

Neural Correlates of Postformal Stages of Reasoning: Biological Determinants of Developmental Stage

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The latest research on developmental stage, according to the Model of Hierarchical Complexity (MHC), shows that there is only 1 domain, that stage develops as $\log_2(\text{age})$ and that the number of neurons of a species can predict the mean stage attained by that species. This can be interpreted as saying that biology controls stage. However, humans attain different stages and the biological mechanism that limits stage is still unknown. Based on these findings, we argue that cognitive neuroscience studies of human intelligence should shift from the general laws that govern development and brain maturation to focusing on interindividual differences across development, so as to complete the picture of human cognition beyond statistical norms. We here propose a study that looks for differences in patterns of the brain activation between subjects performing below and above formal stages. What differentiates this study from others that have been conducted in the field of developmental psychology and cognitive neuroscience is that this will explain for the first time not how, but why, some individuals are hardwired to perform at higher stages than others. We intend to analyze the data across different hierarchical complexity tasks and extract a saturation index (SI) that informs about the processing load of problem solving. Second, we compare the SI across subjects who attained different stages. This knowledge will provide for understanding the biological basis of cognition, for improving the behavioral predictive MHC, and for developing a connectionist model of cognition that emulates development throughout life.

Keywords: developmental stage, postformal stage, stacked neural networks, cognitive neuroscience, neurophysiology

Post-Piagetian theories of development claim for the hierarchical integration of reasoning abilities throughout life. A sequence of ordered stages is usually defined, and the processes that underlie stage transition are debated. All these theories agree that some individuals achieve

highest developmental stages, while others not. The Model of Hierarchical Complexity (MHC) is one of these theories, which formulates that stages are defined by an order of hierarchical complexity (OHC) and demonstrates that the OHC explains 98% of observed behavior (Giri, Commons, & Harrigan, 2014). For this reason, the MHC has a high predictive power when applied to experimental settings. Theoretically, it has also provided for a great degree of understanding of human behavior as its formulations reveal that cognition is primarily a product of a structural property of organisms.

Notwithstanding, the MHC has yet uncovered why some individuals seem to be hardwired differently, leading to differences in stage of performance and, consequently, in behavioral patterns. The work here presented is a proposal for ul-

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mately answering why, not how, some individuals achieve higher developmental stages than others. We propose to look for this answer through the neural correlates underlying stage of performance, namely through power spectra electro cortical activity (sEEG) and neuroimaging correlates (MRI). Hence, this proposal lies in the overlap between developmental psychology and cognitive neuroscience and aims to provide for acknowledgment of the biological basis of higher-order cognition, both at a structural level and at a developmental level. The answer to our question will also further improve the predictive power of the Model of Hierarchical Complexity, as we will ascribe to it longer-term prediction capabilities, and represent an important input for simulating human cognitive development in an artificial intelligence algorithm.

The work is divided into four sections. First, we describe in more detail the axioms of the Model of Hierarchical Complexity and how they apply to predicting behavior; second, we revise some literature findings on the neural correlates of intelligence and cognitive development that support our proposal; third, we briefly present some methodological considerations, specifically in what refers to data analysis; fourth, we discuss how the outputs we plan to extract contribute to improving the prediction capabilities of the MHC and how they fit in the development of an algorithm that simulates human cognitive development. Given the scope of application of the outputs we expect to extract, although this specific study concerns the field of cognitive neuroscience and is defined within the bounds of a neuroscientific study, it is included in a wider line of research concerning computational modeling, developmental psychology, and behavioral prediction, all together harvesting for a stronger theoretical construction.

The Model of Hierarchical Complexity

“Smartness” is defined as the ability to solve problems or tasks, which are measured by an order of hierarchical complexity (Commons & Pekker, 2008). Complexity is here operationalized as the number of concatenation operations a task contains (Commons & Pekker, 2004). Based on these notions, the mathematical Model of Hierarchical Complexity was developed (Commons & Pekker, 2008), yielding a major contribution—the discovery of the order of complexity as the strongest predictor of ob-

servable behavior (Commons, Li, et al., 2014). Following statistical procedures of factor analysis, the MHC shows the existence of 17 discrete and hierarchical orders of complexity throughout an equally spaced ordered sequence (Commons & Jiang, 2014); these orders correspond to stages of development, which serve for characterizing cognitive capacity throughout life.

At each order of complexity (or at each stage), the individual is able to perform the correspondent complexity actions and solve the correspondent complexity tasks. Higher-order task-actions are characterized by the nonarbitrary coordination of lower-order task-actions. The individual becomes capable of organizing and combining immediately lower order actions in a nonarbitrary way, as shown in Figure 1. Nonarbitrariness is the property that imbeds new configurations with meaning.

To the formalization of the progressive growth in hierarchical complexity of mental operations, the MHC relies on the grounding concept of reflective abstraction, proposed by Piaget, which refers to the phenomenon of making “the actions of one developmental level *become* the object of the actions of the subsequent level” (Dawson-Tunik, Commons, Wilson, & Fischer, 2005). However, different from Piagetian perspectives, the MHC presents a conception of intelligence and development that goes beyond formal operations, in that cognitive development is a functional mechanism that pervades throughout life (Commons, Li, et al., 2014; Commons & Pekker, 2008).

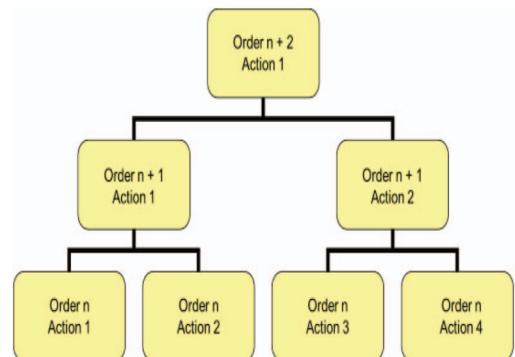


Figure 1. Nonarbitrary coordination of lower-order actions.

This post-Piagetian conception of human development throughout adulthood simultaneously constitutes the major strength and weakness of the model. The major strength because the amount of evidence collected so far models the shared properties of development and inter-individual variability, showing that only some individuals, not all, achieve higher postformal stages (Commons, Li, et al., 2014). The major weakness comes from the fact that the model has not yet explained the reason underlying this interindividual variability: why some individuals attain higher stages than others. The present proposal delineates a method that ultimately answers this remaining question: What limits stage?

Biological Underpinnings of Stage, Skill Acquisition, and Learning

The discovery of the order of complexity as the strongest predictor of behavior across domains (Commons, Li, et al., 2014) turned the MHC into a nonmentalist structure-driven approach. This means that the MHC holds its validity independently of the mental strategies for problem solving. This also means that the existence of a supporting biological structure for cognitive development is under proof.

In fact, the MHC provided recent evidence favoring a biological perspective over stage of development. The first is that stage holds across domains (Commons, Li, et al., 2014; Giri et al., 2014), which suggests a general activation mapping or structure in the brain that supports cognitive performance in all domains, even though concept formation and representation has been consistently shown to activate domain-specific regions (Bauer & Just, 2015). Second, it shows that stage develops as a function of $\log_2(\text{age})$, which suggests that the roots of stage achievements are ontogenic (Commons, Miller, & Giri, 2014). This finding has been supported by cognitive development literature (Wendelken, Ferrer, Whitaker, & Bunge, 2016). Third, there is strong evidence that the number of neurons predicts the mean developmental stage of a species (Harrigan & Commons, 2014). This evidence does not directly provide an argument for stage specific differences in humans, but hints that cognitive capabilities are traced back in the neural architecture across species. Fourth, there is intraspecies evidence of behavioral develop-

ment going together with a dynamic growth of neuronal connections (Qin et al., 2014). Hence, we can trace two valuable premises. One the one hand, a fixed number of neurons is correlated with the mean stage that a species achieves, being it the stage of formal operations in humans (Commons, Li, et al., 2014). On the other hand, the number of connections linking these unit changes throughout development, which points toward a dynamic adjustment of the neural architecture within some fixed anatomical parameters. Taken these evidences together, the MHC suggests that cognitive development is basically dependent upon these structural and functional biological correlates, providing an argument for biology controlling stage.

Several brain-based indicators provide evidence that there is a common ground between brain dynamics and spurts of cognitive development, which follow positive correlations as children grow up. Namely, the number of neurons and synapses, brain mass, myelination, patterns of brain electrical activity, cortical thickness, skull size, all represent a partial brain-based description of cognitive development (Fischer, 2008; Hudspeth & Pribram, 1990). Discontinuities are evident in many of these brain indicators. For instance, Supekar and collaborators (2013) conducted a series of experiments validating the correlation between implicit behavioral measures and development. Namely, gray matter volume and intrinsic connectivity not only can explain, but can further predict performance gains, opposite to explicit behavioral measures, such as neuropsychological assessment scores. These findings built up another sustainable argument for finding stage in the brain and match the brain signatures that have been found across other studies (Cho et al., 2012; McClelland, McNaughton, & O'Reilly, 1995; Qin et al., 2014). The authors (Supekar et al., 2013) further demonstrated that neural correlates capture structural and functional changes as learning and skill acquisition occur, even if in a restricted timeframe of 8 weeks, and even if no stage transition occurs. In general, experiments conducted to date found promising results to the identification of the neural signatures underlying learning, skill acquisition, and development, both with MRI (Cho et al., 2012; McClelland et al., 1995; Qin et al., 2014) and

sEEG data (Fischer, 2008; Hudspeth & Pribram, 1990; Klimesch, 1999).

In regards to MRI data, the majority of studies have been conducted regarding learning and skill acquisition. It has been suggested that skill acquisition in children is a phenomenon accompanied by a shifting from procedural-based strategies to retrieval-based strategies, and that this shifting is mainly associated with the hippocampus-neocortex system (Cho et al., 2012; McClelland et al., 1995). The authors further suggested that this shifting is held across different domains and, thus, that this neural system might be critical for cognitive development in general. A subsequent study was conducted showing that this shift from procedure-based strategies to memory-based ones goes along with a decreased activation in prefrontal regions and increased hippocampal activation. Beyond childhood, retrieval-strategy use continued to improve through adolescence into adulthood and was associated with decreased activation, but more stable interproblem representations in the hippocampus (Qin et al., 2014). A complete review of the role of the hippocampal-prefrontal system in learning and memory is supportive of these results (McClelland et al., 1995).

In regards to sEEG signatures, there is a considerable corpus of knowledge linking brain dynamics and cognitive maturation throughout life (Fischer, 2008). Both tonic and phasic measures of sEEG patterns have been linked to cognitive performance, with the latter being related to performance in problem solving. Relative energy shows systematic growth curves in the occipital-parietal regions, with this growth proceeding through spurts or plateaus, as is observed for cognitive development (Fischer, 2008). Based on these findings, the nested-network hypothesis was proposed, which considers that the emergence of cognitive levels correspond to a large cycle of growth of energy, coherence, and other brain measures. Curiously, increases in alpha energy occur through spurts until adolescence, where individuals are likely to be achieving the stage of formal operations, the mean stage for humans. After adolescence, and mainly between the ages of 60 and 80 years, the pattern reverts, showing a decrease in alpha energy. This has been suggested to be the results of interference of neurological degenerative conditions (Klimesch, 1999). Furthermore, changes in alpha and theta power also show a

positive age-related correlation. Delta and theta bands' power decrease with age, while alpha increases. Interestingly, these changes are also consistent when comparing children without learning disabilities with children with learning disabilities or neurological disorders, pointing toward the relationship between the power bands and cognitive performance (Klimesch, 1999). Taken together these findings, the alpha band has been associated with cognitive performance, mainly speed of processing, memory (Fischer, 2008) and attention (Klimesch, 1999), as well as with general cognitive performance throughout life (Fischer, 2008; Hudspeth & Pribram, 1990; Klimesch, 1999). During problem solving, synchronization and desynchronization of alpha power have been studied. Lower-alpha desynchronization has been systematically assigned to reflect attentional resources during problem solving; upper alpha has been linked to the processing of sensory-semantic information, whereas theta synchronization also appears to be correlated with working memory or episodic memory performance (Klimesch, 1999).

Both MRI and sEEG data provide strong evidence toward a shared developmental path inscribed in the brain. However, the majority of existing studies overlook interindividual differences in cognitive performance. Actually, a closer look to these studies reveals that interindividual differences play an important role. Supekar et al. (2013) showed that although there is a common hippocampal-prefrontal connectivity pattern underlying learning and skill acquisition in several domains, irrespectively of individual differences, performance gains range from 8% to 198%. Moreover, Klimesch (1999) stated that interindividual variability plays as large an effect as that of age-related changes. Besides, within the frequency bands, there is a high variability, too, in how to define subbands. This shows how variable performance gains might be under the same experimental circumstances, which, again, should not be overlooked. Further limitations of existing studies concern the fact that these comprise unsystematic sets of tasks, which results in outcomes contaminated by task-specific variance. In other words, they do not present a sequence of tasks with measured difficulty or processing load. This does not allow to extrapolate the results with confidence to other domains. Still a limitation of existing studies, they restrict their object of analysis to

an early period in life, mainly in neuroimaging studies. This impedes from taking conclusions in regards to the development of higher-order cognition and falls apart of the question we deem to answer: What limits stage?

Hence, we here propose that a different canvas is necessary to uncover the factor that loads on stage variance and that ultimately answers what limits stage. We propose to look at inter-individual differences in development, upon which to observe neural changes. In fact, although development and brain maturation yield significant similarities across subjects, there is also strong evidence of individuals displaying different rates of development (Commons, Li, et al., 2014) and different mosaics of a developmental path (Abellán, Calvo-Llena, & Rabadán, 2015), not to mention the differences that show up in populations with disabilities, neurological disorders, or both. Hence, we propose to conduct a methodology that allows us a comparison between neural activations of subjects who perform at different stages of development. This will allow us to extract not only the shared properties of problem solving in the brain, with problems, solutions, and competence operationalized by an order of complexity, but also to extract the differentiators. Namely, the percent signal activation in regions of interest (fMRI) and power and energy of frequency bands (sEEG). In order to model interindividual variability from these data, we propose to extract what we call the saturation index (SI) for each physiological measure, which represents the processing load along the developmental path of subjects. Ultimately, we expect that the SI of each measure will be correlated and a general SI can be extracted from it. SI is then a within-subjects measure that intends to model the individual dynamics of development. We expect that the potential to achieve a certain developmental stage can be characterized by a specific SI, as if the SI is a dynamic neural signature underlying, or carrying, development. Basically, we consider that the SI will face a faster relative increase for lower stage subjects than for higher-stage subjects, reflecting that an increase in task complexity requires higher cognitive resources for lower-stage subjects than for higher-stage subjects. The SI is, in fact, closely related to the functional meaning of the index of harmony (HI) calculated for assessing and predicting de-

velopmental problems from birth to adolescence in a 10-domain general model of child development (Abellán et al., 2015). Abellán et al. (2015) also considered that the idea of a HI, an individual index of development, is “fundamental to give independence to the comparison of individual development in relation to statistical norms, since it permits each case to be contrasted with itself.” Further on, the SI is the numerical indicator that will allow this study to see continuation in different fields, such as artificial intelligence and behavioral prediction. Hence, we believe that the extraction of an SI as one of the major expected achievements of the present proposal, along with uncovering the regions that are differentially activated in the face of different stages of development, as is shown by some important literature findings.

In one relevant study addressing this issue of interindividual variability (Lee et al., 2006), subjects' IQ was measured as a general cognitive capacity (g-capacity), splitting the sample into two groups—g-superior and g-average subjects. Tasks similar in shape but differing in g-loading were administered to each group of subjects, while their patterns of brain activation were measured through fMRI. A brain signature was found in both groups concerning bilateral activations in lateral prefrontal, anterior cingulate, and posterior parietal cortices. These g-task-related neural substrates were most likely to rely on the frontoparietal network that was previously reported to constitute the neural bases for fluid reasoning and working memory (Lee et al., 2006). A brain signature was also found between groups, with the superior g-group showing much greater percent signal changes of the regions of interest than the average g-group. The most significant gap between groups was in the posterior parietal cortex. These findings are further supported in the literature by a recent result obtained from the Neurodevelopment of Reasoning Ability (NORA) study (see Wendelken et al., 2016). It confirmed the involvement of the frontoparietal network in detecting differential reasoning abilities. The authors found an increased connectivity between the rostro lateral prefrontal cortex and the inferior parietal lobule in the mature reasoning system, in opposition to an immature neural system. The frontoparietal network is also at play when differences are being measured for EEG power spectra. Namely, delta and

theta frequency bands decrease in power with age, while alpha frequency band power increases, with this increase starting at posterior derivations and ending at more anterior recording sites (Klimesch, 1999), which is consistent with recent big data analysis (Taylor, Hobbs, Burroni, & Siegelmann, 2015). Recently, frontoparietal networks have been associated to higher-order cognitive functions majorly because they underlie the representation and management of concepts with the highest levels of abstraction (Taylor et al., 2015).

From the findings reported above, we deduce that the involvement of the hippocampal-prefrontal network occurs when considering longitudinal designs for fMRI data, irrespectively of interindividual differences. This network is involved in a gradual change in problem-solving strategies, from procedural to retrieval based, which occur independently of the rate of learning. However, if the focus shifts to interindividual variability of reasoning abilities and differential learning rates, the regions associated with differential activation are no longer observed in hippocampal activation. These are reported to rely on the frontoparietal network instead (Lee et al., 2006; Wendelken et al., 2016), which is consistent for both fMRI and sEEG data.

Our hypotheses build on these findings. The first four hypotheses stand for characterizing patterns of brain activation across stages and tasks. For MRI data, we expect that different stages will show up in the brain as differential patterns of activation in the frontoparietal network, namely in the prefrontal cortex (PFC) and in the posterior parietal cortex (PPC). We expect a positive correlation between activation in these regions and an increase in the complexity of tasks (H1). We also hypothesize that connectivity between PFC and PPC is positively correlated with stage (H2). We still hypothesize that higher-stage subjects show a decreased activation in the regions of interest when compared to lower-stage subjects, when performing the same task, which order of complexity should be equal or lower than the order of lower-stage subjects (H3). For sEEG data, we hypothesize that tonic alpha power increases and theta decreases with the complexity of the task and that phasic changes also show a higher theta synchronization (H4). The remaining four hypotheses are concerned with modeling the SI.

Fifth, for MRI data, we hypothesize that higher-stage individuals show a slower increase in activation in the regions of interest while solving tasks with increasing order of complexity, than do lower-stage subjects (H5). We also hypothesize that higher-stage subjects show a more pronounced increase in the connectivity between the regions of interest than lower-stage subjects (H6). For sEEG data, we hypothesize that the increase in alpha and the decrease in theta power along increasingly complex tasks is significantly more pronounced in lower-stage subjects than in higher-stage subjects (H7). Finally, we hypothesize that during problem solving, theta synchronization is more pronounced along increasing complexity tasks in lower-than in higher-stage subjects (H8), reflecting a more effortful working memory in the first group.

Goals and Objectives

In sequential order, it is our first objective to confirm existing findings by operationalizing reasoning abilities as the order of complexity that defines stage of development. Our first four hypotheses stand for characterizing mappings of brain activation, both with MRI and sEEG data, which we expect to confirm what has been shown in previous studies. It is our following objective to answer why, not how, some individuals achieve higher developmental stages than others and to look for this answer through the neural correlates underlying stage of performance. We answer this objective through calculating a saturation index that informs the progression of processing load along the problem solving of increasingly complex tasks. This will be done in the remaining four hypotheses of this study. It is still our objective to use the results of this study to improve the behavioral predictive Model of Hierarchical Complexity and to contribute for the development of a connectionist model that attempts to simulate the growth in complexity of reasoning abilities, which will be done within the scope of future work.

Method

Independent and Dependent Variables

We operationalize reasoning abilities by assessing stage of development of participants, as

is determined by the Model of Hierarchical Complexity. The MHC has a high predictive power when applied to behavioral analysis (Giri et al., 2014); it measures the difficulty of tasks to avoid the interference of task variance noise in data analysis; it is in agreement with further mathematical behavioral developmental models that correlate age and stage (Wendelken et al., 2016); and it has recently shown that the majority of intelligence tests fail to detect postformal capacity (Commons, Featherston, Chen, Toth-Gauthier, & Day, 2016). High IQ score probably represents Formal Stage and Systematic Stage 12 performance. The low IQ represents Concrete Stage 9 and Abstract Stage 10 performance. IQ does not measure Metasystematic Stage 13; however, given the existing data on the progression of stage (Commons, Miller, et al., 2014) if an adolescent is performing at the Systematic Stage 12, it is highly likely that the person will move up to Metasystematic Stage 13 (Featherston et al., in press).

For these reasons, we believe that if previous studies found consistent findings given the maturity of reasoning abilities, irrespectively of the operationalization criteria, we will also find these differences, concluding that our methodology is sensitive enough to identify differences in stage. Stage of development will be assessed through instruments developed so far by the Model of Hierarchical Complexity. As dependent variables, we measure MRI and sEEG correlates of task performance.

Experimental Design

This study comprises a cross-sectional experimental design, where the scope of observations will be restricted to abstract, formal and postformal stages of development, namely systematic and metasystematic. For modern humans, the range of stages in intact adults is from Abstract Stage 9 to Postformal Stages 11 and 12. The mean stage of performance has been shown to be the formal operational Stage 10 (Commons, Li, et al., 2014). Stages beyond formal operations (Stage 10), including systematic (Stage 11), metasystematic (Stage 12), paradigmatic (Stage 13), and two other very rare stages, have also been described by the Model of Hierarchical Complexity (Commons, Li, et al., 2014). Hence, according to the MHC, inter-individual variability in attaining higher-order

stages is only pronounced when we move up to formal stages and beyond (Commons, Li, et al., 2014). Subjects will be selected for the study based on their stage of development, irrespectively of educational background. Experimental groups will match in gender and age.

Hypotheses Testing

Data analysis procedure will be based on representation similarity analysis (Kriegeskorte, Mur, & Bandettini, 2008). H1, H2, H3, and H4 are tested to confirm previous findings in what concerns the relationship between the increasing of reasoning abilities and the emergence of differential patterns of brain activation. From this confirmation, we demonstrate that operationalizing reasoning abilities as stage of development does not introduce an uncontrolled bias in posterior data analysis. In the following hypotheses H5, H6, H7, and H8, we attempt to model how mappings of brain activity (representation mappings) progress along the performance in increasingly complex tasks for a specific group of subjects. Afterward, we will compare the representation mappings that show up during problem solving in consecutive complexity tasks, and to that pairwise comparison we will call the differential transition mappings. Representation mappings correspond to each cell on Table 1 and differential transition mappings correspond to the arrows transiting from one cell to the other. Differential transition mappings underlie the functional meaning of the saturation index.

Limitations

Two limitations are attached to this experimental design. First, we cannot know if the subjects who compose each experimental group have already attained their highest stage; we can only be aware that their neural architecture, when compared to matching age subjects, is higher. Given that stage develops as $\log_2(\text{age})$ (Commons, Miller, et al., 2014), we assume that we have a representative sample of the processes underlying stage of development. Still, in order to overcome this limitation, one possibility is to set a lower age limit, also based on the evidence that stage progresses as $\log_2(\text{age})$ (Commons, Miller, et al., 2014); however, this solution is not free from methodological problems, as setting a lower age limit will possibly

Table 1
Representation and Differential Transition Mappings

Task	Group			
	Abstract	Formal	Systematic	Meta-systematic
Concrete				
Abstract				
Formal				
Systematic				
Meta-systematic				

introduce the interference of cognitive degeneration, which might begin occurring at the age of 40 (Klimesch, 1999). The second limitation of this research proposal concerns the fact that we are not evaluating how the neural architecture changes in the face of stage transition, which would be the ideal scenario, but only possible through capturing a once in a lifetime event. As such, we must restrict our observations to evaluate how the neural architecture changes in the face of different complexity tasks and assume that these changes, or adjustments, somehow remain after a new stage has been achieved, similarly to the remaining of a phylogenetic process of evolution and development pervading in the organism.

Innovation, Application, and Future Work

Our research question differentiates this study from others that have been conducted in the field of developmental psychology and cognitive neuroscience. This is a relevant topic of research that has never been addressed. Besides serving the fields of psychology and cognitive neuroscience for obvious reasons, it further serves other branches of application fields. For instance, the field of behavioral assessment and prediction and artificial intelligence. However, before proceeding in future applications, it is worth mentioning that this study requires further empirical data to attest the external validity of the saturation index.

Behavioral Prediction

The Model of Hierarchical Complexity is a behavioral assessment theory of development with a high predictive power ($r = .991$) (Giri et

al., 2014). Mean stage is determined as the logarithmic function of age; hence, younger individuals attaining higher stages than their counterparts are assumed to achieve higher stages in the future. However, there is no clear predictive evidence of this fact nor there is evidence of a biological mechanism controlling it. Because this study is proposed to result in the extraction of the SI—an index that informs about the highest stage to be achieved—we are closer to further improve the predictive capability of the MHC in what concerns later stages of life.

One specific area of application area of application concerns the development of educational and pedagogic practices more adequate to people's general cognitive capacity. If our expected results are ultimately proven, the SI would be a quantitative indicator of differential educational strategies. With a new educational approach set up, we can initiate the reverse research line—whether adequate educational practices actually change the development of the brain along the lines we suggest. Our position is similar to previous research on modeling general properties of development along with individual differences, with the goal of determining how the individual developmental path can be improved and optimized (Abellán et al., 2015). The same principle applies for hierarchical complexity measurements for assessing how and where employees best fit into organizations based on their task performance (Commons & Robinett, 2013). This is important because in many societies in the world, especially among certain sectors, there is a belief that there are no biological differences underlying how smart someone is. People associate differences with

education and motivation. Hence, people who are not hardwired to achieve the highest stages are possibly treated unfairly because the expectations for them are unrealistic. If we find biological differences, it may inform interpretations of behaviors that support a more ethical and fair society.

A second area of application might also concern psychiatry and law. Our results could add a new lens for verifying that observed arrested development of the interpersonal domain has hierarchically complex neural correlates of brain behavior that correspond to observed hierarchical complexity performance. This can inform both psychiatry and law in their respective efforts to adequately approach behavioral deficits and crime to two ends. The first is to improve and correct maladaptive or criminal behavior (Commons & Miller, 2011) by applying the above mentioned renewed educational practices. Once again, appropriate approaches could be informed according to the saturation index calculated for each individual. The second is to predict and prevent future criminal behavior. This would be based on the brain signatures of individuals who carry some neurological limitation and which might be cause, under certain conditions, to suggest a higher probability for social threat. For instance, people with Asperger syndrome are considered the most dangerous people because they show no social perspective taking. The model for predicting crime would be multiplicative, with stage, neurological disorder and social perspective taking interacting together (Commons & Giri, 2016) and all being extracted from the brain. Representation mappings would inform about the relative threat people represent at present as they convey information about current stage of development; the SI would inform about the social threat they might represent in the future, given the stage they are hardwired to achieve.

Computational Cognition—The Hierarchical Stacked Neural Networks Model

The MHC is also the grounding theory for a computational model of cognitive development, called “Hierarchical Stacked Neural Networks.” This is a neural-networks algorithm (computer software) that simulates successive behavioral stages of development of individuals. To allow

a progression in stage (or stack), it adds a degree of complexity to existing neural network models, making it able to meta-learn — that is, to learn about what it is learning. It may reflect on the errors it makes in learning and correct them through downward “reflections,” which reversely accompany the process of “reflexive abstraction.” There is a conceptual isomorphism between the MHC and the algorithm, which stands for ascribing human developmental abilities to Artificial Intelligent systems, not yet seen in the artificial intelligence field (Commons, 2008). In the artificial model, information flows continually from the lower-order stack to the higher-order stack, in the direction of increasing complexity.

The order n outputs of stack s will be fed as inputs to stack $s + 1$, which will generate order $n + 1$ outputs. The space of outputs along the network is an evolving self-organizing one that dynamically gives room for increasingly complex actions. Higher-order outputs are formed by combining and coordinating lower-order ones, in a nonarbitrary way. Each stack consists in a multilayer neural network with a particular structure that makes it generate the hierarchical complex actions of the particular stage it simulates. In the artificial model, each higher-order stack organizes and combines lower-order outputs, in accordance to the inputs it receives (Commons, 2008; Commons & White, 2006/2009).

In a Neural Networks model, the topology (or connectivity pattern between units) partially determines the learning and generalization capabilities, similarly to what happens within the brain. According to our hypothesis, if stages of development are imprinted in the brain and new stages foster the emergence of new patterns, then each new stack will comprise the autonomous emergence of a new pattern, too. Each stack accounts for representation mappings; stack transition accounts for differential transition mappings. Hence, for the complete solution of the algorithm, the three branches of systems neurosciences must be combined—brain activity measurement, behavioral measurement, and computational modeling (Kriegeskorte et al., 2008). The learning mechanism of the model will be partially determined by the SI as a threshold that informs the system if there will be sufficient energy resources to accommodate a higher-order layer of knowledge. Computationally, the SI is most likely to be operation-

alized as a measure of entropy of the system, which is assumed to be proportional to the SI.

Conclusion

The primary goal of this proposed study is to find the biological correlates that explain and limit stage, which has never been addressed before. Existing studies point toward the biological underpinnings of skill acquisition, learning, and development. However, they carry some limitations and lag behind addressing the crucial aspect of individual differences in performance gains and cognitive capacity. Those that address this issue are far from suggesting that biology might actually limit cognitive capacity. This is what we aim to contribute to.

Through MRI and sEEG data, we propose to extract representation and differential transition brain activation mappings, and to further calculate a SI. From this numerical indicator, we expect to have a predictor of the highest stage achieved, as the SI is supposed to inform about the processing load that each increasingly complex task requires. Further work concerns the external validation of the SI in the scope of behavioral prediction, as well as its inclusion in the development of a connectionist algorithm called the Hierarchical Stacked Neural Networks model that aims to ascribe cognitive developmental capabilities to artificial intelligence.

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Received October 23, 2015

Revision received March 14, 2016

Accepted March 14, 2016 ■