineering and computer science at the University of Michigan. Holland was a pioneer of 'genetic algorithms' and the author of several books on complex adaptive systems. The last of his books, Complexity: A Very Short Introduction, was published in 2014 (Oxford University Press) and is reviewed here. The study of complexity is highly important as it can be applied to a variety of settings and subjects. In fact, ideas from different areas within complexity were used for many decades before links between them were discovered and a distinctive field developed.

It is logical for introductory books to begin by defining the subject matter. However, a clear definition of complexity is not that straightforward. Much like life and consciousness, there is no rigorous definition of complexity. Therefore, Holland takes the strategy of introducing the reader to the idea of complexity using well-known examples to illustrate specific features of complex systems, such as diversity and interconnectivity. One major concept Holland introduces is emergence: a phenomenon that occurs when behaviours or properties of a system are more than the sum of the system's parts. For example, neurons in the nervous system can create complex human emotions that cannot be attributed to the simple sum of these neurons. Holland states that emergence is "the primary characteristic that distinguishes complex systems as an important subset of complicated systems" (p.85).

Throughout the remainder of the book, Holland gives an overview of the concepts and terms used within the field using clear and relevant examples. This way, the book provides you with a solid grounding for when you next pick up a paper incorporating ideas from complexity science. In particular, Holland discusses the distinction between complex physical systems, such as predicting the weather, as well as complex adaptive systems, which include rainforest ecosystems, ant colonies, and the economy. After this, the remaining chapters are titled: Agents, networks, degree, and recirculation, Specialization and Diversity, Emergence, and Co-evolution and the formation of niches. Holland ends with a chapter titled: Putting it all together. This is a very important and well thought out section as it ties together what has been discussed by introducing the role of overarching frameworks.

Holland covers a wide array of profound topics in a well-written fashion. However, it still may not be suitable

for someone completely new to the topic. As this book is on the topic of complexity, the fact that it is very short should not fool you into thinking this book is simple. I personally had to read the book twice to gain the level of understanding I desired from the read, and it isn't exactly an easy bedtime read. Luckily a 90 page, 7-inch tall book does not take too long to complete. As a result, I would say this is a somewhat approachable overview. Especially for those interested in dipping their toes into this field via the words of an esteemed expert, this is certainly a worthwhile read.

Despite the oxymoron that is a very short introduction to complexity, Holland achieves his aim of presenting "a general idea of what we know and don't know about complex systems, with an emphasis on how an overarching theory would increase our understanding" (p.90). Additionally, the final "Short Summary" helps to link together the complicated ideas introduced to you throughout the books, and thus appears relatively concise despite being six pages long. Holland fittingly ends by pointing towards the future, stating that the field moves towards a currently undiscovered overarching theory of complexity.





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