On the Neuroscience of Self-Regulation in Children With Disruptive Behavior Problems: Implications for Education

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Self-regulation is increasingly recognized as a key predictor of academic and social competence. A multidisciplinary understanding of this ability is timely and can strengthen theory and practice. The present review aims to inform educators on what cognitive neuroscience can teach us about self-regulation. To do so, we will focus on a decade-long research program examining children with disruptive behavior problems and their peers, and ask whether neural measures of self-regulation can (a) covary with individual differences in behavioral measures of self-regulation, (b) trace developmental patterns, and (c) predict or trace behavioral change with successful treatment of disruptive behavior problems. We show that several studies begin to converge on a set of neural measures derived from the prefrontal cortex that can be consistently linked to processes of self-regulation. Next, we will discuss what these measures mean from a cognitive neuroscience perspective and how this knowledge could influence and/or support psychological models relevant to education.

Keywords: treatment, development, neuroscience, education, self-regulation

Teachers and parents are often challenged by situations in which children act out or become highly frustrated when they do not get their way. Difficulty switching activities, fighting over play/school rules and toy sharing, and constant bickering over what is fair and unfair are examples of situations when a child’s own goals or expectations conflict with the will of others or the reality at hand. These examples are all reflective of issues related to self-regulation. Self-regulation is often defined as an ability to manage thoughts and emotions appropriately and to flexibly adjust internal goals and responses to the changing demands of a situation. In the present article, we will use the term self-regulation in a broad sense, referring to the control of emotion as well as cognition. The terms self-control and self-regulation are used interchangeably. Emotion regulation will be used when the regulation is specific to emotion.
Self-regulation has been a hot topic in the field of education and has been seen as crucial for the development of academic and social competence (Blair & Diamond, 2008; Zimmerman, 2008). Studies have consistently linked an effective self-regulation to better academic performance in students (Graziano, Reavis, Keane, & Calkins, 2007; Gumora & Arsenio, 2002; Nandagopal & Ericsson, 2012; Patrick, 1997) and have even shown that self-regulation was a better predictor of academic success than IQ (Blair & Razza, 2007; Duckworth & Seligman, 2005; Moffitt, Poulton, & Caspi, 2013). Furthermore, a strong self-regulation can form a resiliency against stressors, allow for a better focus on long-term goals, and make students more proficient at cooperating and displaying other socially adaptable behaviors (Eisenberg, Spinrad, & Valiente, 2016; Troy & Mauss, 2011; Williams, 2007).

Emotion regulation is particularly important for developing socioemotional competence. However, difficulties with such regulation can also have negative consequences. For example, when difficulties with emotion regulation are externalized, they can be manifested in aggression and rule-breaking in the school, which takes up administrative resources, distracts students from focusing on their school work, and contributes to teacher burnout and a host of socioemotional difficulties (Allman & Slate, 2011; Loveland, Lounsbury, Welsh, & Buboltz, 2007; Mehta, Cornell, Fan, & Gregory, 2013; Risser, 2013; Tremblay et al., 1992; van Lier et al., 2012). To maintain order, schools in the United States have mostly drawn from behaviorist techniques by coupling negative behavior with punitive consequences (e.g., time-outs, detention) and to reward positive behavior (e.g., token reinforcement strategies; Bear, 1998; Stoughton, 2007). Alternatively, several schools resorted to in- or out-of-school suspensions (see Allman & Slate, 2011; Fabelo et al., 2011, for data on U.S. samples).

Corrective measures employed in schools appear to be effective for most children; however, this is not the case for everyone. A subset of students continue to show a maladaptive profile of aggression and rule-breaking and can be diagnosed with oppositional defiant disorder or conduct disorder. These types of problems are often grouped under the term disruptive behavior problems and constitute half of the referrals to children’s mental health agencies (Patterson, Dishion, & Chamberlain, 1993). Children with disruptive behavior problems are at increased risk for having substantial difficulties with relationships in later life (Burke, Rowe, & Boylan, 2014; Robins, 1966) and dropping out of school (Kokko, Tremblay, Lacourse, Nagin, & Vitaro, 2006; Ledingham & Schwartzman, 1984). Self-regulation, or in this case, emotion regulation, has been seen as a key factor in understanding disruptive behavior disorders (Cappadocia, Desrocher, Pepler, & Schroeder, 2009; Hum & Lewis, 2012; Woltering & Lewis, 2009). Compared to children with internalizing behavior problems, who are seen as overcontrolled, theoretical models have traditionally classified children with disruptive behavior disorders as undercontrolled (Achenbach & Edelbrock, 1978). These models presume that the mental faculties subserving self-regulation are underused and that these children need to exert more effort into controlling their emotions and impulses.

Measuring Self-Regulation

Although everyone agrees researching self-regulation is necessary, figuring out how to measure multifaceted psychological construct such as self-regulation
is challenging. To date, there is no widely used, agreed-on, standardized, and normed measure of self-regulation (see Eisenberg & Spinrad, 2004; Martin & McCellan, 2008, for discussion), and its measurement has typically relied on a variety of questionnaires, cognitive-behavioral tasks, and observational methods.

More recently, neuroscientific methods have provided measures that claim to tap into the basic building blocks of self-regulation (e.g., executive functions; Zelazo & Cunningham, 2007). One of the most powerful arguments for using neural measures is that they increase explanatory power by directly measuring the underlying mechanisms of how we think, feel, and learn. In that sense, neuroscientific measures can provide a unique window into what goes on in our minds when we develop and apply self-control.

It is noteworthy that the field of neuroscience has made great strides bridging the translational gap between neural measures and psychological constructs with an increasing sophistication of theory, measurement, and analytical tools. Those advancements have even led to the emergence of a field called Educational Neuroscience, with the mission to translate the lessons of neuroscience into the theoretical principles of learning (Fischer et al., 2007).

What Is the “Value Added” of Neuroscientific Measurements to Education?

Despite the apparent appeal of a field like educational neuroscience, the direct and systematic application of neural measures to educational practice has been controversial, challenging, and sometimes even frustrating to date (Bruer, 1997; Hruby, 2012; Willingham, 2009). One reason for this, often understandable, frustration is that expectations have often been unrealistically high (Ansari, De Smedt, & Grabner, 2012). Neuroscience has been viewed as a silver-bullet approach that will provide ultimate understanding into the problems that haunt our children, or it is seen as a method directly leading to revolutionary insights relevant to educational instruction or curriculum design. Some may even hold the belief that neural measures will completely replace traditional measures of behavior and performance. Another reason for frustration is that when educational professionals spend effort trying to understand complex neuroscientific findings, the meaning of these measures and the assumptions underlying their methodology are often unclear. Furthermore, neuroscientific findings often present complex mechanistic accounts of specific cognitive processes and may have conclusions that many educators are already familiar with, leading to exclamations of “So what,” “Well, I already knew that,” or “How does this stuff make for better teachers?” Indeed, by analogy, one does not need to be a car mechanic to be a good driver.

Does that mean, however, that neuroscientific findings are irrelevant for education? In keeping with the car analogy, we will argue that having an understanding of what happens “under the hood” can help identify mechanical problems, prevent it from breaking down, and help create the conditions for optimal functioning and durability. We also believe that, in certain situations, neural measures can add unique value over and above traditional measures. However, due to the human brain being infinitely more complex than a car, we will probably need to exert caution in interpreting neural measures over the next couple of decades.
Event-related potentials (ERPs), for example, measure aspects of cognitive processes that occur within a span of several tenths of milliseconds. As such, neural measures can capture elements of cognition that cannot be measured using traditional measures alone. These ERPs can reveal anomalies in distinct phases of information processing that can be linked to, and may have consequences for, behaviors in classroom contexts. Such measures could, when combined with research in real-world settings, aid in the characterization and prevention of disruptive behavior disorders, as well as help with the description of typical and atypical development and in the assessment of treatment outcomes. In sum, realistically speaking, the influence of neuroscience is subtle at first and can, when a large and comprehensive enough body of research has emerged, support but never replace traditional behavioral measures in confirming, adjusting, or perhaps even disproving existing theories or learning principles by providing a mechanistic account.

Goals of the Present Article

The present review has two main objectives. Our first objective is to review research searching for neural indices of self-regulation. Such neural indices, when found, should covary with individual differences of self-regulation and also correlate with behavioral change across development and successful treatment. We will be guided by three research questions: Is there a single set of neural indices of self-regulation that (a) differs between individuals with disruptive behavior problems and those who do not, (b) changes in accordance with the developmental trajectory of self-regulation, and (c) changes with successful treatment that targets self-regulation? Our second objective includes describing whether and how such measures can contribute to our theoretical understanding of disruptive behavior problems and discussing implications for education.

To answer these questions, we will draw heavily from the research program of Dr. Marc Lewis, which investigated neural measures of self-regulation in typical and atypical populations using electroencephalography (EEG). We will focus on the age where formal schooling typically begins—middle childhood and beyond. This also represents a period in development where a child’s self-regulatory capacity copes with increasing social and cognitive demands as well as a growing individual autonomy (Prencipe et al., 2011). Furthermore, for some, it is also seen as a period when behavior problems become increasingly apparent (Kessler et al., 2005; Lahey et al., 2000). Last, for further clarity of terminology, we note that we will focus on a reactive (impulse control, emotion regulation) instead of deliberate (reappraisal, strategic planning) type of regulation due to the nature of the tasks described (Woltering & Lewis, 2009).

Neural Systems Involved in Self-Regulation

To find such neural indices, it is important we first understand neural systems in the brain which are involved with self-regulation. The last few decades have seen several neural models of self-regulation. The anterior cingulate cortex (ACC; see Figure 1), located centrally in the brain on the medial plane of the frontal lobe, features prominently in each of these models and has generally been seen as an important hub in a complex network mediating self-regulation (Bush, Luu, &
Because of its central location, the ACC is well connected in between what are often considered the more cognitive structures, such as the dorsolateral prefrontal cortex, and the more emotional, and phylo- and ontogenetically older regions, such as the amygdala, nucleus accumbens, and hypothalamus (Mills, Goddings, Clasen, Giedd, & Blakemore, 2014). The ACC is therefore ideally situated to coordinate the distribution of mental resources required to regulate bodily, emotional, and cognitive aspects of goal-directed behavior (Chapman, Woltering, Lamm, & Lewis, 2010; Critchley, 2005; Lane et al., 1998; Thayer & Lane, 2000). The ACC is known to be activated in novel situations when habitual responses need to be overridden due to a discrepancy between the current and expected goal state (Botvinick, Braver, Barch, Carter, & Cohen, 2001; Holroyd, Nieuwenhuis, Mars, & Coles, 2004). Since it is rarely accurate to pinpoint one particular function to a single brain region, we will view the ACC as central in a network supporting the flexible regulation of behavior (Lewis, 2005), a flexibility that is often failing in children with disruptive behavior problems who have difficulties regulating situations in which their goals are blocked, or when demands being placed on them exceed their capacity to flexibly respond.

FIGURE 1. Sketch of a semi midsagittal plane of the brain showing the anterior cingulate cortex. For illustrative purposes, limbic structures, such as the amygdala and hippocampus, are protruding and would normally not be visible (drawing by Qinxin Shi).
Method

Search Strategy

The following databases were used in our search: PsycINFO, Pubmed, and Web of Science. Our inclusion criteria (and search keywords) consisted of (a) EEG studies (keyword: EEG), (b) children in late childhood (ages 8–12 years; keyword: child*), (c) children with disruptive behavior problems (keywords: disrupt*, antisocial, conduct, oppositional defiant, and aggress*), and (d) Go/Nogo tasks (keyword: nogo). Studies were excluded if they had children with comorbid attention deficit/hyperactivity disorder or any neurodevelopmental conditions other than internalizing problems (anxiety or depression) as well as studies that did not have an individual-difference (control vs. clinical), developmental, or intervention experimental design. In addition, we searched for publications from the former lab of Dr. Marc Lewis at the University of Toronto and used the ancestry method to identify more papers. Including the Toronto lab papers, this strategy resulted in the examination of 604 sources for eligibility of which 11 sources were included in our review.

EEG Indices of Self-Regulation

EEG-based measures are ideal in capturing the rapid processes involved in cognitive control with children because it can detect changes in neural processing with a millisecond time precision and is safe and relatively quick to apply. The neural indices of processes underlying self-regulation we will discuss here are derived using ERP (e.g., N2 and P3 components), source activation (e.g., estimated ACC activation), and spectral analysis (e.g., theta power). It is important to realize that these methods are not independent and will, to great degree, tap into the same underlying activation patterns that are generated by the brain. Variation in inhibitory N2 and P3 ERP (i.e., averaged bioelectrical waves locked to a stimulus event) amplitudes occurring between 200 and 600 milliseconds is thought to reflect processes underlying self-regulation under a variety of experimental conditions. We will refer readers with no background in ERP to Figure 2 for a brief description of the ERP process during a Go/Nogo task. The inhibitory N2 is believed to reflect processes involved in conflict monitoring, whereas the P3 may be reflective of more evaluative processing (Enriquez-Geppert, Konrad, Pantev, & Huster, 2010; Huster, Enriquez-Geppert, Pantev, & Bruchmann, 2014; Smith, Smith, Provost, & Heathcote, 2010; Van Veen & Carter, 2002). The test–retest reliability of medial frontal negativities related to cognitive control, such as the N2, are estimated to be good across short and long time spans, suggesting they index reliable trait-like measures (Hämmerer, Li, Völkle, Müller, & Lindenberger, 2013; Segalowitz et al., 2010; Weinberg & Hajcak, 2011).

ERPs are measured using a number of electrodes on the scalp, which precludes inferences about where inside the brain the activation is coming from. However, dense array EEG systems (having 128 electrodes or more) allow for what are called source analyses, which can provide rough localization estimates of activation in cortical areas (Michel et al., 2004). Although many brain areas contribute to a single ERP component, the inhibitory N2 and P3 have been consistently source localized to the ACC (Albert, López-Martín, Tapia, Montoya, & Carretié,
FIGURE 2. Simplified schematic demonstrating basic principles of the event-related potential (ERP) process during a Go/Nogo task. In the task, participants need to respond, as fast as they can, to a letter, except when that letter is repeated. Panel A shows an EEG wave (y-axes would be in micro volts) from a target electrode that is being segmented based on the onset of a Go or Nogo stimulus. In Panel B, Go and Nogo segments are being separated based in the Go or Nogo condition after which, as shown in Panel C, all Go and Nogo trials (also called epochs or segments) will be averaged per condition to reveal systematic effects across trials that are time-locked to events (the ERP). Particular peaks and troughs (components) in the ERP have been related to aspects of cognitive processing. For example, the negative (N) going amplitude that occurs roughly around 200 milliseconds is often dubbed the N2 (or N200) component during a Nogo trial and related to cognitive control whereas a positive (P) going components around 100 milliseconds would be labeled P1 and is often related to sensory reactions. Researchers also take the difference in amplitude between the Go and the Nogo conditions as an index of cognitive control.
neuroimaging methods with higher spatial resolution (Crottaz-Herbette & Menon, 2006; Huster, Westerhausen, Pantev, & Konrad, 2010).

Another method of analyzing the EEG signal uses event-related spectral perturbations (oscillatory patterns in the EEG waveform locked to events), which takes advantage of the rhythmic nature of the brain’s electrical potentials. The oscillatory patterns found in the human EEG are not random and changes in frequency–power in particular frequency bands signify communication between and within brain regions. As such, event-related spectral perturbation measures focusing on specific frequency bands can add unique value over and above ERP measures. Particular oscillatory frequencies have been associated with different functions (see Knyazev, 2007, for overview). For example, changes from baseline in theta band power (frequencies = 4–7 Hz) have been of particular interest in explaining complex behaviors, as theta has shown to be involved in the neural integration of information (Buzsáki & Draguhn, 2004). Theta power may reflect the global processing mediated by the ACC that spans large cortico-cortico/limbic regions and could ultimately be mediating our ability to flexibly respond to conflicting situations. As such, many researchers have linked theta activity to processes of self-regulation (Lewis, 2005; Luu, Tucker, Derryberry, Reed, & Poulsen, 2003; Yamanaka & Yamamoto, 2010). Further confirming their role in cognitive control, measures of theta power also share variance with traditional N2 and P3 ERP components in cognitive control situations (Harper, Malone, & Bernat, 2014; Yamanaka & Yamamoto, 2010).

We will next review whether and how this set of related indices derived from the abovementioned techniques can explain individual differences in, trace the developmental trajectory of, and mark successful treatment of self-regulation.

Results

Can Neural Indices Explain Individual Differences in Children With Disruptive Problem Behaviors?

How do the brains of children who have problems with self-regulation work differently from their peers? Woltering, Granic, Lamm, and Lewis (2011) compared school-aged children (8–12 years old) referred by parents, police, or teachers for aggressive and rule-breaking problems with matched peers on N2 and P3 ERP components during a Go/Nogo task. In addition to parent and clinician reports, teacher reports in this sample also confirmed difficulties in the school domain. When these children were compared on N2 and P3 components, group differences were found suggesting the brains of children with disruptive behavior problems were different from their peers during moments of self-regulation. Lamm, Granic, Zelazo, and Lewis (2011) not only replicated these findings by showing larger N2 amplitudes for the disruptive behavior problem group but also conducted a thorough source analysis that confirmed changes in ACC activation. These findings are in line with literature, mostly done in adult offenders, discovering anomalies in these N2 and P3 components (Gao & Raine, 2009; Munro et al., 2007).

An intriguing finding in both studies was that increased activation was found for the disruptive behavior problem group compared to their peers. This was
interpreted as a hypervigilant reaction to inhibiting a prepotent response tendency that, in real conflict situations, could translate into a rigid, threat-oriented behavior. The heightened threat sensitivity also suggested that an underlying anxiety may play a role in the etiology in the externalizing behavior problems of these children. Interestingly, Stieben et al. (2007) found, in a typology study, that the degree of comorbid anxiety in their sample was directly related to N2 magnitudes. Furthermore, behavioral data indicated that the large majority of this sample, although selected for clinical levels of externalizing problem behaviors, also had clinical levels of internalizing problem behaviors. We will discuss the issue of comorbidity more in the Implications section.

We had defined self-regulation as the flexible adjustment of thoughts and actions to obtain internal goals. To demonstrate whether these neural measures related to flexible behaviors in a social context, video observational data were collected from children interacting with their mothers during a conflict paradigm (containing positive and negative discussion topics) and compared to neural indices of self-regulation. The observational data were analyzed using state-space grids (Lamey, Hollenstein, Lewis, & Granic, 2004), which is an analytical technique derived from dynamic systems theory to investigate changes in patterns of dyadic interaction across time (see Granic, Meusel, Lamm, Woltering, & Lewis, 2012). Flexibility can be defined as the dispersion and number of transitions between different emotional states individuals or the dyad may exhibit. Findings showed that reduced flexibility, or increased rigidity, related to higher levels of problem behaviors in these children with disruptive behavior problems.

This result may suggest, for example, that these children are more likely to be entrenched in negative states for longer periods of time. As expected, changes in ACC source activity during the time window of the N2 were related to the degree of flexibility, suggesting that ACC activation mediates the flexible behaviors necessary for self-regulation, which can avoid the rigidity of getting stuck in negative emotional states when situations require adjustment. Figure 3 shows an example of a flexible and rigid interaction pattern within a dyad. Thus, to answer the first research question, we have been able to identify neural indices that vary with the degree of self-regulation. We will next see whether and how those indices will change with development.

**Do Changes in Neural Indices of Self-Regulation Follow a Developmental Trajectory?**

Although no studies have yet traced neural indices of self-regulation throughout broad areas of development in people with disruptive behavior problems, neural indices have been examined in typically developing samples. Findings show a consistent attenuation of the N2 and P3 ERP components with age up to early adolescence (see Figure 4A, for P3; Lamm, Zelazo, & Lewis, 2006; Lewis, Lamm, Segalowitz, Stieben, & Zelazo, 2006; Liu, Woltering, & Lewis, 2014). We note that these neural age effects were specific to the time period of response control, correlated with behavioral indices of self-regulation, and were source-localized to the ACC (Lamm & Lewis, 2010; Liu et al., 2014). Figure 4B, from Liu et al. (2014), represents an area suggestive of the ACC where significant age effects were found with theta power during
cognitive control. Researchers have confirmed that of all cortical structures, the ACC is one of the last cortical regions to mature (Gogtay et al., 2004; Shaw et al., 2008), suggesting that large neural structures underlying self-regulation are still maturing up to young adulthood. Results were interpreted as consistent with the cortical efficiency hypothesis, which states that cortical processing gradually becomes more efficient with age.

We highlight that findings at a neural level, in particular those from Lewis et al. (2006), are remarkably similar to the developmental trajectory of self-regulation reported at a behavioral level. As was shown in Figure 4A, the P3 component shows rapid changes throughout childhood but seem to taper off around the age of 11. This pattern is consistent with behavioral studies of self-regulation, which typically show continued improvement of self-regulation from early to middle childhood but often find that changes are less dramatic, and stabilize by early adolescence (Center on the Developing Child at Harvard University, 2011; M. C. Davidson, Amso, Anderson, & Diamond, 2006; Demetriou, 2000; Harris, 1983; Raffaelli, Crockett, & Shen, 2005). Studies using samples with older subjects suggest that these ERPs follow a gradual attenuation into adulthood, which is also consistent with behavioral accounts (Johnstone, Pleffer, Barry, Clarke, & Smith, 2005; Jonkman, 2006).

Thus, the answer to our question is “yes.” The data reviewed so far suggest that the same neural indices that appear to be sensitive to individual differences in self-regulation seem to trace the developmental pattern of self-regulation. However, we caution readers that more research is required to be conclusive, especially in the form of longitudinal studies across longer periods of time and with children who have disruptive behavior problems. We will next examine whether these neural measures are subject to change after successful treatment.

FIGURE 3. Simplified and hypothetical example of a flexible (left) and rigid (right) dyadic interaction between parent and child using state-space grids (Lamey, Hollenstein, Lewis, & Granic, 2004). Negative, neutral, and positive observed emotions are plotted on the axes for the parent and child.
Do Neural Indices of Self-Regulation Change With Successful Treatment?

To the best of our knowledge, Lewis et al. (2008), Woltering et al. (2011), and Woltering, Liao, Liu, and Granic (2015) are the only three studies to date that investigated changes in the neural correlates of self-regulation with treatment of disruptive behavior problems. Subjects in both studies were children (8–12 years old) who were divided into improvers and nonimprovers after completing the Stop Now and Plan Program (SNAP™). SNAP is an intervention program that combines cognitive behavioral therapy and parent management training and has reliably demonstrated reductions in aggression and conduct problems (Burke & Loeber, 2014). SNAP directly targets self-regulation and uses a broad array of therapeutic techniques, ranging from cognitive restructuring and physiological awareness to impulse control and role-playing, to do so. We note that we did not aim to investigate whether the treatment was effective or not (for which a randomized controlled trial would have been more appropriate) but explicitly focused on the variability between outcomes within a treatment program, that is, why is treatment successful for some but not others.

Lewis et al. (2008) did not find changes in ERP components between subjects with successful or unsuccessful treatment. However, the lack of hypothesized findings may be due to a low sample size (about 13 per treatment group) because Woltering et al. (2011) did find changes in the N2 component (see Figure 5) for...
improvers using a larger sample (about 35 per treatment group) and improved methods (Woltering, Bazargani, & Liu, 2013). Both studies found changes in ACC activation with successful treatment using source analytical techniques, suggesting that the underlying neural correlates of self-regulation changed. A particular strength of these studies was that ERP results were specific to components and time windows involved with response control. Moreover, the degree of neural change with treatment, as indexed by N2 activation, predicted the degree of improvement in self-regulation as measured by questionnaires and performance.

In a follow-up study, Woltering, Liao et al. (2015) investigated whether such changes would still be visible a year after treatment ended by examining theta oscillatory power. As predicted, reductions in theta power were observed for long-term improvers. Interestingly, effects appeared stronger when improvement was determined on the basis of changes in internalizing symptomatology (e.g., anxiety) compared to externalizing symptomatology, further reinforcing the role of anxiety in populations with disruptive behavior problems. The degree of theta change also directly related to the amount of change in internalizing symptoms. Thus, the answer to whether this set of neural indices of self-regulation changed with successful treatment appears to be “yes.”

**Discussion**

Our first goal was to examine whether we could find consistency in neural indices underlying self-regulation (e.g., inhibitory control) across individual difference, developmental, and treatment studies. In our review, we focused primarily on the Nogo N2 and P3 ERP components as well as theta oscillations and source activation linked to ACC activation. We found that these neural measures were
sensitive in distinguishing between individuals with disruptive behavior problems and their typically developing peers. Developmentally, we found evidence that these neural indices show incremental changes from middle childhood to adolescence consistent with their gradually developing self-regulation ability. However, more studies are needed to delineate the trajectory of atypically developing populations. In terms of treatment, studies thus far have shown that these neural correlates of self-regulation change with successful treatment of subjects with emotion regulation problems. We now move on to the second objective, which was determining the implications of this work for theory and practice for education.

**Supporting and Further Specifying the Role of Self-Regulation in Disruptive Behavior Problems**

We confirmed that self-regulation and emotion regulation, in particular, are relevant factors in understanding children with disruptive behavior disorders. Since the hypothesized neural measures are linked to the ACC, we can speculate that functions associated with the ACC will help understand normal and abnormal behavior related to self-regulation. Neuroscientists often consider the ACC and related systems as a discrepancy detector that will continuously monitor and coordinate attempts to bring a current state in line with the expected goal state (Botvinick et al., 2001; Holroyd et al., 2004; Ochsner, Silvers, & Buhle, 2012). This mechanism could form the basis for a flexibility that appears to be important for coping with challenging social interactions and other potential stressors (Diamond & Aspinwall, 2003; Lunkenheimer, Olson, Hollenstein, Sameroff, & Winter, 2011). Abnormalities in this neural system may help explain the rigidity children experience when expectations are violated.

This theoretical framework also has practical implications if we are framing this problem as underlying a cognitive process mediating flexibility. The notion that a number of these children externalize their frustration not because they are not trying, or want to behave as if they lack the cognitive self-regulation tools to flexibly deal with challenging situations, explains the failure of many disciplinary measures currently employed (Allman & Slate, 2011; Fowler, 2011; Skiba, 2014). For example, time-outs and suspensions may be helpful to immediately decrease disrupting emotions in the classroom; however, these measures are not teaching children the socioaffective skills to deal with such situations in the future. In that sense, the disciplinary techniques employed by teachers may not be as effective on the children who are actually the most challenging.

Furthermore, it is important to realize that for children with disruptive behavior problems, aggression and defiance are a means of feeling in control and asserting themselves. Taking that away, without offering a valid alternative, is not likely to yield long-term positive outcomes and could possibly lead to increased feelings of frustration. Solutions directly targeting self-regulation skills align with techniques such as proposed by Ross Greene that help teachers and parents deal with challenging children. The collaborative problem-solving method is built on proactive and collaborative management of problem behaviors and emphasizes mutual understanding, personal agency, and building the self-regulatory competence of the child (Greene, 2001; Greene, Ablon, & Goring, 2003). Note that we are not arguing against the use of well-established behaviorist techniques that rely
on the consistent and systematic coupling of reward and punishment contingencies to overt behavior; however, we would discourage a sole reliance on these techniques for a subset of children.

The Anxiety Model of Disruptive Behavior Problems

We also argue that these results may support a lesser known model of the etiology of disruptive behavior problems. We found increases of neural activation in ERP, source activation, and oscillatory power during time windows of cognitive control to be characteristic of children with behavior problems. This finding suggests that these children are spending too many neural resources trying to regulate their impulses. It may therefore not be the case, as was traditionally thought, that these children are underregulating their emotions; rather, it is possible they are trying too hard and are simply doing so inefficiently. The resulting helplessness these children experience can turn into defiance as a defense mechanism, which is often manifested as oppositional behavior. Children who show a reduction in neural activity after successful treatment may have become more efficient and flexible regulators, and they are able to reduce the tension they bring to social situations. We note that the pattern of neural hypervigilance and overregulation found in many children with disruptive behavior problems is also characteristic of individuals with anxiety (Bishop, 2007; Ressler & Mayberg, 2007). This co-occurrence is not too surprising when we realize comorbidity estimates between severe disruptive behavior problems and anxiety are up to 70% (and this figure likely represents an underestimation; Boylan, Vaillancourt, Boyle, & Szatmari, 2007). The estimates were even higher in the samples described in this article.

A theoretical model, recently put forth by Isabela Granic (2014; see also, Woltering & Lewis, 2013) proposes that anxiety drives and maintains aggression. In this model, anxiety, typically associated with too much inhibitory control, paradoxically leads to aggression. The model explains that an increased threat perception, blocked goals, and a continuous lack of control can lead to an anxious and frustrated state (Dollard, Miller, Doob, Mowrer, & Sears, 1939). This state takes up mental resources, which, when depleted, leads to aggressive outbursts (see Figure 6). The key to this model is a well-known process called “ego depletion,” described by Baumeister, Bratslavsky, Muraven, and Tice (1998), which views self-control as a limited resource, subject to fatigue. At a neural level, prefrontal control systems, such as the ACC, are believed to run out of “brain fuel” (e.g., Gailliot et al., 2007; Heatherton & Wagner, 2011; Inzlicht & Gutsell, 2007), exhausting the ability to self-regulate.

That anxiety or frustration management could be key in understanding child samples of disruptive behavior problems is not a trivial realization and could have extensive practical implications. The anxiety model of aggression we put forward, supported by our neural data, suggests that interventions at schools or clinics should not only focus on the much more noticeable externalizing problems but should also, when appropriate, help reduce and treat comorbid anxiety symptomatology.

Principles derived from social learning theory may be helpful in reducing anxiety. Cognitive modeling techniques allow children to manage unnecessary anxiety through modeling the thought processes from parents, teachers, or more
experienced peers during stressful events. By modeling perspective taking, for example, children who would normally be frustrated when they are not allowed by their teacher to throw a football on the playground may learn that this is not intended to deny them play or as an attack on their self-worth but is instead a larger concern of the football hitting a window and hurting other people. As a result, over time, children can become more flexible in handling challenging social situations by learning to avoid unnecessary conflict and by becoming less impulsive with their initial appraisals of a situation.

Considerations and Future Directions

We wish to make four suggestions that may aid in the proper interpretation of this article as well as lead to future studies. First, we call for developmental studies incorporating neural indices of self-regulation. Although quite a number of studies have examined neural indices of self-regulation between clinical and non-clinical populations, no studies have yet examined a broad developmental trajectory of neural indices in individuals with clinical levels of emotion regulation problems (see Meyer, Weinberg, Klein, & Hajcak, 2012, who call for more longitudinal studies). These types of studies are important as such neural indices could help, in tandem with other social or behavioral measures, identify deviant developmental patterns that could signify “at-risk” populations, such as the life course persistent type identified by Moffitt’s (1993) work. Earlier identification, for example, could lead to intervention programs that could prevent or reduce the adverse effects of poor self-regulation in later life. And even though these effects may be small at first, it is possible they could have downstream effects that may significantly improve individuals’ lives as well as greatly relieve health, judicial, and educational burdens for society (Moffitt et al., 2011).

Second, we also want to emphasize the need for comprehensive and theory-driven models to further validate these neural indices of self-regulation. In the present article, we have largely adopted a pragmatic approach highlighting neural indices that covary with self-regulatory ability across individuals, development,
and treatment. Although these indices are grounded in neural models of self-regulation, most of the research remains correlational, and we have much to learn about the underlying processes that generate them, including what exactly the direction of ERP effects could mean and how these may differ between studies and the different types of neural measures. Another area in need of comprehensive investigation is the specificity of the described neural measures. The present review focused on disruptive behaviors. However, it is possible and likely that the current neural model may be applicable to other psychopathologies, such as anxiety and depression.

Third, we want to stress the need for independent verification and replication in the studies described using these neural measures. Cognitive neuroscience is a relatively young field, and this type of research, particularly with disruptive behavior problem populations, is rare and hard to conduct. Currently, only a handful of studies have investigated the underlying plasticity of neural indices of self-regulation in clinical patients entering treatment, and most studies have come from one lab (e.g., Lewis et al., 2008; Woltering et al., 2011; Woltering, Liao et al., 2015). Ensuring robustness and reliability is crucial before considering applications. Treatment studies, though challenging to conduct, are particularly important because they have a strong potential to lead to applications. For example, neural indices could be used, in tandem with behavioral and social indices to better assess treatment efficacy, or they could help identify predictors of treatment outcome allowing clinicians to better tailor treatment to individual needs.

Last, we do caution against direct and hasty applications in the field of education or mental health. It is tempting to imagine direct applications in diagnosis as biometric risk factors, or treatment assessment; however, more research is needed to do this responsibly. Neuroscientific tools, however sophisticated they may seem, capture only a fraction of the totality of processes that underlie a mental phenomenon such as self-regulation (Logothetis, 2008; Luck, 2014). Furthermore, generalization of neuroscientific findings to applications is indirect or speculative, as optimal measurement conditions often require laboratory settings and experiments that test one specific cognitive function. And even then, translating neuronal activation patterns into propensities for, or manifestations of, actual behavior is challenging as it requires a bridging of multiple levels of analysis (Ansari & Coch, 2006). For a pragmatic approach to real-world application, we recommend a benchmarking approach where neuroscientists work closely with educators and determine the additional value of neural indices in educational contexts (see Ansari, Coch, & De Smedt, 2011; Fischer, Goswami, & Geake, 2010, for a more detailed discussion of this idea).

Finally, we wish to emphasize not losing sight of the idea that self-regulation develops through interactions with others in a dynamic and complex social environment (Bandura, 2008; Trevarthen, Aitken, Van de Kerckhove, Delafielfield-Butt, & Nagy, 2006). This claim also implies that the onus for the development of a strong self-regulation does not lie with the child alone but also with the social engagement of the child’s teachers, parents, and the community at large. There is a real danger in overfocusing on findings from neuroscience (or even standard neuropsychological test batteries) that appear to explain away challenging child characteristics using processes within the child’s biology or psychology.
The variance that neural measures of self-regulation display, as described in this article, can be best seen as a direct product of the interaction between a child’s biology and the very same intersubject social experiences that shaped the child’s self-regulation.

One important practical challenge for the field of affective neuroscience in decades to come is to directly assess neural and physiological responses to social interactions and throughout development through technological advancements and increasingly ecologically valid experimental designs (Schilbach et al., 2013; Woltering, Lishak, Elliott, Ferraro, & Granic, 2015). We currently see the use of these biometric tools as secondary and supportive to traditional measures.

Conclusion

In conclusion, our review highlights the emergence of a set of EEG indices that relate to individual differences in and developmental trajectories and treatment outcomes of self-regulation. Although research on these measures is still in its infancy, findings have the potential to have implications for better identification, prevention, and treatment or optimization related to self-regulation in schools that could lead to better learning and special education outcomes. We hope this review will lead to novel hypotheses generation and critical discussion, which could enhance our conceptualization and understanding of self-regulation and the etiology of disruptive behavior disorders.

Notes

1As indicated by standard scores in the Child Behavior Checklist (Achenbach, 1991) that was filled out by teachers—data not previously reported.
2Although this model has recently come under fire using a large-scale, and also controversial, replication effort (Baumeister & Vohs, 2016; Hagger et al., 2015), we note this effort focused on short-term cognitive aspects of self-regulation and not on long-term processes, akin to cognitive fatigue, relevant to emotion regulation.

References

References marked with an asterisk indicate studies included in the meta-analysis.


Neuroscience of Self-Regulation


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