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

Francisco J. Álvarez-Montero, Hiram Reyes-Sosa, María G. Leyva-Cruz, Valente Fragoza-Padilla

Universidad Autónoma de Sinaloa

Author note

Correspondence concerning this article should be addressed to Francisco J. Alvarez-Montero, Facultad de Ciencias de la Educación, Universidad Autónoma de Sinaloa, Ave. Cedros y Calle Sauces s/n Fracc. Los Fresnos, C.P. 80034. Culiacán, Sinaloa, México.

Contact: francisco_alvarez_montero@uas.edu.mx
Abstract

Learning Styles (LS) are a very popular idea in Education and Psychology. However, most studies indicate that matching the instructional strategy to the students’ LS does not improve learning, and that their inventories do not have acceptable levels of reliability and validity. The research presented here compares the theoretical hypotheses of LS, with what is currently known about the architecture of the human brain, and the way it processes information to make sense of the environment and learn. Thus, providing new evidence on the subject that has not been previously discussed. The analysis shows that the brain is composed of a set of anatomically distributed networks, where there is a permanent cross-modal or multimodal interaction, between different types of specialized neuron modules and brain regions. Something which is not compatible with the notions of unimodality and fractional or partial modality, proposed by LS advocates. Furthermore, evidence on white matter plasticity and synaptic activity, point out that part of the physical infrastructure required to master a new ability, needs to be created on demand, contradicting the hypothesis that LS are innate learning preferences. Finally, although it can be said that there is some level of resemblance between LS and the brain, such an association cannot be easily made.

Keywords: learning styles, human brain, neuroscience, learning.
Introduction

Although one of the main goals of the research community in Education is the discovery of valid ideas supported by convincing evidence (Slavin, 2017; Waterhouse, 2006), in this area, differentiating between myth and reality has always been difficult (Bloom, 1972). As a result, the adoption of educational programs and practices has been based on ideological and political reasons, as well as by novelty and commercialization, rather than on sound scientific evidence (Harris, 2018; Kirschner & van Merriënboer, 2013; Slavin, 2008).

In this sense, 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 literature 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 papers, listed in the ERIC and PubMed research databases, which published between 2013 and 2015, detected that more than 85% of the literature starts and ends 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 almost 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 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 as part of the educational practice, is that learning improves if the teaching matches the students’ styles (i.e., the matching hypothesis). However, all the accumulated evidence so far, indicates that doing so has no impact on the students’ academic performance, knowledge acquisition, cognitive load or mental effort (An & Carr, 2017; Coffield, Moseley, Hall, & Ecclestone, 2004, Cuevas, 2015; Cuevas & Dawson, 2018; Höffler, Precht, & Nerdel, 2010, Husmann & O'Loughlin, 2019; 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 (Álvarez-Montero, Leyva-Cruz, Moreno-Alcaraz, 2018; Coffield et al., 2004; Curry, 1987).

Although Learning Styles have been broadly and deeply discussed in Psychometrics and Experimental Psychology, the debate from a neuroscientific perspective has been scarce and shallow in comparison (Dekker, Howard-Jones, & Jolles, 2012; Howard-Jones, 2014; Geake 2008; Goswani, 2006; Waterhouse, 2006). In this sense, this document presents a more in-depth analysis, of state-of-the art evidence, about the architecture and organization of the human brain, as well as the form in which it processes information, to answer the following research question: Do the neurological mechanisms, through which
the human brain performs its functions, give support or concur in coincide in some way, with the theoretical assumptions of learning styles?

The rest of this article is organized as follows. First, the premises, terminology and models of learning styles are introduced. Second, some the most recent data about the architecture and operation of the human brain is presented. Third, the assumptions on which the learning styles are based, are contrasted to what is known about the brain, and some conclusions are made.

**Learning styles: premises, terminology and models**

There are several reviews in the literature that address the subject of learning styles with different levels of depth (An & Carr, 2017; Cassidy, 2004, Coffield et al., 2004, De Bello, 1990, Ivie, 2009, Pashler et al., 2008). 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 literature reviews on the subject, 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, which reflect the most natural or comfortable way in which people perform an action (Bayne, 1995).

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, which produce a set of binary psychological types:
(1) extraverted sensors, (2) extraverted intuitives, (3) introverted sensors, (4) introverted intuitives, (5) extraverted thinkers, (6) extraverted feelers, (7) introverted thinkers, and (8) introverted feelers.

Jung's objectives, in developing his theory, were related to the self, the others and personal development (Bayne, 1995). 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.

Dembo and Howard (2007, p. 102), as well as Scott (2010, p.10), collected some of the arguments in favor of Learning Styles, and they coincide with the goals of Jung’s theory:

- Research has shown that students who understand their learning styles can improve their learning effectiveness in and outside of the classroom.
- 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.
- 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.
• 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.

Nevertheless, psychological types and Learning Styles differ in one essential point. Jung recognized that it would be impossible to reduce people down to pure types that fit neatly within a simple classification, as he was clear to point out (Beauchamp, Maclachlan, & Lothian, 2005): “one can never give a description of a type, no matter how complete, that would apply to more than one individual, despite the fact that in some ways it aptly characterizes thousands of others” (p. 204). The notion of learning styles, on the contrary, conceives them as mutually exclusive sets, and scoring procedures try to typecast individuals within a single style or category (Coffield, 2013; Kirschner, 2017; Kirschner & van Merriënboer, 2013; Newton & Miah, 2017).

Despite this, in practice, the same score or a very similar one, can be obtained for two or more dimensions of the instrument. This is a phenomenon observed in most psychometric inventories when the subscales share the same format (Cooper, Gonthier, Barch, & Braver, 2017). Learning Styles test developers have been aware of this for quite some time (Barbuto, 1997, McCrae & Costa, 1989, Pittenberg, 1993). Hence, recently, instead of forcibly placing people into just one container, if an individual has the same level of preference for more than one category, she is classified as bimodal, trimodal, quadrimodal, multimodal an so on (Chang-Tik, 2018; Husmann & O'Loughlin, 2019; Mitchell, James, & D’Amore, 2015). In other words, a person can exhibit unimodality (only one style), a fractional or partial modality (some but not all styles) or full modality (all styles), producing results such as the one shown in figure 1.
Furthermore, although Learning Styles in general, have the same theoretical basis, Jung’s psychological types theory or a derivative of it, the literature on the subject shows a high level of conceptual and terminological heterogeneity, as it will be seen next.

**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, 2017, p.1).

- Learning styles are individual characteristics that describe a person’s preferences in a learning environment (Kablan, 2016, p.277).
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).

Each definition has one of more term denoting it. Cassidy (2004), as well as Coffield et al. (2004) identified eleven of them. Moreover, the number of binary learning styles, direct descendants of Jung’s binary psychological types, is astonishingly large. A conservative calculation reported by Kirschner (2017), indicates that there could be as many as \(2^{31}\) binary learning styles. Table 1 shows some of the terms and binary styles that have been identified in the literature.

Table 1

<table>
<thead>
<tr>
<th>Terms</th>
<th>Binary styles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning strategy</td>
<td>Verbalizers versus Imagers</td>
</tr>
<tr>
<td>Learning orientation</td>
<td>Holists versus Serialists</td>
</tr>
<tr>
<td>Cognitive style</td>
<td>Deep Learning versus Surface Learning</td>
</tr>
<tr>
<td>Conative style</td>
<td>Activists versus Reflectors</td>
</tr>
<tr>
<td>Thinking styles</td>
<td>Pragmatists versus Theorists</td>
</tr>
<tr>
<td>Motivational styles</td>
<td>Adaptors versus Innovators</td>
</tr>
</tbody>
</table>

The number of learning styles models, each one accompanied by one or more measuring instruments, is also considerable. Coffield et al. (2004) identified seventy-one models, which they classified into five families, representing a continuum which ranges
from those that consider styles as fixed traits, to those that see them as flexible and open to change. Each of these families is briefly addressed next, as well as some of their most representative models.

**Learning styles families and models**

The first family considers learning styles as established traits at birth. However, the causes differ among the proponents of this family. For example, Dunn et al. (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 model (Dunn, 1990), Gregorc’s model (1984) and the VAK/VARK model (Carbo, 1984, Fleming, 2001, Smith & Call, 1999).

The second conceives styles as generalized habits of thought which form the enduring structural basis of behavior (Coffield et al., 2004; Messick, 1994). Something very similar to the concept of cognitive abilities (e.g., logical-mathematical reasoning and verbal reasoning) measured in standardized tests for university admissions. 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 personality traits. 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 the whole brain model developed by Herrmann (1991).

The fifth family considers styles as learning strategies and orientations. Models in this family are closely related to achievement goal theory (Senko & Tropiano, 2016), and self-regulation (Panadero, 2017), since people initially address a learning task with a specific plan and orientation, but may end up changing them according to the demands of the task (Coffield et al., 2004). Some of the 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 shows the learning styles families and some of the models in each family.

Table 2

Learning styles families and some of their associated models

<table>
<thead>
<tr>
<th>Fixed traits</th>
<th>Thought habits</th>
<th>Personality traits</th>
<th>Flexible preferences</th>
<th>Learning Strategies</th>
</tr>
</thead>
<tbody>
<tr>
<td>The Dunn &amp; Riding’s model</td>
<td>Apter’s model</td>
<td>Honey &amp; Entwistle’s model</td>
<td></td>
<td></td>
</tr>
<tr>
<td>The VAK/VARK model</td>
<td>Jackson’s model</td>
<td>Herrmann’s model</td>
<td>Sternberg’s model</td>
<td></td>
</tr>
<tr>
<td>Gregorc’s model</td>
<td>Myers-Briggs’ model</td>
<td>Kolb’s model</td>
<td>Vermunt’s model</td>
<td></td>
</tr>
</tbody>
</table>
As it can be appreciated, due to the conceptual heterogeneity regarding the Learning Styles, the research question posed at the introduction cannot be answered without asking additional questions, which are the following:

- Does the brain perform its functions using only one neurological mechanism, a subset of them or all of them at the same time? In other words, does the brain work using a fraction of all its potential or does it use all the resources at its disposal?

- Does the brain have a fixed or rigid neurological and physical structure or a flexible one which adapts dynamically to different situations?

The next section addresses these questions.

**The Human Brain**

The division 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 (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 information processing in the brain is done through the sequential or serial activation of neurons along a hierarchy of cortical areas or regions (Bressler, 1995). Third, that innate mental faculties such as speech, require the use of separate brain regions located in one of the two hemispheres, which act independently of each other (Knight, 2007).
However, the development over the last 25 years of non-invasive techniques for brain activity analysis (Aine, 1995, Sakkalis, 2011, Sui, Adali, Yu, Chen., & Calhoun, 2012, van Straaten & Stam, 2013), has refuted some of these notions and radically changed others. Now, it is known that although the brain represents only 2% of the body’s’ mass, it uses 20% of its energy, requiring twice the glucose amount of the heart, with neuron intercommunication consuming most of this energy at a stable rate, and increasing it at most 5%, while engaging in cognitively demanding tasks such as reading or solving problems (Buckner, Andrews-Hanna, & Schacter, 2008; Hasenstaub, Otte, Callaway, & Sejnowski, 2010; Magistretti & Allaman, 2015; Raichle, 2010). In other words, a large part of brain activity is ongoing all the time, and tasks such as learning, increase it only marginally, as depicted in figure 3.
Thus, unlike many electronic devices, the brain does not have an energy saving mode, and leaving any area or region inactive, or with less energy than others, could lead to brain dysfunction (Beyerstein, 2004). Such permanent global activity is explained by way the brain is organized, and the amount and type of information processing that it makes possible. These elements are described in the next two sections.

**Brain Architecture and Organization**

The brain is a complex network (Boccaletti, Latora, Moreno, Chavez, & Hwang, 2006), formed by nodes and connections through which information is transported, shared and processed. The brain network is structured in the following way (Bullmore & Sporns, 2009, Park & Friston, 2013, Sporns, 2013): 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. Such organization provides these modules with enough computing power to carry out 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

---

Figure 3. Brain activity “at rest” and during cognitively demanding tasks.
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 4 shows a simplified version of this notion, with 4 modules in square boxes, and the hub nodes connecting them, 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, 2013). These hubs are organized in an anatomically distributed network off their own (see Figure 5) that has been labeled as the Rich-club network.

Besides this network, there are three other ones which are involved in human cognition in general (Liang et al., 2015; Young et al., 2017): The Default Mode Network (DMN), the Executive Control Network (ECN) and the Salience Network (SN).

The DMN plays a critical role in synchronizing all parts of the brain so that, like racers in a track competition, they are all in the proper "set" mode when the starting gun goes off (Raichle, 2010). It is involved during creative cognition, internal reflection, and while playing an instrument, (Bashwiner, Wertz, Flores, & Jung, 2016; Loui, 2018; Meyer et al., 2019, Poerio et al., 2017), as well as in episodic and declarative or semantic memory retrieval (Kim, 2016, Wirth et al., 2011). Furthermore, there is evidence showing the DMN overlaps with the Rich-club network (van Den Heuvel & Sporns, 2011, 2013). The network
covers regions on both hemispheres which include (McCormick & Telzer, 2018): the medial prefrontal cortex (mPFC), the posterior cingulate cortex (PCC), the left superior frontal gyrus (lSFG), the right SFG (rSFG), the left hippocampus (lHIP), the right HIP (rHIP), the left angular gyrus (lAG) and the right AG (rAG). Figure 6 shows a simple anatomical description of the DMN.

Figure 6. Basic architecture of the DMN.

The ECN, as its names implies, is in charge of controlling and monitoring the so-called executive functions, which are a set of mental processes that make possible to manage working memory functions, as well as mentally play with ideas; take the time to think before acting; tackle novel, unanticipated challenges; resist temptations; switch between tasks, and stay focused during goal-oriented behavior (Diamond, 2013, Friedman & Miyake, 2017). Moreover, recent results point out that the ECN and the DMN, which often act antagonistically, interact with each other during creative activities such as musical improvisation, poetry production and idea generation (Benedek & Fink, 2019; Maillet, Beaty, Kucyi, & Schacter, 2019). The ECN is distributed along the brain encompassing
areas such as (Hermans, Henckens, Joëls, & Fernández, 2017): the mPFC, the left dorsolateral prefrontal cortex (lDLPC), the right DLPC (rDLPC), the left frontal eye field (lFEF), the right FEF (rFEF), the left dorsal posterior parietal cortex (lDPPC) and the right DPPC (rDPPC). Figure 7 depicts an overview of the ECN.

![Figure 7](image.png)

Figure 7. Basic structure of the ECN.

The SN monitors de salience of importance of external inputs and internal brain events, in order to mediate different degrees of cognitive control, which involves a multinetwork dynamic switching between the DMN and ECN (Koutstal, 2012). The SN could prompt the DMN, for example, to relax the level of cognitive control, introduce spontaneity, or signal de ECN to heighten the degree of attention and deliberate control (Koutstaal, & Binks, 2015). The SN is also anatomically distributed in regions covering (Hermans, Henckens, Joëls, & Fernández, 2017): the left anterior insula (lAI), the right AI (rAI), the dorsal anterior cingulate cortex (DACC), the thalamus (TH), the midbrain (MB),
the left temporoparietal junction (ITPC), the right TPC (rTPC), the left inferotemporal cortex (IITP), and the right ITP (rITP). Figure 8 presents an outline of the SN.

Figure 8. Basic composition of the SN

This kind of cooperation between different large-scale networks, provides the brain with great computing power, and enables it to process information fast and reliably. The mechanisms through which this is accomplished, are described in the next section.

**Information Processing and adaptation in the brain**

Through network interaction it is possible, for neuron modules specialized in a specific type of information, to make use of or affect nodes that process information of another kind, which can be situated in different brain regions. This is necessary because the brain receives information through different channels, and only by combining it, in a process called multisensory integration (Murray et al., 2004), it obtains a robust representation of the environment and of the human body itself.
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) the secondary auditory cortex also processes visual and tactile stimuli; b) speech perception increases the activity of both the auditory and 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, the corresponding motor response is faster and more efficient.

Neural activity for such tasks, propagates like a wave through most of the cortical mantle (Luczak, McNaughton, & Harris, 2015), affecting high and low-level areas of the brain (Murray, 2004). Nonetheless, this is done almost simultaneously, because information travels inside the brain, at very high speeds. 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), that is 0.013 seconds. With such low response times, even neuron modules that are distributed in different hemispheres, such as the ones that process natural language (Friederici, 2011), show temporally sustained and overlapping responses indicating parallel processing (Bressler, 1995).

However, the brain does not have fixed topology beyond the networks described previously. It can adapt to new situations, rewire itself and grow, to be able to perform a new and complex task efficiently. In a recent study on the effects of literacy in the brain of
illiterate adults, Skeide et al. (2017) found that learning to read, requires the joint and synchronized use of the visual cortex and the subcortical areas associated with oculomotor control and selective visuospatial attention (i.e., the pulvinar nuclei and the superior colliculus). This involves the creation of new synaptic connections which act as an interface, allowing people to process written language (see Figure 9).

Figure 9. 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 with dyslexic children, by Huber, Donnelly, Rokem, & Yeatman (2018), identified that reading instruction causes the growth of white matter in areas related to language (i.e., the left arcuate and inferior longitudinal fasciculi) and in those in charge of controlling precise and voluntary movements (i.e., the corticospinal tract). This shows that the effects of learning are not limited to the regions directly related to the skill to be learned. In addition, studies with humans and animal subjects indicate that even activities
outside the classroom, such as learning new motor skills, might have the same effect (Fields, 2015; Sampaio-Baptista & Johansen-Berg, 2017).

The next section discusses the evidence about the brain presented previously and compares it with the theoretical assumptions of learning styles.

**Discussion**

It is important to underline that the goal of this article was not to demonstrate how learning could be improved by taking advantage of the human brain architecture, the way it processes information, makes sense of it and tackles novel situations, but rather, to evaluate if the claims of learning styles had some sort of neurological basis, by contrasting them, with what is currently known about the brain. From the perspective of psychometrics and experimental psychology, there is enough evidence to classify learning styles as a myth. However, the literature lacked a neuroscientific analysis. In this sense, it turns out, the brain and learning styles, have very little in common.

The brain is always active, working at 100% of its capacity, and cognitively challenging tasks increase the intensity of its activity by only a small margin (5%). It is organized into a set of different networks, which dynamically interact with each other, to provide support for functions involving externally and internally oriented processes such as: reading, musical improvisation, creative thinking and poetry generation. When faced with new learning situations, it grows, by creating new synaptic connections, creating bridges between areas that were not originally linked, and increasing the amount of white matter. Furthermore, the evidence regarding (multi)sensory integration clearly indicates that, sense modalities such as vision, touch, audition and so on, are not handled separately. Brain areas do not act as independent mechanisms for cognitive functions, there is cross-modal interaction between them, and only a small part of the brain is dedicated to
individual operations or specific information processing (Bressler & Menon, 2010, Kayser, 2007).

Learning styles, on the contrary, try to reduce the human psyche to a single fixed unit that acts independently of other styles. The recently introduced notions of bimodality, trimodality, quadrimodality, etc., are closer to the way the brain works. However, the brain can only work in a fully multimodal form, by using in a parallel form, all the neurological mechanisms and resources at its disposal. Fractional multimodality, as contended by styles proponents, would imply the occurrence of one of the two following situations. Either, a decrease in synaptic activity and/or a loss of synapses or white matter, which could disrupt cognitive function, and indicate the presence of neurodevelopmental or neurodegenerative diseases such as autism, some epilepsies, Parkinson and Alzheimer (Fedorovich & Waseem, 2018; Filley & Fields, 2016). Or a reroute of all the brain’s resources, to selectively process information in a partial multimodal form. However, the evidence indicates that this second possibility does not take place, at least in healthy and sensory impaired individuals (Zangaladze, Epstein, Grafton, & Sathian, 1999).

With respect to the different Learning Styles families, the studies about reading instruction, with illiterate adults and dyslexic children, show that the synaptic connections and the necessary amount of white matter, which are required to process written language, are not present by default in the brain. They are the product of the effort and experience of a person, in a learning environment. This fact refutes the assertion of the first family of Learning Styles, and its associated models (e.g., the Dunn & Dunn model and the VAK/VARK model), which consider them as congenital elements. It is not possible to have innate learning preferences, when the physical elements required to support a learning task, are not completely present, and need to be created on demand. It remains to be proven if
this is a general phenomenon during learning. Nevertheless, all the evidence on white matter plasticity supports this assumption (Fields, 2015; Sampaio-Baptista & Johansen-Berg, 2017).

The third family considers styles as personality types based on Jung’s theory. Nevertheless, Jung’s ideas about personality have been, since long, abandoned in favor of empirically proven personality theories (Chamorro-Premuzic, Von Stumm & Furnham, 2015), whose links with the human brain have been proved (DeYoung et al., 2010). In this sense, Gerlach et al. (2018) used data from 1.5 million participants, that had answered different instruments based on the Five Factor Model (FFM) of personality, and although they claim to have identified four distinct personality types, they also acknowledge that: (1) there is considerable overlap between types; (2) the distinction between meaningful and spurious types is blurred. In other words, the four types are not mutually exclusive sets, and form a superset covering the four types, with most people concentrating around the central axis (see Figure 10). These findings concur with the neuroscientific evidence presented here, of a fully multimodal brain, and challenges the theoretical foundations of the third family of styles.

The second, fourth and fifth families show some level of compatibility with the architecture and functioning of the brain. Since the second family cannot be differentiated from cognitive abilities, measured by optimal performance tests (Coffield et al. 2004), it is related to the ECN, which oversees attentional control during goal-directed behavior. The last two families recognize that styles are flexible and can change depending on previous experiences and the context. This coincides with the way the brain deals with novel learning situations and adapts accordingly.
Nevertheless, it is important to underline that although there is some resemblance between Learning Styles and brain functioning, such relation is not present in their theoretical body. Unlike some modern instructional theories, that identify the cognitive structures and mental processes underlying learning (Sweller, 2016), which in turn can be associated to specific brain areas and networks, nothing is known or even hypothesized about the relation of learning styles with themselves, nor with any cognitive system and its related operations. As a psychological concept, regardless of the family or model, it remains undefined in this sense. It is also unclear, the connection of styles with other important psychological constructs, known to influence learning, such as motivation and self-efficacy, which are included, for instance, in theories of self-regulated learning (Panadero, 2017).

Summing up, the notions of unimodality and fractional modality, within Learning Styles, have no neurological basis whatsoever. Their theoretical body remains highly unspecified with respect to cognitive structures, processes and other psychological constructs. Additionally, as the case of personality types clearly points out, pigeonholing people into univocal bins, is a very complex and difficult task, even when the inventories
are theoretically and empirically sound, which was Jung's conclusion all along (Beauchamp, Maclachlan, & Lothian, 2005). Despite this, much remains to be done to debunk the notion of Learning Styles. The concept remains highly popular within and outside the scientific community, and there is a thriving industry supporting it (Cuevas & Dawson, 2018; Pashler et al., 2008), which has found in Learning Styles its goose of the golden eggs.

References


https://doi.org/10.1080/10790195.2007.10850200

http://dx.doi.org/10.1177/0956797610370159

https://doi.org/10.1146/annurev-psych-113011-143750

https://doi.org/10.1080/0748763900060303

https://doi.org/10.1080/00220671.1995.9941181

https://doi.org/10.1007/s10648-004-0003-0

https://doi.org/10.1515/revneuro-2017-0090


Gottfredson, L. S. (2009). Logical fallacies used to dismiss the evidence on intelligence testing. In R. P. Phelps (Ed.), *Correcting fallacies about educational and...*


Learning-to-read-profoundly-transforms-the-brain.


https://doi.org/10.1126/science.280.5363.572


