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Advances in the Use of Neuroscience Methods in Research on Learning and Instruction

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Abstract

Cognitive neuroscience offers a series of tools and methodologies that allow researchers in the field of learning and instruction to complement and extend the knowledge they have accumulated through decades of behavioral research. The appropriateness of these methods depends on the research question at hand. Cognitive neuroscience methods allow researchers to investigate specific cognitive processes in a very detailed way, a goal in some but not all fields of the learning sciences. This value added will be illustrated in three ways, with examples in field of mathematics learning. Firstly, cognitive neuroscience methods allow one to understand learning at the biological level. Secondly, these methods can help to measure processes that are difficult to access by means of behavioral techniques. Finally, and more indirectly, neuroimaging data can be used as an input for research on learning and instruction. This paper concludes with highlighting the challenges of applying neuroscience methods to research on learning and instruction.

Frontline: Cognitive neuroscience offers a series of tools and methodologies that allow researchers in the field of learning and instruction to complement and extend the knowledge they have accumulated through decades of behavioral research. The appropriateness of these methods depends on the research question at hand.

Keywords: Cognitive Neuroscience; Methods; Mathematics Learning; Educational Neuroscience

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1. Introduction

Non-invasive brain imaging methods, such as Event-Related Potentials (ERP) or functional Magnetic Resonance Imaging (fRMI), represent a series of tools and methodologies that allow researchers in the field of learning and instruction to complement and extend the knowledge they have already accumulated through decades of behavioral research (e.g., Cacioppo, Berntson, & Nusbaum, 2008; De Smedt, Ansari, et al., 2011). The potential application of these methods depends on the research question at hand. After a brief discussion of relevant brain imaging methods, I will use the field of mathematics learning to illustrate three ways in which these methods can be used in research on learning and instruction. This paper concludes with highlighting some challenges of applying such methods to research on learning and instruction.

2. Neuroscience methods

When considering different methods that are used by neuroscientists to study the structure and function of the brain, it is important to point out that neuroscience is a very broad field that includes a variety of disciplines ranging from cellular and molecular neuroscience to cognitive neuroscience (e.g., Squire et al., 2013). I restrict the focus here to cognitive neuroscience and its methods (Ward, 2006), because this sub-field of neuroscience is the closest to research on learning and instruction, given its focus on the neural mechanisms that underlie human cognition and behavior. A detailed description of these cognitive neuroscience methods is beyond the scope of this contribution and excellent introductions are provided by Ward (2006) and Dick, Lloyd-Fox, Blasi, Elwell, & Mills (2014). Sometimes, psychophysiological measures, such as skin conductance, heart rate or eye-movement data, are also denoted as neuroscience methods. Although these methods tap into the nervous system, they are not direct measures of brain structure or function and therefore they are not considered here.

The transmission of information in the brain from one cell to the other occurs through electrical signals, and this electrical activity of the brain can be captured by methods such as electroencephalography (EEG), which requires a cap of electrodes to be mounted on the head of a participant, and magnetoencephalography (MEG) (Ward, 2006). On one hand, the advantage of these methods is that they can measure the activity of the brain in response to a particular stimulus (i.e. event-related activity) at a very accurate temporal scale and they are particularly suited to investigate when a process is taking place. On the other hand, a large number of stimuli of a particular type (typically a few dozens) are needed in order to reliably estimate the brain signal in response to that stimulus.

Another series of methods are magnetic resonance imaging (MRI) techniques, which use large magnetic fields and the magnetic properties of hydrogen atoms in brain tissue or in blood to visualize brain structure and brain function, respectively (Ward, 2006). These data are acquired in a specific and very noisy environment, the MRI scanner, in which participants have to lie still and are not allowed to move more than a few millimeters. This category of methods can investigate the structure of the brain, i.e. the gray or white matter, and how this structure is related to performance or changes as a result of learning. Interesting examples are provided by Supekar et al. (2013), who showed that the size of the hippocampus predicted the performance gains in response to one-on-one math tutoring and by Keller and Just (2009), who showed that intensive remedial reading instruction resulted in changes in white matter in poor readers.

MRI also allows us to investigate brain function, a technique that is called functional MRI or fMRI, which is one of the most common techniques used in cognitive neuroscience (Ward, 2006). Functional MRI is an indirect way of assessing the brain's activity and measures the level of oxygen in the blood. The assumption is that an increase in oxygen level is the result of the vascular system's response to an increase in brain activity. MRI methods are very accurate on a spatial scale and are particularly suited to investigate where in the brain a particular process is taking place. Due to the practical constraints of the MRI-environment (e.g., noise, no movement) the type of tasks that participants can complete is limited, yet progress is being made over the last years to use more complex tasks, such as playing video games (Anderson et al., 2011) and even face-to-face interaction (e.g., Redcay et al., 2010).

It is crucial to point out that the measures reviewed above, i.e. signals indicating brain structure or function, can only be meaningfully interpreted by linking them to cognitive theories (e.g., Cacioppo et al., 2008; De Smedt, Ansari, et al., 2011). Furthermore, the collection of behavioral data represents a necessary step in most studies in cognitive neuroscience (e.g., Ward, 2006). In all, a detailed cognitive theory of the phenomenon under investigation is crucial to design and interpret cognitive neuroscience data and to apply cognitive neuroscience methods to the field of learning and instruction.

3. Application to research on learning and instruction

How can the cognitive neuroscience methods reviewed above advance the field of learning and instruction? This depends on the research question at hand, and only some but certainly not all types of research questions in the field of learning and instruction might benefit from the use of cognitive neuroscience methods. Stern and Schneider (2010) provided a nice analogy for determining when these cognitive neuroscience tools and theories could be appropriate. They compared this issue with the use of a digital road map. When using a digital road map for looking at the field learning and instruction, the appropriate resolution of the map depends on what the map viewer is looking for, alleys (micro-level) vs. highways (macro-level), and users can zoom in and out between different levels of resolution. Some questions only focus at the broader context of learning (macro-level), as is the case in large-scale research on educational systems, and are at a low level of resolution. Others aim to unravel the very specific cognitive processes that underlie learning, and this requires a map at very high resolution (micro-level). It is at this micro-level of understanding of such specific cognitive processes that cognitive neuroscience methods can be applied in the field of learning and instruction. I will use the field of mathematics learning to illustrate three ways in which cognitive neuroscience methods can be useful for research in learning and instruction (see also De Smedt et al., 2010; De Smedt, Ansari, et al. 2011; De Smedt & Grabner, 2015).

3.1 Understanding learning at the biological level

Neuroimaging data allow us to examine at the biological level how people learn. Such data can provide converging evidence for findings that have been obtained through psychological and educational research. This convergence of findings from different research methodologies has the potential to provide a better and more complete understanding how typical and atypical learning takes place (e.g., De Smedt, Ansari, et al., 2011; Lieberman, Schreiber, & Ochsner, 2003). For example, how do people acquire and apply different strategies to solve elementary arithmetic problems, such as 5 + 9 or 4 × 3? Decades of behavioral research have revealed that these problems are either solved by using fact retrieval from declarative memory or by using procedural strategies, such as counting, and developmental data indicate that children develop an increasing reliance on arithmetic fact retrieval, while the use of procedures to solve such elementary problems decreases over time (e.g., Siegler, 1996). Research in cognitive neuroscience is now beginning to understand on how this learning of arithmetic is reflected at the neural level (e.g., Arsiladou & Taylor, 2011; Zamarian, Ischebeck, & Delazer, 2009).

In a series of studies, we have tried to investigate this issue with EEG (De Smedt, Grabner, & Studer, 2009; Grabner & De Smedt, 2011; Grabner & De Smedt, 2012). In these studies, adults had to solve a series of addition, subtraction and multiplication problems, while their brain activity was recorded with EEG, and they had to verbally report on a trial-by-trial basis on the strategies they used to solve the presented problems. These studies had two aims. First, we wanted to verify whether these two types of strategies were reflected in different brain activity patterns and whether fact retrieval training resulted in changes in brain activity that reflected a shift in strategy use. Second, we aimed to test if cognitive neuroscience methods, such as EEG, can be used as a way of methodological triangulation to further validate the use of verbal report data. These data are typically used in behavioral research to investigate strategy use but their validity has been debated (e.g., Kirk & Ashcraft, 2001).

The EEG data revealed different patterns of activity for the two types of strategies: oscillations in the theta band (3–6 Hz) were associated with fact retrieval whereas oscillations in the lower alpha band (8–10 Hz) were related to procedural strategies (Grabner & De Smedt, 2011). When we trained participants in using fact retrieval strategies, we were also able to show that the well-known behavioral shift from procedural strategies to fact retrieval as a function of training was also reflected in specific changes in brain activity, i.e. training-related activity increases in the theta band and decreases in the lower alpha band (Grabner & De Smedt, 2012). Combining verbal strategy reports with reaction times on specific problem types and neuroimaging data allowed us to further examine the validity of these verbal reports. This type of methodological triangulation confirmed that verbal strategy reports are a valid way to capture strategies in mental arithmetic. In all, this convergence of findings obtained by different research methods at behavioral and biological levels provides a more solid empirical ground for our theories on strategy development.

3.2 Measuring difficult-to-access processes

Neuroimaging data can provide a level of analysis and measurement that cannot be accessed by behavioral data alone. Examples of this application can be observed in the study of individual differences between learners and in understanding the origins of atypical development. De Smedt, Holloway, & Ansari (2011) used fMRI to investigate brain activity in 10-12-year-old children during addition and subtraction and compared children with low and average levels of arithmetical competence, who significantly differed in their performance on a standardized arithmetic fluency test. Although both groups of children did not differ in a simple calculation task at the behavioral level (i.e. accuracy, speed) during the acquisition of the fMRI data, the authors observed significant group differences in brain activity in the right intraparietal sulcus, a brain region that is known to play a key role in the processing of numerical magnitudes: Children with low levels of arithmetical competence showed higher activation in this region during the solutions of problems with a relatively small problem size. The interpretation of these data in the context of neurocognitive theories of numerical magnitude processing and arithmetic development (e.g., Ansari, 2008; Butterworth, Varma, & Laurillard 2011) suggests the use compensatory strategies and generates predictions that should be further exploited in subsequent research. For example, it might be that the children with low arithmetical competence in the study of De Smedt, Holloway, et al. (2011) continued to rely to a greater extent on quantity-based strategies (such as counting or procedural calculation) on those problems that children with relatively higher arithmetical competence already retrieved from their memory, a possibility that should be evaluated in subsequent research. In all, this indicates that brain imaging data can uncover subtle processing differences between groups of learners that may not be detected through the measurement of behavioral data alone, illustrating the high resolution level which cognitive neuroscience methods are able to capture.

3.3 Input for research on learning and instruction

Studies in cognitive neuroscience can also have an indirect impact on research in learning and instruction, by drawing our attention to specific fine-grained cognitive processes that are implicated in different types of learning (see Aue, Lavelle, & Cacioppo, 2009 for a similar rationale in the field of psychology). Such data have the potential to generate new hypotheses that can be tested in research on learning and instruction.

For example, neuroimaging studies on how the brain processes numbers have revealed that the intraparietal sulci (IPS) are consistently active whenever we have to perform numerical and arithmetical tasks and that this structure supports the processing of numerical magnitudes (e.g., Ansari, 2008; Dehaene, Piazza, Pinel, & Cohen, 2003). Brain imaging studies in children with developmental dyscalculia, a learning disorder that is characterized by severe and persistent difficulties in acquiring mathematical competencies, point to structural and functional abnormalities in the IPS in these children (e.g., Butterworth et al., 2011; Price & Ansari, 2013 for a review). This all suggests that the processing of numerical magnitudes is potentially a key to successful mathematical development and this processing might be compromised in developmental dyscalculia (DD). This suggestion has fueled a large number of psychological and educational studies that have empirically confirmed this hypothesis at the behavioral level (see De Smedt, Noël, Gilmore, & Ansari, for a review), by consistently showing that individuals with DD have significant impairments in their ability to compare (symbolic) numbers. More broadly, these studies have also furthered our understanding of individual differences in typical mathematical development, as the ability to compare (symbolic) numbers is predictive of subsequent mathematical development (see De Smedt et al., 2013, for a review). This research has impacted on studies in the field of learning and instruction, through the development and evaluation of specific interventions (e.g., De Smedt et al., 2013) and diagnostic instruments that can be used for the screening and early identification of at-risk children (Nosworthy, Bugden, Archibald, Evans, & Ansari, 2013). It is important to point out that even if these studies do not collect measures of brain activity or structure, they rely to some extent on insights gleaned from cognitive neuroscience studies. Used in this way, cognitive neuroscience data might set the stage for new educational research and it can, albeit indirectly, enhance our understanding of learning.

4. Challenges

The application of cognitive neuroscience methods to research on learning and instruction also imposes some challenges and caveats that one needs to be aware of (see also Ansari, De Smedt, &

Grabner, 2012; De Smedt & Grabner, 2015), which are not specific to the domain of mathematics learning. These challenges deal with the issue of external validity or generalizability as well as the scope of biological data and explanations (e.g., Beck, 2010).

It is important to point out that most of the existing studies in cognitive neuroscience involved adult participants and that these methods are not so easy to apply in children. This is because the acquisition of neuroimaging data is very sensitive to movement and motion artefacts in children often negatively impact on data acquisition. Progress is being made in the reduction of such artefacts, for example by training children to keep still when such data are being collected (de Bie et al., 2010). At a more theoretical level, cognitive neuroscience findings obtained in adult participants cannot be readily generalized to the developing brain and the learning of children and adolescents, as the human brain undergoes massive structural and functional changes throughout childhood and adolescence (Ansari, 2010).

The tasks used in most cognitive neuroscience studies are very elementary and differ from the rich and complex tasks that are typically solved in everyday learning environments and that are used in research learning and instruction. Such complex tasks cannot be easily administered in cognitive neuroscience studies for various reasons. As indicated above, there are practical constraints related to the laboratory environment in which neuroimaging data are being collected. In order to obtain reliable data on brain activity during a particular task, a large number of trials of the same task need to be presented. These tasks need to be very elementary, because the larger the number of cognitive processes in a particular task, the more difficult it will be to disentangle these cognitive processes physiologically. One way to resolve this is to correlate data acquired in very constrained laboratory settings to ecologically valid measures of learning (see Price, Mazzocco, & Ansari (2013), for an example).

One important caveat deals with the scope of a neuroscientific data and explanations. There might be an inappropriate belief that neuroscientific data are more convincing, informative and valid than behavioral data (Beck, 2010). On the contrary, knowledge gained through cognitive neuroscience methods should be considered at the same level of data obtained by standard behavioral methods in learning and instruction. There should be no knowledge hierarchy, but an appreciation of multiple sources of data to better understand how learning takes place and how it can be fostered (De Smedt, Ansari, et al., 2011).

5. Conclusion

The application of neuroscience methods to research on learning and instruction depends on the level of the research question. When interested in very specific low-level processes, neuroimaging data have the potential to help understanding learning at the biological level, to measure processes that are difficult to access via behavioral data and to generate and test hypotheses for educational phenomena that can be subsequently investigated via behavioral research on learning and instruction.

Keypoints

- The application of neuroscience methods to research on learning and instruction depends on the level of the research question.

- Cognitive neuroscience methods allow researchers to investigate specific cognitive processes in a very detailed way, a goal in some but not all fields of the learning sciences
- Neuroimaging data have the potential to understand learning at the biological level, to measure process that are difficult to access via behavioral data and to generate hypotheses for subsequent research on learning and instruction.

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