Educational Neuroscience: Defining a New Discipline for the Study of Mental Representations

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ABSTRACT—Is educational neuroscience a "bridge too far"? Here, we argue against this negative assessment. We suggest that one major reason for skepticism within the educational community has been the inadequate definition of the potential role and use of neuroscience research in education. Here, we offer a provisional definition for the emerging discipline of educational neuroscience as the study of the development of mental representations. We define mental representations in terms of neural activity in the brain. We argue that there is a fundamental difference between doing educational neuroscience and using neuroscience research results to inform education. While current neuroscience research results do not translate into direct classroom applications, educational neuroscience can expand our knowledge about learning, for example, by tracking the normative development of mental representations. We illustrate this briefly via mathematical educational neuroscience. Current capabilities and limitations of neuroscience research methods are also considered.

DEFINITION AND ROLE OF AN EMERGING DISCIPLINE

Does neuroscience have the potential to expand our knowledge about education, learning, and pedagogy? Typically, there are two extreme viewpoints. Some commentators are confident that neuroscience is going to reform the discipline of education (Geake, 2005; Geake & Cooper, 2003). Others are deeply skeptical and feel that neuroscience has no value for education at all (Davis, 2004). Here, we argue that a major reason for this rift is the inadequate definition of the potential role and use of neuroscience research in education. An important aspect of education is the systematic shaping of the cognitive system of the child. The developing cognitive system depends in part on the structure and function of the brain ("neuroconstructivism"; e.g., Mareschal et al., 2007; Westermann et al., 2007). Accordingly, education involves the shaping of individual brains via targeted experience in the classroom ("teaching"). Recent neuroscience research has made a huge advance toward the understanding of brain function and its development.

Here, we provisionally define educational neuroscience as the combination of cognitive neuroscience and behavioral methods to investigate the development of mental representations. By mental representation, we mean the activity of neural networks of the brain which code information in the form of electrochemical activity. Traditionally, cognitive psychology defined and investigated representations at a higher level of description (e.g., Marr, 1982) and treated them as if they were symbolic in nature. Human cognitive behavior can be analyzed very successfully using an assumption of symbolic representations (e.g., Piaget, 1962). However, it is now clear that all mental activity relies on brain function. Further, considering the activity of neural networks of the brain can constrain and guide models of cognition, resulting in a better understanding of these higher levels of description (this is discussed in detail later; e.g., Szűcs, Soltész, Jármi, & Csépe, 2007; Temple & Posner, 1998). Therefore, educational neuroscience needs to consider mental and biological phenomena in a common framework. In fact, the most important aspect of cognitive neuroscience is that it interprets high-level descriptions of

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the mind (such as psychological theories and symbolic representations) and lower level data (about the activation of neural networks in the brain) and low-level theories (e.g., about neuronal function) within a common framework. A similar integrative framework is required to enable educational neuroscience to move toward its ultimate goal: understanding how brain function gives rise to mental function.

A crucial insight concerning mental representations is that no complex representation can be localized in a single part of the brain. Complex phenomena are coded by the interplay of various interconnected neural networks. For example, the mental representation of number relies on several different codes. Examples include (among others) networks that code nonnumerical magnitude, primarily in the parietal cortex, and networks that store memorized arithmetic facts, primarily in the angular gyrus and language-processing areas of the brain. These mental representations enable the cognitive understanding of symbolic number and the manipulation of numerical symbols (Ashcraft & Stazyk, 1982; Dehaene, 1997; Dehaene & Cohen, 1995; Dehaene, Spelke, Pinel, Stanescu, & Tviskin, 1999). The coordinated activity of the particular neural networks constituting the mental representations for number and the mental processes operating on these representations gives rise to the understanding of numerical concepts.

The fact that mental representations depend on distributed neural networks is very challenging for disciplines like education, yet also very exciting. The central premise of our concept of educational neuroscience is that the study of mental representation offers a level of analysis common both to cognitive neuroscience and to traditional behavioral approaches to learning and pedagogy. As we illustrate, the claim that all mental representations are based on the activity of neural networks entails the interpretation of educational and neuroscience data within a particular theoretical and methodological framework.

A BRIDGE TOO FAR?

Clearly, neuroscience and education study the brain at very different levels. Therefore, it can be argued that the connection of the two fields is a "bridge too far" (Bruer, 1997). If our more focused definition of educational neuroscience is accepted, this need not be the case. Bruer's 1997 influential paper made a number of key points. For example, Bruer argued rightfully that misconceptions and overgeneralizations originating from neuroscience research will only result in speculative educational applications. Accordingly, he cautioned that such overgeneralizations should be erased from the minds of educators. We agree completely. Speculative applications and false beliefs (or neuromyths; Della-Sala, 1999; Goswami, 2004, 2006; Organisation for Economic Co-operation and Development, 2002) will hamper the development of the field. Bruer also identified a primary cause of these misconceptions. Early educational neuroscience drew naïve links between results in neuroscience and in education that were incompatible. These links were indeed a bridge too far. Bruer typically criticized attempts to relate very distant levels of neuroscience (usually animal experimentation) and education. Examples included relating the facts of synaptic proliferation, critical or sensitive periods, and the effects of enriched environments on synaptic growth to educational theories about the optimal timetable for teaching and the conditions in which teaching should occur (Goswami, 2006). Since the publication of Bruer's article, however, cognitive neuroscience has grown very rapidly, and some of the promising areas of overlap that he identified (e.g., literacy research) are now quite advanced.

Another key point made by Bruer (1997) was that the integration of neuroscience and education involves the coordination of three disciplines rather than two. These disciplines are education, neuroscience, and cognitive psychology. Neuroscience is the study of the human nervous system. Education aims to discover the optimal ways of shaping and enriching the cognitive system of the individual. Psychology provides the tools for analyzing individual cognitive systems. Hence, cognitive psychology is a necessary intermediary between neuroscience and education. Although it is impossible to integrate neuroscience and education as a whole, it is possible to integrate the most compatible levels of research activity within education and neuroscience via a focus of interest in cognitive psychology: the study of mental representation.

EDUCATIONAL NEUROSCIENCE: THE CENTRAL IMPORTANCE OF DISTRIBUTED REPRESENTATIONS

We suggest that studying the development of mental representation can set educational neuroscience apart from cognitive neuroscience in general. Psychologists used to consider mental representations as akin to conceptual units of the mind. Most cognitive theories assumed symbolic representations, which were discrete in form and all or nothing in terms of functionality (the metaphor of the "algebraic" mind, see Elman, 2005).

However, neuroscience research showed that human information processing relied on extended interconnected neural networks in the brain. All mental activity relies on distributed mental representations that are embodied in neural networks. With the advent of connectionism (the study of learning by simple neural networks), it has even become possible to build simplified computational models of mental representations. Mental representations are graded in nature. A representation can be graded in terms of, for example, the number of relevant neurons firing, their firing rates, the coherence of the firing patterns, and how clean they are for signaling the appropriate information (see Munakata, 2001).

These insights in turn have led to different metaphors for the cognitive system from symbolic metaphors. For example, Clark (2006) argued that the entire cognitive system should be conceptualized as a "loose-knit, distributed representational economy" (p. 373). During development, it is perfectly possible that some elements that are developed in the economy might conflict with other elements. This is inevitable, as there is no homunculus or single central reasoning engine that determines cognitive development. Rather, there are many interacting parts of the overall reasoning machinery that may develop at different rates. The activity of all these parts is cognition (see Goswami, in press-a).

The idea that there is no all-knowing, inner central executive that governs what is known and that orchestrates cognitive development is very important for education. It means that education must deal with the "vast parallel coalition of more-or-less influential forces whose … unfolding makes each of us the thinking beings that we are" (Clark, 2006, p. 373). We argue here that this challenge for education becomes clear from a consideration of the nature of neural networks. However, we acknowledge that similar issues have been identified by cognitive–behavioral theories that built on Piaget's stage-based notion of the development of symbolic cognitive representations, such as the neo-Piagetian theories of Case, Halford, and Fischer (e.g., Case, 1991; Fischer & Bidell, 2006; Halford, Wilson, & Phillips, 1998). For example, Fischer and his colleagues discussed cycles of development of cognition and brain, which they argued demonstrated important stage-like properties. Children were shown to demonstrate clear spurts in optimal performance at certain age intervals for cognitive skills with a specifiable kind of structure. As research on cortical activity can also reveal strong spurts, Fischer has further argued that cortical changes can be related to cognitive changes and that this offers an opportunity to relate mind, brain, and education (Fischer, in press).

NEURAL MARKERS OF MENTAL REPRESENTATIONS

The development of distributed mental representations can be studied by integrating the theoretical and methodological frameworks of cognitive psychology, connectionism, neuroconstructivism, and education. This integration requires the study of neural variables. Connectionism offers a new framework for studying learning, by building computational models of mental representations from networks of simple processing units. Neuroconstructivism offers a new framework for studying development, by considering the biological constraints on the neural activation patterns that compose mental representations. Cognitive psychology has revealed the essential characteristics of certain classes of mental representation crucial for education, such as phonological representations for literacy acquisition and the approximate analogue magnitude representation for the acquisition of number.

Educational research seeks the optimal way of developing children's representations. The crucial advantage of incorporating neural variables is that they allow the observation of brain activity. For example, electroencephalography (EEG) is a direct measure of the electrical activity in networks of neurons. If a meaningful relationship can be identified between hypothetical cognitive processes and neural representations and neural variables, the neural variables can become the neural markers of the particular mental representations and processes that yield these cognitive processes. These neural markers enable the study of mental function even in the absence of attention. This extra source of information has been made possible by technological advances, in particular the development of powerful brain-imaging technologies. These technologies offer a unique way of understanding the relationships between mental representations and educational performance. Much of current cognitive neuroscience comprises the mapping of the cognitive constructs hypothesized by cognitive psychology (e.g., working memory, knowledge of grammatical rules) onto mental representations in the human brain. We are suggesting here that neural measures of these mental representations can in themselves be important for education—because neural markers are systematically related to cognitive constructs. Hence, the isolation of neural markers and their analysis throughout development provides a way of studying the development of the mental representations underlying cognitive development.

For a successful educational neuroscience, we need to connect neural variables to educational performance. Neural variables can generate new knowledge that affects psychological theorizing and can inform the course of educational research. As two examples, consider arithmetic and language. First, as described further below, cognitive neuroscience has discovered that the amplitude of event-related brain potentials can index the activation of magnitude information in the human brain (Dehaene, 1996; Pinel, Dehaene, Riviere, & LeBihan, 2001; Szűcs et al., 2007; Temple & Posner, 1998). Therefore, this variable can be considered the neural marker of magnitude processing. Discovering this marker made it possible to measure the timing of magnitude processing in the brain. Recent studies revealed that the magnitude information associated with numbers is activated as rapidly by young children as by adults. In contrast, the behavioral reactions of children are much slower than those of adults in magnitude processing tasks (Szűcs et al.; Temple & Posner, 1998). The cognitive–behavioral performance of children lags behind their magnitude processing skills (as indexed by the neural marker, event-related potentials). One challenge for a theory of mathematical pedagogy then becomes to explain why children do not perform as well as adults in simple numerical tasks.

Another example of a potential neural marker is the N100 for language development. The N100 is the early negativity in the amplitude of event-related brain potentials when sounds are registered, as recorded by electrodes placed on the scalp. Although the N100 varies developmentally in latency and amplitude, it is consistent in indexing the early processing of the properties of auditory stimuli by the brain. The N100 can be measured in sleeping babies to assess responsivity to speech sounds (e.g., Cheour et al., 1997). Neural markers such as the N100 can hence provide data on the neural representation of speech sounds when there are no cognitive or behavioral variables at all. Thus, aspects of language function can be measured very early and without requiring attention. This means that neuroscience methods are able to address educational research questions that are not amenable to the traditional research methods in cognitive–behavioral psychology (Dehaene, 2003). Using neuroimaging, mental representations can be studied in populations for whom informative behavioral measures are difficult to generate, such as preverbal infants, and in populations for whom informative behavioral data are difficult to collect, such as children with attentional difficulties.

A NEW COLONY OF RESEARCHERS

In fact, if we want to integrate neuroscience and education, sending information between education and neuroscience across bridges is not the answer. Simply taking the results and interpretations of (cognitive) neuroscience, relating them to an educational context, and then drawing conclusions for education does not integrate the two disciplines. What we really need is a new colony of interdisciplinary researchers trained both in cognitive neuroscience and in education and a new theoretical framework based around mental representation that takes into account the concerns of both educators and neuroscientists (Fischer et al., 2007). The new theoretical framework should take educational, cognitive, and neuroscience variables into consideration throughout the process of empirical inquiry. This integration must occur when designing experiments, when collecting data, and when interpreting the results.

EXAMPLE: EDUCATIONAL NEUROSCIENCE AND MAGNITUDE REPRESENTATION

In this section, we briefly review evidence regarding the development of the magnitude representation of numbers. Data suggest that numerical magnitude is represented by a nonspecific mental representation which also codes the magnitude of physical entities. The magnitude representation is already functioning very early in life, and it probably undergoes continuous development during childhood. Neural variables suggest that the interpretation of numerical magnitude occurs equally fast in children and in adults. However, children's behavioral performance in number comparison tasks lags behind that of adults. Recent studies suggest that this happens because the well-developed magnitude representation has to work against a background of less developed behavioral control abilities in children compared to adults. This example draws attention to the importance of mapping the interrelated structure of mental representations and processes if we want to understand children's performance and development properly.

The Magnitude Representation

Recently, cognitive–behavioral and neuroscience research has identified a core component of arithmetic knowledge, the mental representation of magnitude. This mental representation is thought to be evolutionarily grounded and is functional from very early in life. For example, it has been found that infants can discriminate between displays containing 8 versus 16 dots or even 16 versus 32 dots. However, they are unable to distinguish 8 versus 12 dots or 24 versus 32 dots (Xu & Spelke, 2000; Xu, Spelke, & Goddard, 2005). This is because the *ratio* of the number of dots to be discriminated governs successful performance. This ratio must be around 1:2, and certainly better than 2:3, in order for infants to show successful magnitude discrimination (for a full review, see Feigenson, Dehaene, & Spelke, 2004). The closer the ratio is to 1, the worse infant performance is. Related research has shown that number discrimination is ratio sensitive not only in infants but also in human adults and in animals. Both animals (Mechner, 1958; Meck & Church, 1983) and human adults prevented from verbal counting (Gallistel & Gelman, 2000; Whalen, Gallistel, & Gelman, 1999) make more errors when they have to discriminate numerically closer than numerically distant quantities. Further, the larger the to-be-discriminated numerosities, the larger this difference must be in order to maintain discrimination. The pattern of errors found in infants, adults, and animals can be described by the same function, the *Weber function*. This function describes a general ability to discriminate between physical properties of the world, for example, line length and luminance. Because the same Weber function describes magnitude discrimination, it has been concluded that number, numerosity, and magnitude are represented as a property of the physical world by an evolutionarily grounded number sense (for reviews, see Dehaene, 1992, 1997; Dehaene, Dehaene-Lambertz, & Cohen, 1998). The number sense is a mental representation based on analogue magnitudes.

Further research suggested that understanding *symbolic* numerical information (e.g., Arabic numerals) relied on the analogue magnitude representation as well. The discrimination of symbolically presented numbers is also ratio dependent: participants take more time and are less accurate when comparing Arabic digits representing closer than more distant quantities. This distance effect has been found for both one- and two-digit numbers (Hinrichs, Yurko, & Hu, 1981; Moyer & Landauer, 1967). For example, when human adults have to decide whether an Arabic digit between 1 and 9 is smaller or larger than 5, their reaction time is slower and their accuracy is poorer for numbers closer to 5 (e.g., 4) than for numbers further from 5 (e.g., 1). This phenomenon is called the *symbolic distance effect*. The assumption is that numbers are translated (transcoded) into a ratio-sensitive general magnitude representation for interpretation (Dehaene, 1997; Moyer & Landauer, 1967). Thus, behavioral research suggests that magnitude relations, or the meaning of symbolic numbers, are coded in the brain by an analogue magnitude representation. This is one mental representation for number.

Imaging studies have shown that a vital component of this representation for magnitude is located in the parietal lobes of the human brain (parietal cortex is important for coding spatial relations; for a review, see Dehaene, Molko, Cohen, & Wilson, 2004). The activity of this brain area has been shown to be correlated with the numerical distance effect in a number of studies (Cantlon, Brannon, Carter, & Pelphrey, 2006; Fias, Lammertyn, Reynvoet, Dupont, & Orban, 2003; Kaufmann et al., 2005; Piazza, Izard, Pinel, Le Bihan, & Dehaene, 2004; Pinel, Piazza, Le Bihan, & Dehaene, 2004; Pinel et al., 2001). This parietal area is also selectively sensitive to numerical information, even when the manipulation of numerical meaning is not required (Eger et al., 2003). Moreover, a study in which participants compared either the physical size or the numerical magnitude of Arabic digits found that partially similar parietal brain areas participated in representing both physical size and numerical magnitude. This finding suggested that the representation of numerical and physical magnitude literally overlaps in the brain via shared networks of neurons (Pinel et al., 2004). Currently, the most influential theory assumes that the representation of numerosity develops from our ability to represent the objects in the space surrounding us (Dehaene & Changeaux, 1993). Animals are born with a strong bias to categorize objects according to their physical properties, and these properties include magnitude and numerosity. The mental representation of magnitude is most probably abstracted from these primitive representations of the environment (Dehaene & Changeaux, 1993). As the young infant and child develop, these precursor representations in the parietal cortex became adapted to representing numerosity as experienced in the world (see the "neuronal recycling hypothesis" discussed in Dehaene, 2007).

The Development of the Magnitude Representation

The ability to discriminate between numerosities follows a measurable developmental path. Between the ages of 2 and 5, children improve at discriminating sets of objects with a ratio of 2:3 (Huntley-Fenner & Cannon, 2000; Starkey & Cooper, 1995). Between 5 and 7 years of age, children's estimates of the number of items in an array get continuously more accurate (Huntley-Fenner, 2001). The symbolic distance effect also changes with development. Children's response time curve, plotted as a function of numerical distance between the pairs of numbers to be compared, is steeper than that of adults (see Figure 1), and the slope attenuates from kindergarten to grade 7 (Sekuler & Mierkiewicz, 1977). Sekuler and Mierkiewicz (1977) proposed that the difference in slopes between children and adults arises because initially children have less magnitude representation than adults. They proposed that younger children experienced

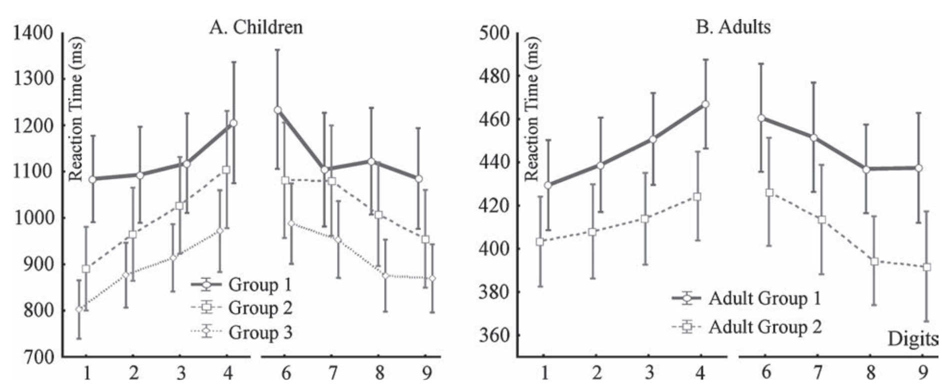

Fig. 1. The distance effect in three groups of 6-year-old children (Panel A) and two groups of 21-year-old adults (Panel B). There were approximately 20 individuals in each group. Note that the scale of the reaction time axis is different for children and for adults (Szűcs & Shen, unpublished data).

smaller subjective differences between absolute quantities than older children and adults. The gradual development of the number sense was thought to result in an improved ability to perceive the difference between quantities. Hence, development was hypothesized to lead to an attenuation of the slope of the distance effect.

However, the pattern of the nonsymbolic distance effect does not differ significantly in Amazonian Indian tribes who use only a few number words and educated French people (Pica et al., 2004). This suggests that the mental representation of magnitude is a fundamental component of the representation of number. The nature of the environmental inputs necessary for the adequate development of the magnitude representation is not yet clear. For example, while vision seems to play an important role in understanding magnitude relations, congenitally blind adults who learned to discriminate numbers via placing pegs in a peg board show a normal distance effect (Szűcs & Csépe, 2005b). This suggests that a phenomenologically normal magnitude representation can develop even in the absence of vision. Further, a general change in the properties of the response curve from childhood to adulthood may also contribute to the difference in slope of the distance effect in children versus adults. Hence, factors other than the properties of the magnitude representation may affect the pattern of the distance effect. Brain-imaging markers of the distance effect and other experimental effects can dissociate the neural systems that play distinct roles in arithmetic tasks. Therefore, educational neuroscience may enable a clearer picture concerning the cognitive processes relevant for arithmetic performance.

Recent functional magnetic resonance imaging (fMRI) studies have already shown the brain-imaging markers of the magnitude representation in young children. For example, in Cantlon et al. (2006), 4-year-old children and adults watched dot patterns without doing any particular task. A stream of stimuli consisting of a certain number of dots (e.g., 16) was presented. Occasionally, a different number of dots was presented (e.g., 32). When the number of the dots changed, the researchers found that the activity of the intraparietal sulci changed in a similar way in both adults and children. This suggests that the intraparietal sulci are sensitive to numerosity in comparable ways in both children and adults. It is important to note that, while in one condition of the experiment, the number of dots changed and in another condition, the shape rather than number changed (from circle to rectangle). This did not affect activity in the intraparietal sulci. Cumulative surface area, element size, density, and the spatial arrangement of the dots were varied trial by trial, in order to make sure that the participants were reacting to the change in number and not to some other change in the physical parameters of the stimuli which are correlated with number (Clearfield & Mix, 1999). Other fMRI experiments showed similar number sensitivity in the brains of young children when they compared Hindu-Arabic digits (Ansari, Garcia, Lucas, Hamon, & Dhital, 2005; Kaufmann et al., 2006). Interestingly, two of these studies reported that numerical distance effects in 10-year-old children were expressed more in the frontal lobes of the brain than in the parietal lobes. In contrast, adults usually show the strongest distance effects in parietal areas (Fias et al., 2003; Kaufmann et al., 2005; Piazza et al., 2004; Pinel et al., 2001, 2004). This suggests that the organization of the neural networks, and hence of the mental representations playing a role in simple arithmetic tasks, may change during development. EEG studies have suggested an explanation for these developmental effects.

Neural Mechanisms Change During Development

A difference between children's and adults' performance is that children respond more slowly in numerical discrimination tasks compared to adults. A possible explanation for these slower discriminations is that children access numerical information more slowly than adults. An EEG study by Temple and Posner (1998) demonstrated that this explanation is probably incorrect. In their experiment, 5-year-old children and adults saw the Arabic digits 1, 4, 6, or 9, and they had to signal with a button press whether each digit was smaller or larger than 5. Both children and adults demonstrated the symbolic distance effect, and on average, children's reaction time was about 1,500 ms, while adults responded in about 500 ms. However, inspection of the imaging data demonstrated that both groups showed a similar pattern in the amplitude of event-related electrical brain potentials in response to numerical distance. This amplitude effect occurred as early as 200 ms after stimulus presentation. A similar amplitude effect has consistently been found in other studies with adults (e.g., Dehaene, 1996; Pinel et al., 2001; Soltész, Szűcs, Dékány, Márkus, & Csépe, 2007; Szűcs & Csépe, 2005a, 2005b). Considering its correlation with the symbolic distance effect, this amplitude effect most probably indexes the activity of the neural representation of magnitude. Therefore, it can be considered a neural marker of the magnitude representation. The finding that 5-year-old children display the same neural marker of the magnitude representation with the same time course as adults suggests that both adults and children interpret numerical information with similar speed. The large discrepancy between children's and adults' reaction time does not appear to reflect immature numerical discrimination skills nor smaller subjective differences between absolute quantities. Rather, Temple and Posner (1998) hypothesized that the differential behavioral performance of children and adults arose from underdeveloped executive functioning in children. Temple and Posner's study is an excellent example of how cognitive neuroscience measures can constrain and guide psychological theorizing.

In a recent study, we confirmed the hypothesis of Temple and Posner (1998) and demonstrated that immature response organization and response-inhibition skills affect children's cognitive functioning in number comparison tasks (Szűcs et al., 2007). In our study, children decided which of the two simultaneously presented digits represented the larger number. Sometimes, the numerically larger number had a smaller physical size than the numerically smaller number (in bold) (e.g., 2 **9**). By monitoring neural markers of response-hand activation, we observed that, when there was a conflict between numerical and physical information, children first showed motor planning consistent with pressing the response button with the wrong hand. For example, when they had to decide which number was numerically larger and they were shown a display of "2 7," they first activated the left hand. They then had to inhibit this action, as they actually used the correct right hand when making the button press. This suggests that the executive resources controlling behavior were taxed to a much larger extent in children than in adults during the processing of numerical information. We hypothesize that the distance effect changes in localization in children compared to adults because executive functioning is less well developed in children. The attentional, response-inhibition, and behavioral skills constituting executive functions in general rely on the prefrontal cortex, which undergoes protracted development. The frontal distance effects found in children using fMRI (Ansari et al., 2005; Kaufmann et al., 2006) are probably due to immature frontal function, as executive functions (response inhibition, motor planning) will inevitably play a role in arithmetic performance (Espy et al., 2004; Swanson, 2006). In fact, recent studies suggest that the impairment of executive functions guiding attention and controlled processing may play a role in calculation impairments in developmental dyscalculia (Kaufmann & Nuerk, 2006; Soltész et al., 2007).

Mapping Developing Representations and Their Influence on Performance

As the above example illustrates, educational neuroscience reveals that the properties of the mental representation of magnitude and interconnections between the areas of the brain embodying mental representations for number change during child development. Accordingly, the gradual development of the neural systems helps to explain the performance of children in arithmetic tasks. This enables us to study the exact relationship between the development of mental representations and children's performance and strategy choices in arithmetic. For example, according to Siegler's (1996) "overlapping waves" theory, children will use multiple representations for solving cognitive tasks. Contextual variables, schooling, individual history, and maturation factors will all affect which representation dominates cognitive performance in certain situations (Siegler & Booth, 2004; Siegler & Opfer, 2003). Educational neuroscience can help to determine the developmental state of mental representations, the developmental state of the processes guiding their interactions, and their relationship to response processes, all of which will play an important role in determining the cognitive armory and strategy use of children.

Development of an educational neuroscience research base also enables us to study how schooling builds on children's preschool numerical and general capacities and how direct teaching about numbers and their relations affects the development of the distance effect. In fact, educational research drawing on cognitive psychology has already identified a set of understandings which form the central conceptual structure for number. This central conceptual structure relies on certain precursor knowledge about number and quantity (Case & Griffin, 1990; Griffin, 2003; Griffin, Case, & Siegler, 1994). One of the components of this precursor knowledge is the comprehension of magnitude relations between numbers. The numerical distance effect is a behavioral and neural marker of this comprehension (Szűcs & Griffin, 2007). The research of Griffin and colleagues suggests that there is a strong relationship between the developmental state of children's preschool mental representations for number and their school performance. Further, Griffin and colleagues have shown that targeted enhancement of the representations underpinning arithmetic has a beneficial effect on school performance (Griffin & Case, 1997). One future focus of educational neuroscience regarding number should be to investigate the normative development of the mental representations required for adequate school performance. These educational neuroscience investigations will go beyond cognitive psychology in delivering understandings that can help with curriculum development (Case & Griffin, 1990; Griffin, 2003; Griffin, Case, & Siegler, 1994; Singer, 2007).

THE LIMITATIONS OF CURRENT NEUROSCIENCE METHODS

Educational neuroscience has two main foundations. One is theoretical, the belief that the development of mental representations can best be understood by combining behavioral and neural measures. The second is methodological. Cognitive neuroscience is made possible by sophisticated technological tools which enable the observation of brain function in vivo. This entails a caveat. Even if it becomes accepted in education that understanding brain function leads to a better understanding of mental representation, it is still important to be able to make observations about brain function that are useful for advancing our understanding of educational phenomena. This is not guaranteed simply by adopting neuroimaging methods. The methods of cognitive neuroscience limit what we can and what we cannot investigate in important ways. For example, complex tasks such as creative problem solving may elicit different strategies from different participants, and it is far from clear which physiological markers should be measured. Most importantly, the researcher must be aware of which aspects of brain activity a particular neuroscience method is able to characterize and how this information can be related to the research questions of interest. In this section we draw attention to the most important pragmatic issues that need to be considered when deciding whether a certain neuroimaging technique may be of value for investigating certain educational questions (for excellent general reviews on diverse imaging technologies, see Byrnes & Fox, 1998; Casey, Davidson, & Rosen, 2002; Davidson, Thomas, & Casey, 2003; Meek, 2002; Taylor & Baldeweg, 2002). It will become clear that, despite beliefs propagated by the popular media, we are far from a situation in which interested parents can commission a scan of their child's brain in order to provide useful information for their child's teachers.

Technological Issues

Structural brain-imaging techniques (e.g., magnetic resonance imaging, computed tomography) are able to provide an anatomical image of the living brain inside a living subject. These techniques can be used to follow the developmental path of certain brain structures (Paus et al., 1999), and they can shed light on abnormal brain structure and brain development (Isaacs, Edmonds, Lucas, & Gadian, 2001). Functional brain imaging delivers a dynamic picture of the activity of the human brain. EEG measures the electrical currents generated by nerve cells (neurons) in real time, usually by electrodes placed on the scalp of human subjects. Thus, EEG reflects the direct electrical activity of neurons at the time of measurement. However, it is mathematically impossible to tell where exactly the recorded electrical signals were generated within the brain. Therefore, EEG has superb temporal resolution but poor spatial resolution. Building upon EEG, magnetoencephalography (MEG) measures the magnetic field generated by neuronal activity and provides better spatial resolution than EEG while preserving the temporal resolution. However, MEG cannot substitute for EEG. First, MEG and EEG are sensitive to signals generated in different brain areas. Second, as MEG requires supraconduction, it is much more expensive than EEG.

In contrast to electromagnetic methods, fMRI measures blood flow within the brain. Spatially, it is capable of observing brain activity with a half-centimeter accuracy (note that this is still very distant from imaging the separate activity of individual nerve cells, or even of neural networks, which comprise tens of thousands of cells). The weak point of fMRI is that it lacks temporal accuracy. Changes in blood flow take approximately 6–8 s to reach a maximum value after stimulation. Hence, while the temporal accuracy of EEG and MEG is on the millisecond scale, the accuracy of fMRI can only be measured in seconds. Considering that even complex mental processes can happen within a fraction of a second, the temporal resolution of magnetic imaging methods is not enough to track mental processes. We know from behavioral–cognitive psychology that most important processes are very rapid. For example, printed words are recognized within 180 ms. Developmentally, 50 ms is a long time for the brain. Hence, a child who is 50 ms faster in responding to stimuli will have an advantage over other children. None of this individual variability can be captured by fMRI.

Each neuroimaging technique thus has its own strengths and weaknesses. Similar caveats apply to less frequently used functional imaging methods, like positron emission tomography and optical imaging. Each brain-imaging technique detects *some* aspects of brain activity, and each has its own strengths and limitations. The information content delivered by each method may be quite different from other methods. Often, the exact relationship between the data measured by different techniques is not even known. For example, it is still unclear how exactly the electrical activity measured by EEG and the metabolic activity measured by fMRI relate to each other (Logothetis, 2003; Logothetis, Pauls, Augath, Trinath, & Oeltermann, 2001).

Clearly, there is no preferred choice of neuroscience technique for educational neuroscience. The most appropriate technique has to be chosen considering the research questions of interest. For example, if an educational question requires the precise localization of the brain areas playing a key role in a given task, fMRI is the method of choice. In contrast, if an educational question requires razor-sharp temporal resolution, EEG should be used. If both temporal and spatial information are of interest, a combination of EEG and fMRI may be needed.

Issues Related to the Laboratory Setting

Besides the choice of equipment, there are pragmatic limits on what can be measured inside neuroscience laboratory settings. These pragmatic considerations are particularly important for education research. Neuroscientific measurements usually take place under very stringent environmental settings. The participant may be sitting in a dimly lit, sound attenuated testing chamber (EEG). Participants cannot move too much and cannot blink or stand up whenever they want to. They may have to concentrate for long periods on a repetitive task. Alternatively, the participant may be inserted into a small opening in a loud tube, where they have to lie motionless (fMRI). Usually, the participant looks at a computer monitor and has a response device in hand and may also wear earphones. Her task may be to press a button whenever he or she sees or hears a certain type of stimuli and to press another button when she encounters another type of stimuli.

These constraints are necessary in order to guarantee effective measurement and therefore experimental power. However, they are not very conducive to testing young children. A primary concern is to ensure that the minute biological signals of interest can be detected despite the presence of environmental noise and participant motion (e.g., eyeblinks distort electrical brain potentials). Children are much worse at controlling their spontaneous movements than adults. Rigor can be achieved by repeatedly presenting stimuli belonging to a certain experimental condition and by repeatedly measuring the biological variables in this condition. This may require many hundreds of trials and a fairly long experiment. Paradigms requiring too much time are simply impossible with young children. Yet, multiple presentations of stimuli are necessary if a statistically reliable signal is to be extracted. A physiological marker cannot be identified from a single presentation of a stimulus of interest.

In summary, neuroscience techniques alone are not omnipotent nor are they infallible. Neuroscience provides information about mental representations via its own specialized data acquisition and data analysis techniques. These techniques form an interface between the world and the knowledge base of neuroscience. Being knowledgeable about the techniques of producing and processing data is in fact a key prerequisite for understanding research results in depth and judging their real value. Complex educational questions must be analyzed and translated into simple tasks within the neuroscience laboratory and placed within a framework of meticulously designed experimental procedures which together may shed light on an educational question. Hence, educational professionals need some grounding in the research methods of educational neuroscience (Ansari & Coch, 2006; Eisehart & DeHaan, 2005).

Reasons for Optimism

Nevertheless, there are already some positive examples of how neuroimaging techniques can address traditional educational questions in a new way. For example, multisensory teaching methods have long been believed to be beneficial for learning. Recently, fMRI has been used to explore children's development of mental representations for letters as they learn to read and write. James (2007) gave letter recognition practice to young preschool children who were just beginning to learn to read. The training formed part of their initial reading activities. The children learned to pick out target letters from four alternatives (including reversed letters), to recognize the letters in storybooks, and also to form and write the letters. The children were prereaders at the beginning of the study according to a formal assessment, and they learned to recognize the target letters during the training. Significant improvement in writing the letters was found following the training. fMRI scans during *visual* presentations of the letters were taken both before and after the training. As a control condition for the neural processes involved in visual recognition, the children were also scanned when viewing familiar shapes like hearts. Using a subtraction procedure, James showed that, prior to receiving writing training, presentation of the letters caused either no activation in the left fusiform gyrus (the putative Visual Word Form area; see Dehaene, Cohen, Sigman, & Vinckier, 2005) or modest activation. Following training, visual presentation of the letters led to strong selective activation of the left fusiform gyrus and also led to activity in ventral premotor areas. Control children who did not receive training did not show activity to the letters in either neural area. The activation of *motor* areas during a *visual* task (letter recognition) following training suggests that the writing experience created a multisensory mental representation for familiar letters for these children. Whether this supplementary motor activation indicates deeper learning of letters awaits further study.

Researchers have been able to use EEG to study possible neural markers for risk for both specific language impairment and developmental dyslexia. Accurate identification of neural markers would enable earlier diagnosis and earlier intervention, thereby enabling targeted training to be delivered prior to schooling when the language system is most plastic. For example, EEG has been used to study infant processing of natural language via a measure called mismatch negativity (MMN). MMN is an index of the ability to detect a difference between two auditory stimuli, such as two words differing in stress. Studies with infants suggest that different stress patterns are distinguished early and that the stress patterns characteristic of the ambient language rapidly attain a special status in long-term memory. For example, Weber, Hahne, Friedrich, and Friederici (2004) studied German infants' sensitivity to stress patterns using MMN. Ninety percent of bisyllabic German nouns are stressed on the first syllable (the trochaic pattern) rather than on the second syllable (the iambic pattern). Weber et al. investigated infant sensitivity to changes in trochaic and iambic patterns. They reported that infants aged 4 months did not distinguish two-syllable words by stress. By 5 months of age, however, infants clearly separated the iambic and trochaic patterns, showing a strong MMN for the trochaic items. Adults investigated in the Weber et al. study showed clear MMNs to both syllabic stress patterns. This pattern of EEG findings suggests that language experience helps the infants to focus on the stress patterns characteristic of their spoken language, a template for which is then stored in the phonological lexicon. Demonstrations such as this enable EEG techniques to be used to study the auditory processing of cues to rhythm and stress in children with developmental dyslexia (Goswami, in press-b). Behaviorally, these children are relatively insensitive to auditory cues to speech rhythm, such as the rise time of amplitude envelope onsets (Goswami et al., 2002). Pilot data suggest that this behavioral insensitivity is also reflected in

MMN response, raising the possibility of a neural marker of risk for developmental dyslexia (Thomson, Goswami, & Baldeweg, 2006).

Another EEG measure, the N400, may provide a neural marker of risk for specific language impairment. Friedrich and Friederici (2006) gave a standardized language development test to 30-month-old German infants who had been followed longitudinally. They then grouped the infants on the basis of their expressive language abilities. Children with age-adequate skills at 30 months were found to have displayed an N400 (an EEG measure of semantic integration) at the age of 19 months. For children who had deficits in expressive language skills at 30 months, however, the N400 at 19 months of age was found to be absent. The N400 may hence provide a neural marker of risk for later language impairment. If such measures prove robust at the individual level, which remains to be established, then EEG would offer a number of potential neural markers of risk for later language and reading impairments.

HOW SHOULD EDUCATIONAL NEUROSCIENCE PROCEED?

As the preceding examples of educational neuroscience in practice suggest, in our view, the key potential of educational neuroscience is that brain-imaging technologies can be used to measure mental representations in the typically developing human brain. Educational neuroscience can thus investigate direct links between mental representations and educational outcomes. Neuroscience research does not depend on the "medical model," looking for weaknesses in certain brains, seeking remedies for these, and documenting the efficacy of different interventions. While neuroscience can achieve this, the true potential of educational neuroscience is the documentation of typical developmental pathways for learning in a detail that has been impossible to achieve using behavioral methods alone. This enterprise will take time and will not deliver immediate applications for the classroom (Stern, 2005). However, the mapping and understanding of normative development are an enterprise whose payoff will have positive benefits for the lives of millions of children. Knowing more about the development of normal brain function and structure is crucial to understanding performance and plasticity (Goswami, 2004; Koizumi, 2004; Posner & Rothbart, 2005). Plasticity enables learning, and understanding learning is crucial to education.

We agree with Bruer (1997, 1998, 2002) that current neuroscience research has little to translate into classroom practice. Developing classroom applications cannot be the purpose of a single or even a dozen educational neuroscience studies. This would clearly be an unrealistic goal. Using an analogy that has already been drawn, no one can promise to develop a new medicine using a sample size of some dozens of subjects (*Nature Neuroscience* Editorial, 2004), especially not in a few years. Developing a new drug usually takes 15–20 years. It is unlikely that it would take less time to develop a new educational method, which may have to take into consideration hundreds of variables, and at the end may affect the lives of millions of children. The responsible introduction of new teaching methods ideally requires a large number of empirical studies ranging from the level of mental functions to the wider context of social implications (Slavin, 2002; Bhattacharje, 2005). This means that, while educational neuroscience may be able to address applied questions in the long run, current educational neuroscience research must focus on basic science. All applied sciences have to rely on empirical and theoretical basic research. There is no reason to assume that educational neuroscience will be an exception.

In order to discover the optimal neural markers for educational questions, the relationship between the recorded physiological variables and the mental phenomena of interest must be clear. Establishing such a connection is far from simple. We see two current challenges for integrating neuroscience methods into important areas of educational research. One is that current neuroscience methodologies are best suited to group analyses. Yet, effective learning requires consideration of the individuality of each student. A major methodological challenge for educational neuroscience is thus the design of experimental paradigms better suited to the expectations of those educational researchers interested in individual performance. This may be easier for EEG than for fMRI (e.g., the study using the absence of the N400 as an individual neural marker of risk analyzed individual data; see Friedrich & Friederici, 2006). The second challenge is that education cannot really be captured by measuring the isolated biological activity of a student (or a teacher). Education is a rich process of interaction. Currently, the investigation of the interactions characteristic of successful learning is outside the scope of neuroscience.

However, the field is changing all the time. Social neuroscience is developing as a distinct field and in time may produce methods and frameworks capable of addressing these educational research questions. Two final points are crucial for the sound development of educational neuroscience. First, researchers must avoid seeding neuromyths when they are communicating with the press and attempting to draw practical conclusions from their data (Bruer, 2002). Second, a mutually enriching relationship between theory and practice must be an organic part of educational neuroscience from the outset. Educational researchers and teachers, with their extensive practical experience, need to be involved in formulating research questions (Geake & Cooper, 2003; Geake, 2005; O'Boyle & Gill, 1998; Szűcs, 2005). Their practical knowledge should also contribute to setting strategic directions for educational neuroscience research.

In conclusion, we have sought to establish that neuroscience provides a theoretical framework and technological tools for considering the nature of mental representations and how they change with development and with education. Educational neuroscience requires that both neuroscience and educational data be interpreted in a common framework. One of the most exciting aspects of educational neuroscience is the ways in which its new technologies can make unique contributions to old questions. Skinner (1954) said that learning is a science, while teaching is an art. Educational neuroscience can make a unique contribution to the study of the science of learning via the direct investigation of mental representations. In time, the scientific discoveries that will be generated about learning should have the potential to make valuable contributions to the art of teaching as well.

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