Learning styles and the human brain: what does the evidence tell us?

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Author note

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Abstract

Learning styles are a widespread idea that has high levels of acceptance in education and psychology. The promises of adopting the construct range from gains in academic performance, to the development of respect for the self and others. Nevertheless, from a scientific perspective it remains highly controversial. Most studies indicate that matching teaching to the learning styles of students does not improve learning, and that their psychometric instruments do not show enough reliability and validity. In this sense, this paper investigated if the postulates of learning styles are consistent with the way the human brain process information. Moreover, the trend of the accumulated evidence about learning styles was analyzed, using a simple algorithm, to determine if they are a proven, debatable, improbable or denied phenomenon. Results show: (1) that learning styles, along with the multiple intelligence theory and the left or right-brained hypothesis, are not compatible with what is currently know about the inner workings of the brain; (2) that the trend of the evidence, although still limited, does not favor learning styles; (3) that as a phenomenon styles are classified as improbable.

Keywords: learning styles, neuroscience, human brain, connectivity principle, convergence principle.

Introduction

At the heart of science is an essential balance between two seemingly contradictory attitudes, an openness to new ideas, no matter how bizarre or counterintuitive they may be, and the most ruthless skeptical scrutiny of all ideas, old and new. This is how deep truths are winnowed from deep nonsense (Sagan, 1997, p. 287). Failing to rigorously test hypothesis and theories produces an excess of positive and inflated findings (Fanelli, 2010, 2012; Fanelli & Ioannidis, 2014), which cannot be replicated later (Camerer et al., 2018; Open Science Collaboration, 2015).

In the field of education, one of the main goals of the research community, is the discovery of valid ideas supported by a preponderance of compelling evidence (Slavin, 2017, Waterhouse, 2006). However, differentiating between myth and reality in this area has historically been difficult (Bloom, 1972). Thus, leading to the adoption of educational programs and practices, based on ideological and political reasons, as well as novelty and commercialization, rather than by the available evidence (Slavin, 2008). As Hattie points out (2008), everything seems to work in education, when it comes to improving student achievement.

From this perspective, one of the many notions that have been introduced in education in the last 50 years, is that of learning styles. This idea is very popular and enjoys good acceptance. A review of academic and scientific information by Lilienfield, Lynn, Ruscio, & Beyerstein (2010) reports 1,984 articles in refereed journals, 919 conference presentations, and 701 books or book chapters about learning styles. A subsequent analysis of 220 of papers, listed in the ERIC and PubMed research databases and that were published between 2013 and 2015, detected that more than 85% of the literature start and end with a positive view of learning styles (Newton, 2015).

Furthermore, in a survey of 242 primary education teachers from the United Kingdom and the Netherlands, Dekker, Lee, Howard-Jones & Jolles (2012) found that more than 93% of teachers are convinced that: “Individuals learn better when they receive information in their preferred learning style (e.g., auditory, visual, kinesthetic)” (p. 3)". More recently, the same survey applied to 932 teachers from the United Kingdom, the Netherlands, Turkey, Greece and China (Howard-Jones, 2014) produced the same results.

However, as it has already been proved in other areas (Gottfredson, 2009, Nirenburg, McShane, & Beale, 2004, Rao & Andrade, 2011), extensive citation, as well as the popularity and acceptance of ideas, methods, constructs and instruments does not imply that they are scientifically valid and provide positive results. For example, one of the most promoted benefits of adopting learning styles in the educational practice, is that learning improves if the teaching matches the students’ styles. This is known as the matching hypothesis. However, all the accumulated evidence so far, indicates that doing so has no impact on the students’ knowledge acquisition, cognitive load or mental effort (Coffield, Moseley, Hall, & Ecclestone, 2004, Cuevas, 2015; Cuevas & Dawson, 2018; Höffler, Prechtl, & Nerdel, 2010, Massa & Mayer, 2006, Moser & Zumbach, 2018, Pashler, McDaniel, Rohrer, & Bjork, 2008).

In other words, there is no evidence of interactions (Cook, 2012; Pashler et al. 2008; Yeh, 2012) between aptitudes (i.e., learning styles) and treatment (i.e., matching the presentation of information to the learners’ styles). Moreover, learning styles measurement instruments do not reach adequate levels of reliability and validity (Coffield et al., 2004, Curry, 1987, Kirschner, 2017), and there is proof that letting students choose the format and modality, in which the learning material will be presented, negatively impacts their performance (Clark et al., 2010; Cuevas & Dawson, 2018; Kollöffel, 2012).

Based on the above, the goal of this article is twofold. On the one hand, to analyze the available evidence in neuroscience, regarding the architecture and functioning of the human brain, to answer the following question: are the architecture and the mechanisms through which the human brain works compatible with the postulates of the learning styles? On the other, to examine the tendency of the accumulated evidence on learning styles to determine if they are a proven, debatable, improbable or denied phenomenon?

The rest of this article is organized as follows. First, the way to evaluate the accumulated evidence, about a phenomenon, and establish its trend is discussed. Second, the premises, terminology and models of learning styles are introduced. Third, some the most recent data about the architecture and operation of the human brain is presented. Fourth, the assumptions on which the learning styles are based, are contrasted to what is known about the brain, and some conclusions are made.

Trend of the accumulated evidence: proven, debatable, improbable and denied phenomena

A phenomenon can be defined as a fact, event or entity that is observed or thought to exist, and whose cause or explanation is in question or under study. In this sense, elucidations about a phenomenon can be scientific or pseudoscientific (Lilienfeld, Lynn, & Ammirati, 2014, Thyer & Pignotti, 2010). However, distinguishing the elements that belong to one set or another is not an easy task for two reasons. First, because the difference between them is one of degree rather (Lilienfeld & Landfield, 2008, Lilienfeld et al., 2014). Second, because the scientific and pseudoscientific adjectives have a high degree of imprecision (Thyer & Pignotti, 2016).

Consequently, in this article it is argued that it is much better to talk about the trend of the accumulated evidence about a phenomenon, thus avoiding falling into the endless debates about what science and pseudoscience are (Lilienfeld & Landfield, 2008, Lilienfeld et al., 2014; Thyer & Pignotti, 2010). Furthermore, it is contented that analyzing the state of the accumulated evidence makes it possible to distinguish between proven, debatable, improbable and denied phenomena. For this, a simple classification algorithm is proposed, based on the principles of connectivity and convergence developed by Stanovich (2012), which are explained below.

The connectivity principle

This principle establishes that any theory that attempts to explain a phenomenon must consider previously confirmed empirical facts directly related to it. In such a way that it does not contradict this verified knowledge. An example recently popularized by the press, about the connection between what is known and a new proposal, is the Higgs boson. The standard model of particle physics explains many of the interactions between elementary particles. However, it does not explain why some particles have mass and others do not. The theory developed by Higgs (1964) explains this phenomenon without denying any of the elements of the standard model that had previously been confirmed experimentally (Ynduráin, 2000). So much so, that recent studies indicate that the existence of the boson and its associated field is potentially true (Aad et al., 2012; Chatrchyan et al., 2012).

Another example, but in the opposite sense of the previous one, is that of telepathy (mind reading). Proponents of extrasensory perception argue that people with this gift can read the thoughts of people on the other side of the world, as well as those of people in an adjoining room. Nevertheless, this implies the existence of an entity capable of transmitting signals at any distance without power decrease, which violates empirically proven facts such as the law of the inverse of the square of the distance (Cabrero-Fraile, 2004, p.9).

Similarly, the facilitated communication method, whose proponents claim that helps people with autism and other disabilities communicate through a keyboard or similar mechanism, violates well-established principles in neurology, genetics, and cognitive psychology (Jacobson, Mulick, & Schwartz, 1995, Stanovich, 2012, p.126).

The convergence principle

This principle defines convergence as a discrete or discontinuous variable, which is susceptible to increase or decrease, and that can only take certain values represented by categories. Nevertheless, although assigning a value to the convergence variable depends on the amount of studies available, the guidelines on how to assign one are very general. In his description of the convergence principle, Stanovich (2012) only explains two values for this variable, namely conforming and limited, but the number of studies these adjectives designate, are not part of the discussion. Consequently, this task ends up being in part a value judgment. Furthermore, the conforming and limited adjectives do not cover most of the values that can be assigned to the variable. For example, it is known that convergence can be contradictory or nonconforming (Gotwals, Stoeber, Dunn, & Stoll, 2012, Hite et al., 2010) as well as nonexistent or null (Pashler et al., 2008).

Hence, the categories that are proposed as values for the convergence variable are the following: positive conformance, negative conformance, positive limited, negative limited, nonconforming and null. The first two represent scenarios where all or most of the studies prove or deny a phenomenon. The next two are for cases where there is a tendency towards confirmation or refutation, but the amount of evidence is small. The last two, for situations where the studies are contradictory or there is no evidence at all.

Algorithm to determine the trend of the accumulated evidence about a phenomenon

Figure 1 shows the proposed algorithm. For most cases if the principle of connectivity is violated, the phenomenon is considered inconceivable. Only in the case that the evidence indicates positive conformance, the algorithm classifies a phenomenon as debatable. In particular, because if all or the vast majority of investigations confirm the explanations of a phenomenon, it is worth debating why this happens, although connectivity is violated. If it is not possible to assign a value to the convergence variable, then this indicates that the algorithm needs to be modified to extend the number of values this variable can have.

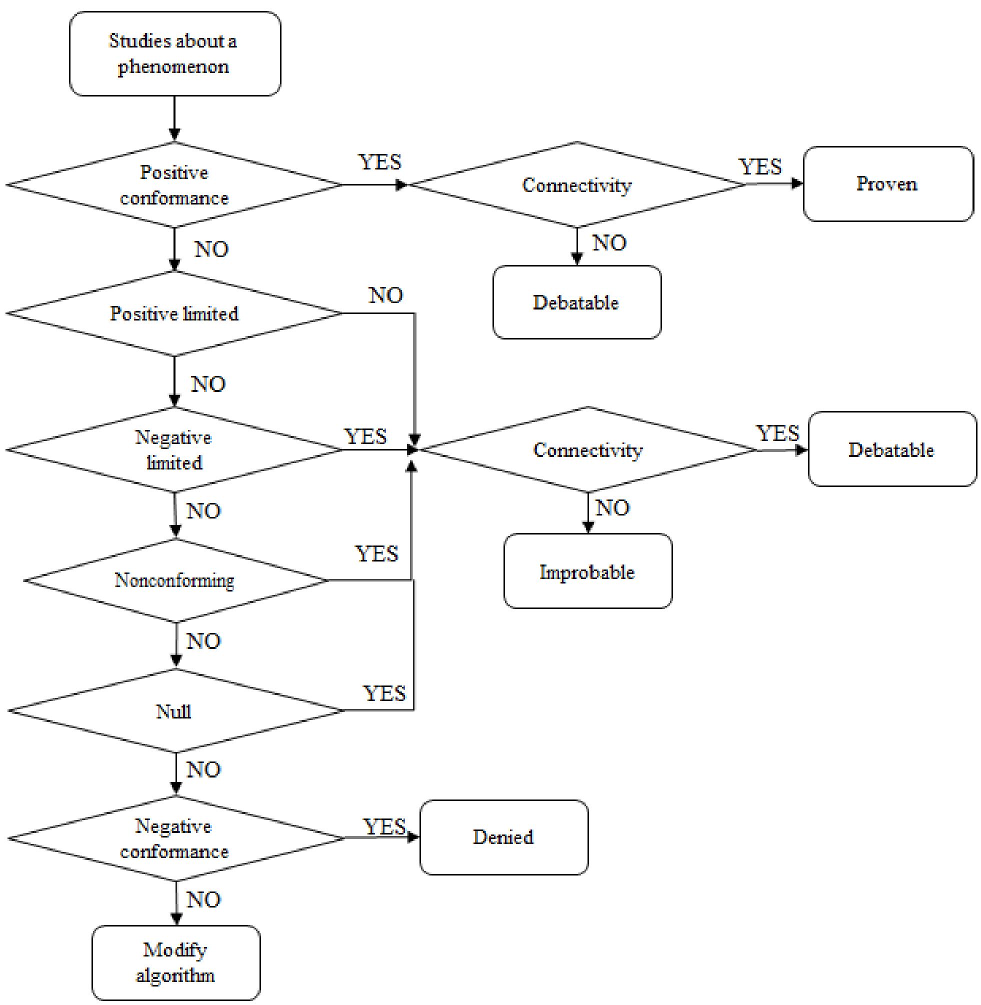

Figure 1. Algorithm to determine the trend of the accumulated evidence and classify a phenomenon.

With respect to the algorithm, it is important to emphasize that the studies used as input, must have an acceptable level of quality (Alvarez-Montero, Rocha-Ruiz, Leyva-Cruz, Moreno-Alcaraz, Alvarez-Arredondo, 2018). A study's quality affects the interpretation of the its results (Mattingly & Kraiger, 2018, Slavin & Smith, 2009). In the behavioral and social sciences, good quality means the studies: 1) used experimental and control groups (Mayer, 2014; Slavin, 2003) with similar demographic data and similar pre-intervention performance; 2) declared the descriptive statistics necessary for the calculation of effect sizes (Mayer, 2014; Mattingly & Kraiger, 2018); 3) had an adequate sample size (Button et al., 2013; Peters & Crutzen, 2017; Slavin & Smith, 2009).

The next section introduces the postulates, terminology and models of learning styles.

Learning styles: postulates, terminology and models

There are several reviews in the literature that address the subject of learning styles with different levels of depth (Cassidy, 2004**,** Coffield et al., 2004, De Bello, 1990, Ivie, 2009, Pashler et al., 2008, Sadler-Smith, 1997). Consequently, this section synthesizes the fundamental aspects of learning styles, already discussed in previous articles, beginning with the origins and goals of the construct.

Origins and goals of learning styles

Although not explicitly recognized in the reviews of the literature on the subject, mentioned above, the notion of learning styles is closely related to the psychological type theory, introduced by the Swiss psychiatrist and psychologist Carl Jung in 1923 (Barbuto, 1997; McCrae & Costa, 1989; Pittenger, 1993). This theory categorizes people by their propensities or functions of attitude, judgment and perception. In addition, such leanings reflect the most natural or comfortable way in which people perform some action (Bayne, 1995). That is, they represent certain preferences or spontaneous decisions which in turn influence behavior.

Each of these functions has two mutually exclusive components, an attitude and a function (Barbuto, 1997), one of which is the dominant feature of the individual's personality (Pittenger, 1993). The attitudes are extraverted or introverted and the functions sensing, intuitive, thinking and feeling. Therefore, the cartesian product of attitudes by functions produces eight psychological types: extraverted sensors, extraverted intuitives, introverted sensors, introverted intuitives, extraverted thinkers, extraverted feelers, introverted thinkers, and introverted feelers.

According to Bayne (1995, p.1), Jung's type theory pursues three objectives related to the self, the others and personal development. The first aims to help people determine or confirm the ways in which they, and their "type of person", can be more efficient and realized. The second seeks to aid to comprehend and value other people, especially those with a different type. The third tries to support people in understanding key aspects of their personality through their lives.

Some of the most recent reviews about learning styles, indicate the goals of styles concur with the goals of Jung's psychological type theory presented before. Examples of such affirmations are the following:

- Research has shown that students who understand their learning styles can improve their learning effectiveness in and outside of the classroom (Dembo & Howard, 2007, p. 102).
- Understanding how you learn best can also improve your concentration. When you're working in your preferred learning mode, you probably find

that you are better able to concentrate on your study tasks (Dembo & Howard, 2007, p. 102).

- If you approach studies using your preferred learning style(s), you should be able to study for the same amount of time (or less), remember more, get better grades, raise your level of self-confidence, and reduce your anxiety as you tackle classroom life (Dembo & Howard, 2007, p. 102).
- It is necessary taking time to discuss with students their learning style and that of their classmates as a means to develop empathy and respect for self and others (Scott, 2010, p. 10).

Nevertheless, psychological types and learning styles differ in one essential point. According to Barbuto (1997), the theory of types does not assume the existence of pure types, in the sense that one is totally of one type and not of another. The types exist in the human mind, but in different proportions and represent a system to describe individual differences. They do not seek to categorize people into one of eight available types. The notion of learning styles, on the contrary, conceives them as mutually exclusive sets, and tries to pigeonhole individuals within a single style (Kirschner, 2017; Kirschner & van Merriënboer, 2013), although in practice, some of the scales for measuring learning styles do not assign a zero to any of the styles measured (Barbuto, 1997, McCrae & Costa, 1989, Pittenberg, 1993).

Based on the coincidence between the objectives of the theory of types and those of learning styles, the area would be expected to present a high level of conceptual and terminological homogeneity, but this is not the case. The following two sections show that there is a high level of heterogeneity.

Definitions and terminology

Since the 1990s, it has been recognized that there are as many definitions of learning styles as there are theorists in the area (De Bello, 1990). Some of the most recent definitions published in high impact journals are the following:

- Learning style is broadly defined as the beliefs, habits, preferences, as well as social, emotional and physiological factors, that affect how an individual navigates and adapts to a learning environment (Knoll, Otani, Skeel y Van Horn, 2016, p.1).
- Learning styles can be regarded as (a) differential preferences for processing certain types of information or (b) for processing information in certain ways (Willingham, Hughes & Dobolyi, 2015, p. 266).
- Learning styles are defined as the characteristic cognitive, affective, and psychological behavior that serve as relatively stable indicators of how learners perceive, interact with, and respond to the learning environment (Scott, Rodriguez, Soria, & Campo, 2014, p. 57).

The number of terms denoting the term learning styles, as well as the possible number of styles, represented as psychological binary types (e.g., extraverted sensors), is also quite broad. In the case of the latter, Cassidy (2004) as well as Coffield et al. (2004), identified at least eleven. While for the former, a conservative calculation made by Kischner (2017), indicates that there are at least 2^{31} possible binary learning styles. Table 1 shows some of the terms and styles that have been identified in the literature.

Table 1

Terms and binary types of learning styles

Terms	**Binary styles**
Learning style	Convergers versus divergers
Learning strategy	Verbalizers versus imagers
Learning orientation	Holists versus serialists
Cognitive style	Deep versus surface learning
Conative style	Activists versus reflectors
Thinking styles	Pragmatists versus theorists
Motivational styles	Adaptors versus innovators

This plethora of definitions and terms is due to the fact that there is also a large number of conceptual models, each accompanied by one or more psychometric instruments. For example, Coffield et al. (2004) identified seventy-one models of learning styles, which they classified into five families. Each of these families is briefly addressed next, as well as some of their most representative models.

Families and conceptual models of learning styles

It is important to underline that the families introduced in this section, represent a continuum, ranging from those that consider styles as a fixed trait, to those that consider them flexible and open to change. Additionally, each model proposes different learning styles with distinct measurement instruments. However, it is outside the scope of this paper to discuss these scales.

The first family considers learning styles as established traits at birth. However, the causes differ among the proponents of this family. For example, Dunn, Griggs, Olson, Beasley, & Gorman (1995) state that the causes are genetic or biological. While other proponents such as Gregorc establish that the cause is God (Coffield et al., 2004, p. 2). Models in this family include: the Dunn & Dunn (Dunn, 1990) model, the Gregorc (1984) model and the VAK / VAKT / VARK model (Carbo, 1984, Fleming, 2001, Smith & Call, 1999).

The second conceives styles as structural properties of the cognitive system, which are generalized habits of thought, that in turn form the enduring structural basis of behavior (Messick, 1994). This makes them very similar to the abilities (e.g., logical-mathematical reasoning and verbal reasoning) measured in standardized tests for university admissions (Alvarez-Montero, Mojardin-Heraldez, & Audelo-Lopez, 2014). An example of a model in this family is Riding's model of cognitive styles (Sadler-Smith & Riding, 1999).

The third family regards styles as aspects of personality. Consequently, the models in this family, claim that there is a strong relationship between personality and efficiency or performance. Three representatives of this family are the Myers-Briggs model (McCaulley, 1987), Apter's motivational style model (Apter, Mallows, & Williams, 1998) and Jackson's model (Jackson & Lawty-Jones, 1996).

The fourth family views styles as stable but flexible preferences that can be influenced by the experience of people and the demands of the environment (Kolb & Kolb, 2005). Therefore, it is possible that each learning situation forces people to choose a style, and that two learning situations are not dealt using the same style. Examples of models in this family are: Kolb's experiential learning model (Kolb & Kolb, 2012), the Honey & Mumford (2006) model and Herrmann's (1991) whole brain model.

The fifth family considers styles as learning strategies and orientations. It is closely related to achievement goal or goal orientation theory (Senko & Tropiano, 2016), as well as with self-regulation and metacognition (Panadero & Alonso-Tapia, 2014), since people initially address a learning task with a specific plan and orientation but may end up changing them according to the demands its demands (Coffield et al., 2004). Some models in this family are: Entwistle's model (Entwistle & McCune, 2004), Vermunt's model (Vermunt & Vermetten, 2004) and Sternberg's mental self-government model (Zhang & Sternberg, 2000).

Table 2 summarizes the 5 previous paragraphs and the next section addresses the architecture and functioning of the human brain.

Table 2

Learning styles families and some of their associated models

Styles as traits established at birth	**Styles as habits of thought**	**Styles as aspects of personality**	**Styles as flexible preferences**	**Styles as learning strategies**
Dunn and Dunn	Riding	Apter	Honey & Mumford	Entwistle
Gregorc		Jackson	Herrmann	Sternberg
VAK/VAKT/VARK		Myers-Briggs	Kolb	Vermunt

Architecture and Functioning of the Human Brain

The division or parceling of the human brain into several anatomically localized and functionally distinct areas (Bressler, 1995; Bressler & Menon, 2010; Friston, 2011), generally referred to as Brodmann's areas (see Figure 2), is well known. There are areas that control the understanding and production of natural language, hearing, vision, mobility, working memory and decision making (Geake, 2008, Zilles & Amunt, 2012). From this perspective several hypotheses were reached. First, that most neurons remain silent until they are needed for some activity, such as reading, at which point the brain activates and spends energy on the necessary signaling for the task (Raichle, 2010). Second, that the processing of information in the brain is done through the sequential or serial activation of neurons along a hierarchy of cortical areas or regions (Bressler, 1995). Third, innate mental faculties such as speech, only require the use of specific brain regions located in one of the two hemispheres (Knight, 2007).

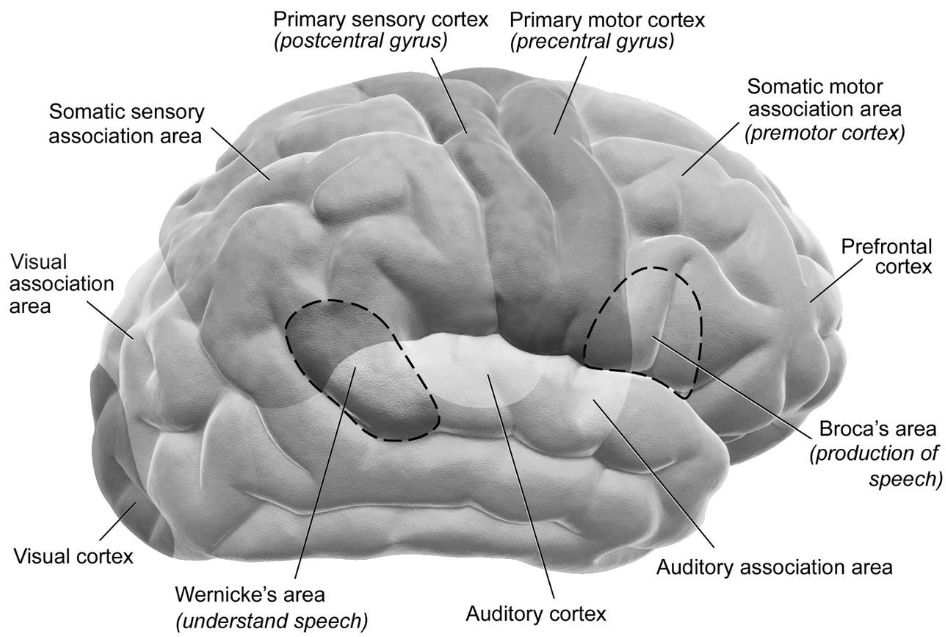

Figure 2. Brodmann's areas (Blausen.com staff, 2014).

However, the development over the last 25 years of non-invasive techniques for the analysis of the structure and functioning of the brain (Aine, 1995, Sakkalis, 2011, Sui, Adali, Yu, Chen., & Calhoun, 2012, van Straaten & Stam, 2013), has denied some of these notions and complemented others. Now, it is now known that the human brain uses 20% of the body's energy, although it only represents 2% of its mass, that it consumes more than twice as much glucose daily as the heart, that neuronal activity spends between 50% and 80% of that energy and that cognitively demanding tasks such as reading or solving problems, increase at most 5% that consumption (Buckner, Andrews-Hanna, & Schacter, 2008; Hasenstaub, Otte, Callaway, & Sejnowski, 2010; Magistretti & Allaman, 2015; Raichle, 2010).

In other words, a large part of brain activity (i.e., neurons talking to each other), is ongoing all the time. Furthermore, tasks such as learning, problem solving and reading, are only a small addition to this global activity. Therefore, unlike many electronic devices, the brain does not have an energy saving mode, and it is not possible to leave any area or region inactive without catastrophic consequences for people (Beyerstein, 2004). There are two reasons that justify this permanent global activity: the architecture of the brain and the functionality that it makes possible.

Architecturally, the brain is a complex network (Boccaletti, Latora, Moreno, Chavez, & Hwang, 2006), formed by nodes and connections between them that makes possible the sharing, processing and transportation of information. The brain network is structured in the following way (Bullmore & Sporns, 2009, Park & Friston, 2013, Sporns, 2013, Sporns & Swi, 2004): each node represents a set or clique of neurons and the nearby nodes are grouped forming communities or modules. The members of these communities have a high degree of interconnection or local integration (see Figure 3). This gives the modules much computing power and makes it possible for them to offer specialized information processing.

Nevertheless, this does not imply total connectivity between cortical areas, with direct accessibility from each area to any other. Cortical areas are not broadly interconnected (Bressler, 1995; Bressler & Menon, 2010). Since the nodes only show high levels of interconnection at the module level, communication between other modules and other areas in the brain is done through specialized nodes, called hubs, which exhibit a high level of interconnection among themselves (Van Den Heuvel & Sporns, 2011). Figure 3 shows a simplified version of this notion, with 4 modules in square boxes, and the hub nodes connecting at the center inside a circle.

Hub nodes play a central role in the efficiency level of the network, since they are responsible for maintaining the total distance of travel within the brain to a minimum (van Den Heuvel & Pol, 2010). Moreover, they distribute the workload of a module among other communities, reducing the possibility of a critical failure (Van Den Heuvel & Sporns, 2011). These hubs are organized in a network off their own (see Figure 4) that can be labeled as the Rich-club network (Van Den Heuvel & Sporns, 2011).

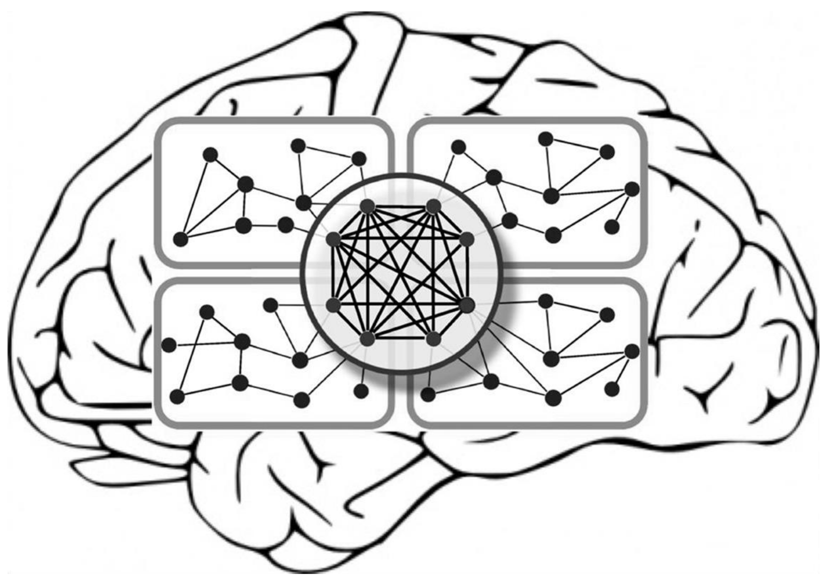

Figure 3. Neuron modules interconnected by hubs. From "Hierarchy and dynamics of neural networks," by M. Kaiser, C.C. Hilgetag, & R. Kötter, 2010, *Frontiers in neuroinformatics*, *4*, 112. Copyright © 2010 Kaiser, Hilgetag and Kötter.

Even when people are in a resting state, that is, when they are not performing cognitively demanding tasks such as learning, problem solving, reading or scrutinizing their environment, there is a brain network at work. This network is known as the Default Mode Network (DMN), which covers anatomically separated areas in the left outer and, in the right inner hemispheres (Buckner, Andrews-Hanna, and Schacter, 2008, Raichle, 2010, 2011). Figure 5 shows the brain areas that comprise the DMN.

According to Raichle (2010), it is speculated that the basic function of the DMN is the synchronization of all parts of the brain so that, like the runners in a track competition, they are all "in their marks", when the starter gun goes off. For example: "always have the motor system of the brain ready for when you feel the tickling of a fly on one arm". In addition, there is evidence that the DMN overlaps with the nodes of the Rich-club network (Van Den Heuvel & Sporns, 2011), and tells the executive control network to decrease its activity during creative cognition, the use of imagination, internal reflection, and while playing an instrument, (Beaty, Benedek, Silvia, & Schacter, 2016).

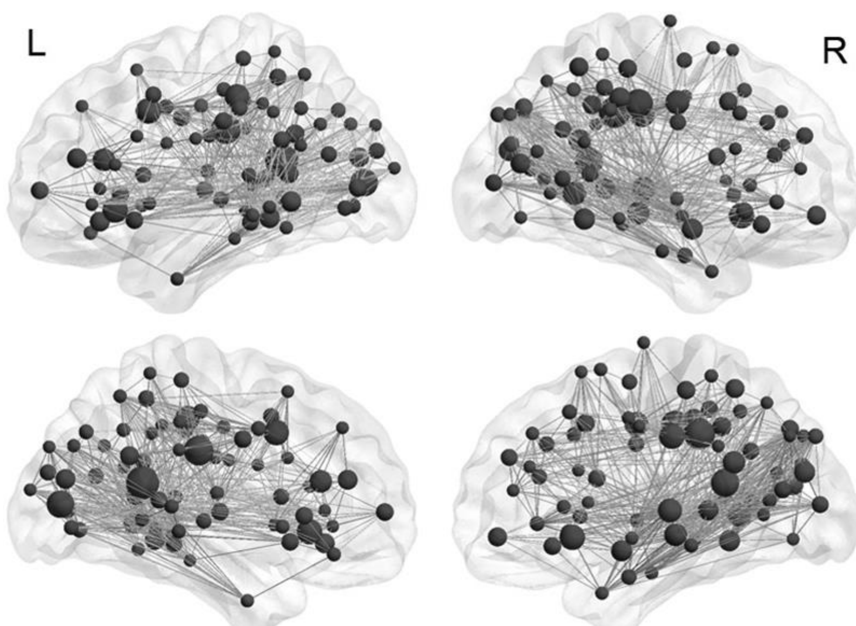

Figure 4. Rich-club nodes forming a distributed network on the left and right hemispheres. From “Hierarchy and dynamics of neural networks,” by N. Shun et al., 2018, *NeuroImage: Clinical*, *19*, 232-239. Copyright © 2018 Shun et al. & Elsevier Inc.

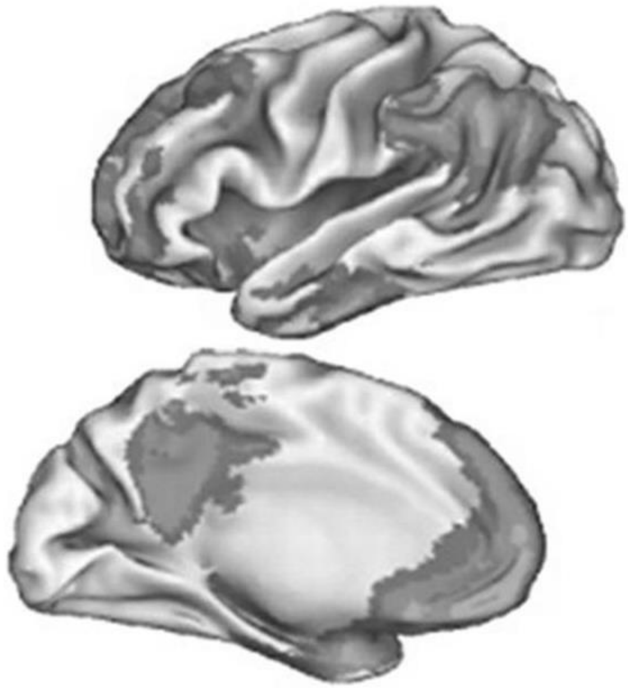

Figure 5. The DMN spread on different brain regions and hemispheres. From "Multimodal imaging of Alzheimer pathophysiology in the brain's default mode network," by J. Shin et al., 2018, *International Journal of Alzheimer's Disease*, *2011*. Copyright © 2011 Jonghan Shin et al.

Interaction between different networks in the brain makes it possible, for a network specialized in a specific type of information, to make use of or affect nodes belonging to networks that process information of another kind, and that are perhaps in different brain regions. This is necessary because the brain receives information through different channels, and only by combining it, in a process called multi-sensory integration (Murray et al., 2004; Pasqualotto, Dumitru, & Myachykov, 2016; Zangaladze, Epstein, Grafton, & Sathian, 1999), it is possible to obtain a robust representation of the environments and the body. Furthermore, although processing starts in a specific cortical region, it propagates like a wave through most of the cortical mantle (Luczak, McNaughton, & Harris, 2015), affecting high and low-level areas of the cortex (Murray, 2004).

In this regard, Zangaladze, Epstein, Grafton, & Sathian, (1999) reported that the visual cortex is involved in non-visual perception in blind humans and in the tactile discrimination of objects in non-blind individuals. Later, in a review of sensory integration studies, Kayser (2007) found that: a) certain regions of a superordinate auditory region (i.e., the secondary auditory cortex) also process visual and tactile stimuli; b) speech perception increases the activity of both the auditory and the visual system when acoustic and visual stimuli are perceived simultaneously; c) if the auditory cortex simultaneously receives auditory and tactile stimuli, its neurons fire more strongly than they would if auditory stimuli were received alone. More recently, Pasqualotto, Dumitru, & Myachykov (2016) provide evidence that when both visual and auditory input inform about the same danger, an appropriate motor response is more rapid and efficient.

Nonetheless, the neural activity described before is not sequential. This is done almost simultaneously, because the brain reacts at very high speeds. For example, it is known that speakers translate thoughts into words in 40 milliseconds (Van Turennout, Hagoort, & Brown, 1998), and that image processing can take as little as 13 milliseconds (Potter, Wyble, Hagmann, & McCourt, 2014). With very low response times, even neurons that are distributed in both hemispheres, such as the ones that process natural language (Friederici, 2011), can show temporally sustained and overlapping responses indicating parallel processing (Bressler, 1995).

Recent evidence, indicates that the topology of synaptic connectivity needed for the concurrent processing in sensory integration, is very complex. By applying algebraic topology (Rotman, 2013), to digital reconstructions of rat neocortical microcircuitry, Reimann et al. (2017) present evidence that this is done by building, then sweeping, a tower of multidimensional geometric structures starting with bars (1D), then tables (2D), next cubes (3D), and following with more complex structures that can have as many as eleven dimensions. Figure 6 shows a simplified version of this construction process.

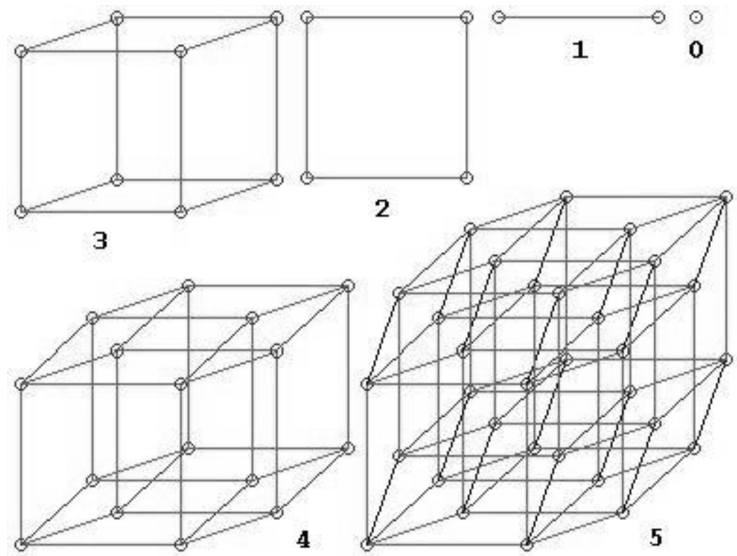

Figure 6. From simple to multidimensional geometric structures (Bednarik, 2018). CC BY-SA 3.0.

Therefore, the brain is not a network with a fixed topology. It can rewire itself, generate new synaptic connections where there were none and eliminate them if necessary (Le Bé & Markram, 2006), and there is evidence that this restructuring can be done at the tissue level too. Liu et al. (2018) report the results of a longitudinal case study, where a six-year-old boy had his occipital lobe and most of the temporal lobe removed through a lobectomy. These areas, situated in the right hemisphere, are necessary to process visual and auditory information. However, after the surgery the left hemisphere started to perform face recognition tasks, which are normally done on the right side, as well as its usual functions of word recognition.

In a recent study on the effects of literacy in the brain of illiterate adults, Skeide et al. (2017) found that learning to read involves the reorganization and synchronization of outer layer and inner layer brain structures. This effort creates new connections between the mesencephalon and the diencephalon, represented by the superior colliculus and the pulvinar nuclei respectively (see Figure 7), and the occipital cortex (i.e., the primary visual area of Figure 2). That is, reading involves the joint and synchronized use of the occipital cortex and the subcortical areas associated with oculomotor control and selective visuospatial attention, creating an interface between the visual and language areas.

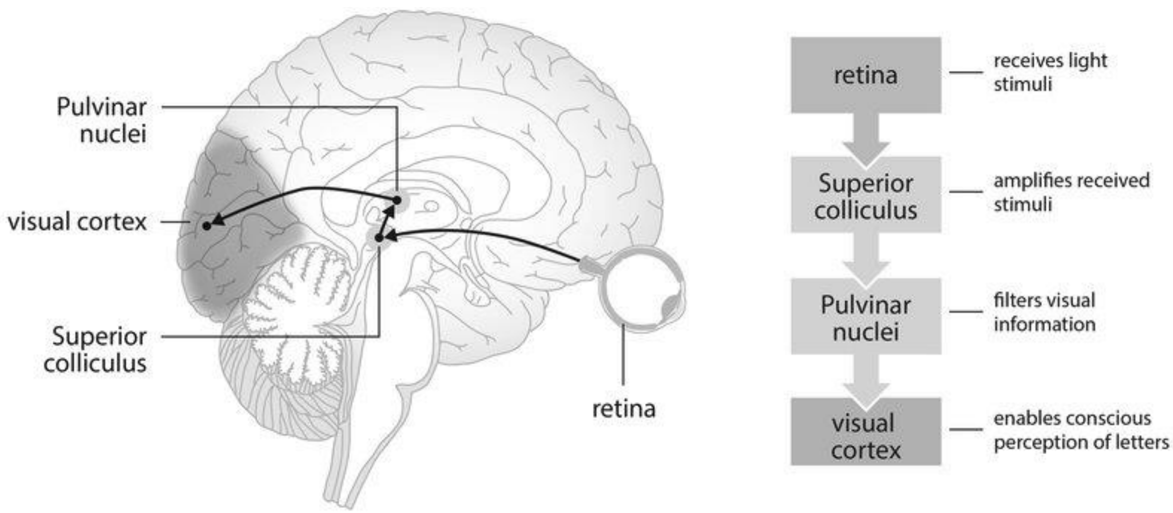

Figure 7. Written language processing path from the retina to the visual cortex. From "Amazingly flexible: Learning to read in your thirties profoundly transforms the brain" by MPI CBS (https://www.cbs.mpg.de/Amazingly-flexible-Learning-to-read-profoundly-transforms-the-brain). Reprinted with permission. Copyright ©MPI CBS.

A similar study to the previous one with dyslexic children, by Huber, Donnelly, Rokem, & Yeatman (2018), discovered that the teaching process changes the physical structure of the brain, indicated by a simultaneous growth of white matter, in areas related to language: the left arcuate and inferior longitudinal fasciculi which are white matter tracts. However, these changes are also observed in the corticospinal tract, that controls precise, voluntary movements. This indicates that the effects of learning, in terms of white matter increment, are not limited to those areas directly related to the skill that is intended to be taught. So much so, that studies with small mammals indicate that the same phenomenon may happen while learning new motor skills (McKenzie et al., 2014).

The next section discusses the evidence about the brain presented previously and compares it with the postulates of learning styles, and other popular but doubtful notions in the field of education.

Discussion

On the one hand, the case for learning styles is a difficult one. The most important point is that it is unknown what a learning style is. Definitions of the construct seem to include every psychological correlate of human success known to science, and some even pack physiological factors. Categorization attempts coincide with this fact, indicating that a style can be a God given feature, an ability, a personality trait and anything in between. This is potentially dangerous, as the overabundance of definitions, categories and instruments transform the construct into an open concept, and such concepts are pseudoscientific and immune to any refutation attempts (Lilienfeld et al., 2014).

On the other, the last 25 years of brain studies have shed a lot of light into the inner workings of the brain. It is known beyond reasonable doubt, that it is a complex network of almost constant metabolism, consisting of specialized modules and hub nodes, which are anatomically distributed. Nodes and modules form subnets operating at high speeds, which can interact with each other to process information concurrently, by activating neurons in regions anatomically distant from each other, generating topologies with a high level of geometric complexity. Additionally, although part of the brain's topology is biologically pre-established, it can adapt relatively quickly to new situations, creating synaptic connections between areas that were not originally linked, as well as incrementing the amount of white matter and rerouting information to other areas, when the original region in charge of processing the data, has been anatomically lost.

Based on the above, cognition as a phenomenon, can be see as the result from the dynamic interactions of distributed brain areas that operate in large-scale networks (Bressler, 1995, Bressler & Menon, 2010). Moreover, the long-held ideas that sense modalities such as vision, touch, audition and so on are processed separately, and that brain areas act as independent mechanisms for cognitive functions, is misleading (Bressler & Menon, 2010) and can no longer be regarded as true (Kayser, 2007), as only a small part of the brain is dedicated to individual functions or specific information processing.

These findings have severe consequences for the learning styles notion, as well as for other widespread ideas such as the left-brained and right-brain hypothesis, and the theory of multiple intelligences. The distributed nature of the brain functions denies the existence of left or right hemisphere thinkers. For instance, the modules responsible for natural language processing are distributed in the two sides of the brain. The evidence shows that for the moment, a person can become left or right brained, if and only if the area responsible for a specific cognitive function has been physically removed and if the person's brain is still in a developing stage. The way multisensory integration works refutes the multiple intelligences notion. If cognition is the product of a collectively distributed effort in the brain, and "intelligence" is a subcomponent or synonym of cognition, then it follows that the term "multiple intelligences" does not make sense. Some researchers such as Shearer & Karanian (2017) claim that there is robust evidence in neuroscience supporting the multiple intelligence theory. However, their conclusions are based on the old notion of brain modularity and, as Bressler & Menon (2010) underline: "Even the functions of primary sensory areas of the cerebral cortex, once thought to be pinnacles of modularity, are being redefined by recent evidence of cross-modal interaction" (277).

In the case of learning styles, the fact that stimuli received through two different senses increases neuron activity to the point of making neurons fire more strongly, and that information about the same object, provided through different senses, enables a quicker and more efficient response, renders the whole VAK/VAKT/VARK model of learning styles obsolete. In fact, any learning style model claiming to improve learning through a unisensory or single stimulus approach, would be misleading. Furthermore, the studies about teaching reading to illiterate adults and dyslexic children, show that the synaptic connections necessary for such task, do not exist previously in the brain. They are the product of effort and experience, which also involves a growth in the amount of white matter. Therefore, the claims of the family of learning styles which considers them as features established at birth, do not hold. It is not possible to have any learning preferences, when the physical elements that support it are initially non-existent. What the evidence about the functioning of the brain does support, are those theories that claim that people learn better when the material is presented, under certain conditions, using two presentation or sensory modalities, such as visual and auditive (Cuevas, 2016, Mayer, 2017).

Additionally, a recent study on personality types -clusters of personality traits or dimensions-, which used the results of 1.5 million participants from different inventories based on the Five Factor Model of personality (Gerlach, Farb, Revelle, Nunes Amaral, 2018) found that: (1) there is a considerable overlap between different clusters and (2) the distinction between meaningful and spurious clusters is blurred. In other words, people do not fit into clear-cut containers, and the differences between them are extremely hard to determine even with state-of-the-art methods.

Based on the above considerations, the answer to our first research question is, that the postulates of learning styles are not compatible with the architecture and the way the human brain works and process information. Unless that, as Waterhouse (2006) states, learning styles use brain mechanisms different from the ones described in this paper.

The second research question asked if learning styles are a proven, debatable, improbable or denied phenomenon. From the discussion on the functioning of the brain, it is clear that styles violate the connectivity principle. Most of the evidence indicates that teaching in the styles preferred by students does not improve academic performance. However, only 14 studies deny this hypothesis (Cuevas & Dawson, 2018, Moser and Zumbach, 2018, Pashler et al., 2008), 7 prove it (Cuevas & Dawson, 2018; Moser & Zumbach, 2018) and 6 are nonconforming (Moser & Zumbach, 2018). Therefore, the trend of the evidence on learning styles is negative but limited, and since the construct does not show connectivity, it can be classified as an improbable phenomenon. Consequently, the recommendation made by Coffield et al. (2004, p. 140), of not basing pedagogical interventions on learning styles remains valid.

Still, much remains to be done for learning styles to be debunked. The construct remains highly popular within and outside the scientific community. The amount of evidence refuting the matching hypothesis is still scarce, and some studies support it. Furthermore, the number of learning styles and the variety of psychometric instruments complicate any refutation attempts. Only collective and distributed efforts, such as the ones done recently for the replicability of findings in the behavioral and social sciences

(Camerer et al., 2018; Open Science Collaboration, 2015) could accomplish this task. Despite this, just as happened with the construct of social intelligence, the trend of the evidence indicates that research on learning styles will likely be long, frustrating and fruitless (Landy, 2014).

This paper closes with an advice made by Varazzani (2017) to behavioral researchers, that can also be applied to educational scientists: "…without a basic understanding of neuroscience, behavioral scientists open themselves up to being tricked by junk science peddlers. But armed with an understanding of the brain, behavioral scientists are not only robust against these threats but also are equipped with powerful new tools to design persistent solutions to sticky behavioral problems. To be a better behavioral scientist, it is no longer possible to ignore the brain.".

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