The Working Mind

Meaning and Mental Attention in Human Development

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7 Mental Attention, Intelligence, and Consciousness

We analyze the mental-attention (mental effort) mode of processing and summarize developmental data to illustrate its quantitative maturational growth (the *M*-measurement system). We discuss mental attention as a major constituent of intelligence, justifying the distinction between developmental intelligence (sensorimotor and/or symbolic) versus individual-difference (ordinary psychometric) intelligence. Consciousness may be a striking consequence of applying mental attention. Innate "hardware" mechanisms (maturational constraints, hidden operators, and principles) and various sorts of learning cause emergence of consciousness via *M*-processing and *LM* learning. Consciousness is a flow of dynamic representational syntheses that use schemes as units—driven by executives and *F-SOP* resources, which automatically combine into a "stream of consciousness."

> In general, *attention* is a *tending of the ego toward an intentional object,* toward the unity which "appears" continually in the change of the modes of givenness.
>
> —Husserl, 1973, p. 80

> Thought [a product of mental attention] is a relationship with oneself and with the world, as well as a relationship with the other; hence it is established in the three dimensions at the same time.
>
> —Merleau-Ponty, 1968, p. 145

> Separate causal factors operate through development to affect somewhat separately cognitive processes and produce individual differences.…Further evidence is needed to elucidate the nature of these factors.
>
> —Noll & Horn, 1998, p. 280

We discussed automatic attentional processes in the previous chapter, along with some organismic factors that in normal people may cause automatic behavior. Mental attention applies on schemes to control and enhance the working mind's stream of consciousness, the working mind's momentary internal complexity (i.e., the field of activated schemes in memory; Greenberg & Pascual-Leone, 1995, 2001). Mental attention enhances this dynamic internal complexity by increasing activation of some task-relevant schemes, coordinating them into objects of knowledge, procedures, adjunct information, or acts, and thereby creating spatial-temporal or verbal fields of consciousness or centrations (see epigraph by Husserl). This focal centration on schemes refers to outer or inner reality (see epigraph by Merleau-Ponty). Such intentional attention is characteristic of humans and other animals, as ethologists and behaviorists know well.

In the current psychological research literature, executive function (EF) refers to brain processes that (among other tasks) mobilize, control, and allocate mental attention. As Buss and Spencer (2014) define it, EF is both an active inhibitory function (related to our central attentional interrupt or *I*-operator) and a working memory function (related to but distinct from our activation-boosting *M*-operator); the two together highlight within mental centration task-relevant information. To these two constructs researchers add control processes (related to our executive schemes) that regulate allocation, re-allocation, and control of the two resources. Note that, in our Theory of Constructive Operators (TCO), executive control processes are (in contrast to *M, I,* and other resources) sets of more-or-less complex high-level operative schemes, which we call *executives* (or *E-operator*). The TCO and EF theories address some of the same control functions of organismic reality, yet they are two very different sorts of theory. They may complement one another, as the TCO and Cowan (2016) and Engle (2002, 2018) theories of working memory (WM) in fact do.

Unlike EF theory, the TCO provides a metasubjective analysis, that is, analysis of tasks' strategies studied from within the subject's own processing. This demands use of units of processing, the schemes, which explicate the vague but important notion of "information." For this reason, the "E" that stands for "executive" in EF theories should not be confused with our symbol *E*. Our *E* explicitly stands for a general executive function and, within situations, an activated *set of executive schemes* monitoring the psychological (brain-and-body) organism as a working functional totality. Also, our theory enables a method of task/process analysis using *constructive operators* (i.e., subjective operators—*schemes*—and hidden-resource *operators*) to clearly differentiate between automatic-perceptual attention versus effortful-mental attention. Such distinction is not clear in EF theories. Nor can EF theories analyze with clarity differences between the neo-Gestaltist field factor (our *F*-operator—lateral inhibition in the brain) versus automatic attentional inhibition—our automatic *I*-operator or attentional interruption. Note that we differentiate between automatic versus effortful attentional inhibition: the latter is part of mental attention.

Our model of mental attention encompasses operators *E*, *M*, *I*, and *F*, which can apply to boost activation of explicit semantic and action units, the schemes. Driven by *E*, however, any hidden operator could serve as a scheme booster. Hidden operators serve to control, adapt, or create schemes, allowing the TCO to quantify the individuals' capacity of mental attention, also assessing the tasks' mental demand (see chapters 8 and 9). EF theories cannot do so. Finally, theories of EF fail to explain how and why mental-attentional capacity increases in a graded manner until adolescence, even when such theories accept that effortful/endogenous attention is carried by genes and grows developmentally (e.g., Cowan, 2016; Cowan, Ricker, Clark, Hinrichs, & Glass, 2015; Hansell et al., 2015). EF theories need more clarity in explaining how this developmental growth affects intelligence and consciousness. Such issues can be clarified if our TCO approach is coordinated with current theories.

The significance of mental attention and its products (such as symbolic processing and problem solving) is apparent when we compare the intelligence of humans and other animals. Humans can confront reality/Reality in its complexity by going beyond immediate perception. But other animals are driven by appearances, proximal objects, or stimuli (e.g., Rock, 1983). As Zubiri, philosopher of the "*sentient intelligence*" (Zubiri, 1999), put it, "intelligence…is the capacity a man has to confront things as realities, not just as stimuli" (Zubiri, 1966/2001, p. 194, translation by JPL). By *realities* Zubiri meant what psychologists have called distal objects, that is, experiential as well as semiotic referents interpreted by learned schemas or complexes of coordinated schemes. These complexes emerge as functional invariants from practical activities. By *experiential* we mean *concretely real* and not conceptual, that is, what Husserl (1973) called "prepredicative" and Merleau-Ponty (1968) called "felt flesh" (embodied) experience.

Acquisition of complex distal objects (and their corresponding operative processes) occurs by coordinating schemes to extract functional invariants. This involves observation and learning of functionally related characteristic aspects (e.g., reliable features, cognitive distinctiveness) that express aspects of distal objects and related operative schemes. These organized collections of functionally necessary aspects make up what Zubiri (1999, 1966/2001) called the functional *essence* of experienced reality (in our view relative to agency and praxis). Complex realities (distal objects or distal processes) cannot be noticed or internalized until these essential (probabilistically invariant) data and interrelations are synthesized and internalized into functional totalities (organized schemes or schemas). To carry out this internalization a person usually must keep many aspects in mind simultaneously.

The minimal number of aspects needed to internalize a scheme, and the number of schemes required to solve a task, express their order of effective complexity. Such essential constructive complexity is estimated via task analysis (see chapters 8 and 9), which quantifies the tasks' mental-attentional *M*-demand. Intelligence (supported by mental attention and the already acquired knowledge schemes) is the discovery and internalization of *essential realities* of tasks (e.g., distal complex objects, distal processes), which is done by going beyond the mere stimuli or proximal objects (i.e., the information given) into the actual, manifest or hidden, processes of agency and praxis.

Going beyond the Information Given

In earlier chapters, we suggested how misleading factors affect complexity of a task (e.g., its executive and *M*- and *I*-demand). We emphasize the difference between "mere stimuli" and "realities" (distal objects, distal processes) by referring again to the wine and water problem (see chapter 6). In this problem, participants are asked to imagine two containers, C1 (with only water Wa) and C2 (with only wine Wi). A spoonful (S1) of wine from C2 is transferred to C1.Then a spoonful (S2) of liquid from C1 is transferred to C2. The question is whether now there is more wine in the water container (Wi[C1]) or more water in the wine container (Wa[C2]). As shown in chapter 6, a logical strategy for solving the problem, represented algebraically, is as follows:

$\underline{\mathrm{S} = \mathrm{S2} = \mathrm{S1}}$

$\underline{\mathrm{Wi[C1]}} == \underline{\mathrm{S1} - \mathrm{Wi[S2]}}$

$\underline{\mathrm{Wa[C2]}} == \underline{\mathrm{S2}\ -}\,\underline{-\mathrm{Wi[S2]}}$

$\Rightarrow$ Wi[C1]==Wa[C2]

The underlines demarcate separate constituent schemes. The markers (= and –) are repeated to emphasize separation of the six schemes. The three-line sequence prior to the arrow (➔) demarcates three sets of coordinated schemes, each set constituting a complex scheme, that is, S (scheme of the actual spoon), or Wi[C1], or Wa[C2]. Scheme Wi[C1] has two constituents (marked by underlines), whereas scheme Wa[C2] has three. This is because we assume that the subject's synthesis of Wi[C1] took place earlier, and its constituents are now partly chunked.

A "mere stimulus" level of analysis is to consider S2 to be a spoonful transfer of liquid from C1 to C2 and think that because S1 carried only wine but S2 carried both wine and water, there is more wine in C1 (Wi[C1]) than water in C2 (Wa[C2]). This view ignores the relational complexity of the broader situation. The deeper "reality" is that S2 contains both wine (Wi[S2]) and water (Wa[S2]) and that Wa[S2] (the water carried back to C2) has the same liquid amount as the wine left behind in C1 (because the water in S2 is precisely equal to the wine not being returned in S2); thus Wi[C1] = Wa[C2].

The arrow in the algebraic representation stands for the principle Schemes' Overdetermination of Performance *(SOP)*.

Thus, six essential distinct schemes (shown in the algebraic task analysis) must be attended to in order to solve the problem, making this task not accessible before early adolescence (Pascual-Leone, 1970; Pascual-Leone & Johnson, 2005). This sort of task-analytical model predicts age-bound, developmental substages described by Piaget and Case (Case, 1998; Pascual-Leone, Johnson, & Agostino, 2010). Such substages (levels of *M*-capacity) are basically invariant across very diverse populations and across types of tasks, suggesting that mental attention is a maturational capacity. Cowan and others have indeed concluded, with their own experiments, that this construct (which they call WM) is maturational (Cowan, 2016; Cowan et al., 2015; Hansell et al., 2015). Let us examine some evidence from developmental simulation and neuroscience suggesting the need for independent (some maturational) mental attentional or WM brain processes.

Need for an Independent Scheme-Activation Boosting Function in Humans

Associative learning, unless aided by an independent mental attention (a *separate* activation-boosting function), cannot explain emergence or growth of cognitive processes. Early research on neural networks, when properly interpreted, showed such limitation (Elman, 1993; Mars, Sallet, Rushworth, & Yeung, 2011; Munakata & Stedron, 2001). Elman's neural modeling of working memory suggested that WM (from our perspective, mental-attention activation), in interaction with associative learning mechanisms, is essential to cope with misleading aspects ("noise") in language learning (Elman, 1993; Elman et al., 1996). He attempted to design a network that could learn by itself grammatical properties of English sentences, using sentences of various lengths or degrees of complexity. This network had to predict what word would come next at each point in a sentence. Sample sentences included "Boy chases dog," "Mary walks," "Boy who dogs chase feeds cat," and "Girl who chases dogs hits cats." The network failed to learn the task (could not learn positional constraints that regulate sequencing of words indexing grammatical categories).

Notice that long sentences in this task should initially be misleading, because they induce grammatically invalid associative-sequence links between words (or within the learning program's hidden-units space), and so do not help to abstract basic grammatical rules. To see why long sentences are misleading, consider the meaning of a sentence such as, "Boy who dogs chase feeds cat." Its meaning is clarified by analyzing the sentence using informal operator-logic, based on our method of task analysis. The words *boy, cat,* and *dogs* stand for *objects* (*figurative schemes* symbolized by lowercase words plus a postfixed asterisk *). *Feeds* and *chase* are *procedures or operatives* (symbolized by capitals) that we place to the left of the objects on which they apply. Finally, we symbolize *adjunct information* relative to a particular object or procedure by affixing to the object this information enclosed in square brackets (i.e., [...]). In the sentence just given the relative clause (i.e., "who dogs chase") is adjunct information about the boy, which we can represent as boy*[...]. Using this notation, we informally represent the experiential meaning of the sentence as follows:

"Boy who dogs chase feeds cat" →
FEEDS(boy*[*WHO*: CHASE(dogs*,boy*)], cat*) **(f1)**

In this formula, *WHO*: stands for the pronoun *who* referring to the belief-expectancy that this boy was/is chased by dogs. The first term (or logical argument) of the operatives FEED and CHASE stands for the subject of the action, and the second term stands for the object. The corresponding verbal sentence is before the arrow (→). A comparison of the sentence and its meaning-formula shows that the sentence is misleading because it fails to make explicit the sort of scheme (operative, figurative, expectancy) each word stands for and does not give the hierarchical level of words in the sentence—explicit in our formula. The more a word is nested within parentheses or brackets, the more concrete or lower it is in the flexible hierarchy. All this is, of course, given in the grammatical structure, which is only implicit and was not trained into the learning-program network.

When the network failed to learn the task after its exposure to sentences of varying complexity, Elman proceeded to grade the input. First, he presented very short sentences, and when the network had learned to cope with them, he progressively introduced more complex ones. This allowed the network to learn the task, responding correctly to the whole set. Elman reasoned that this solution, by initially simplifying the input, may mimic nature (children's ontogenetic development), which initially endows the child with a small WM capacity. A small WM capacity should allow the child to receive and process only short sentences. In this manner, children initially would be constrained to learn simple inputs (much less misleading, because their word order relates to grammatical categories). After this level of language competence had been acquired (and the child's WM capacity had grown with maturation), longer sentences could be processed.

To simulate and test this idea, Elman added a WM parameter to the network. "Young" developing networks were able to read patterns in the sentence only over three or four contiguous words, because their WM was erased (units in the network's memory were reset to random values) at that point. As the network "aged" and acquired more experience, the number of words that could be retained within WM was progressively increased. This was in contrast to the initial “old” network, in which WM (number of context units) had no limit. Both types of network (“young” and “old”) were exposed to sentences of varying complexity from the beginning of training. Elman found that only the developing “young” networks, with WM that started small and increased progressively, were able to master all sentences. The reason for the failure of “old” networks should be apparent by looking at formula **f1**. The “old” network attempted to extract invariant sequence patterns of words across sentences of any length, but complex sentences, because they contain implicit nesting of simpler sentences, mislead any learning process based in abstracting invariant ordinal relations between or across words.

Elman et al. (1996) discussed neural network experiments by Shrager and Johnson (1996) and by Rebotier and Elman (1996). These experiments independently reinforce conclusions drawn from Elman’s earlier research. They show that *abstract logical structures* (i.e., complex relational structures defining various possible categories of relations between two input sources such as A and B) could not emerge in the network (**N**) unless two conditions were met.[1] (**N1**) Input to the network units (or to the neurons in the brain) must enter the network in a suitably organized fashion, in the sense that (relative to this input) the total population of units (neurons) must be organized in a nested hierarchy of areas. In this way, input first arrives at the first-level areas of units (i.e., semantically most concrete). It is then transmitted to the second-level areas, then to the third-level, and so forth (each progressively more abstract). The input activation is always transmitted along with the processing that earlier areas in the hierarchy have produced. (**N2**) To enable learning of complex relational invariants based on input sources A and B, units (neurons) must have been primed by means of at least one source of unit activation that is *independent* from both the input source and the associative-learning network of units in question. Shrager and Johnson called this independent priming source of activation a “trophic factor” that arrives in waves. Elman et al. (1996) referred to it as “a neurotrophic dynamic (whether produced by a natural wave of trophic factor or by some other endogenous or exogenous phenomenon)” (p. 140).

Well before this neural-network experimental demonstration of the need for a neurotrophic dynamic factor, and even before the concept of working memory had been introduced in the literature, we had recognized in our cognitive-developmental theory the need for such a factor (Pascual-Leone, 1969, 1970, 1987, 1995, 1996b, 2000b; Pascual-Leone & Johnson, 1991, 1999, 2017; Pascual-Leone & Smith, 1969). We call this neurotrophic dynamic factor(s) mental or effortful attention, and the *M*-operator is fundamental here. We define *M* as a developmentally growing endogenous mental-attentional capacity that can simultaneously boost activation of a limited number of schemes. This number (i.e., the power of *M*-capacity) increases with chronological age and serves as bootstrap for enabling transitions to new developmental stages (Piagetian or neo-Piagetian), provided enough learning opportunities are available. Misleading situations mark occasions when subjects cannot solve the task unless they effortfully use their *M*-capacity, if the task's mental (*M*-) demand is not greater than the subjects' available *M*-power. This is the reason why stable stages of development are reliably found only in misleading situations (Pascual-Leone, 1987, 1996b). Misleading situations are always relative to the person's repertoire of prior knowledge (and his or her *F-SOP* factor [see table 7.1] that induces misleadingness in the current situation).

Essential Function of Mental Attention and Its Plausible Evolutionary Emergence

With the theory of schemes alone, one cannot explain *general* organismic constraints (those applying across all kinds of schemes or situations) like "central" WM capacity limits, "central" inhibitory mechanisms, structural versus content learning, "central" (executive driven) resolutions of scheme competition in the network, nor emergence of truly novel performances via unplanned dynamic syntheses. We discussed in the previous chapter general organismic ("central") processes that intervene to cause automatic attention. We now discuss in more detail processes that intervene to produce mental attention.

It is often believed that prefrontal lobes control task-relevant processes elsewhere in the cortex (e.g., posterior areas) that are not automatic and whose performance must be synthesized. Prefrontal lobes are the brain's control area, indexing mental attention (including executive schemes). However, their control power is limited. Ruchkin, Grafman, Cameron, and Berndt (2003) expressed this idea with the metaphor of a restricted number of attentional "pointers." A better formulation consists in assuming that the brain, in addition to a *repertoire of schemes* (neural circuits and networks that carry "information"), possesses the set of general-purpose functional resources we call *hidden* or silent *operators* (Pascual-Leone, 1987, 1995; Pascual-Leone & Johnson, 1991, 2005, 2011, 2017; Pascual-Leone, Johnson, Baskind, Dworsky, & Severtston, 2000). These hidden operators would be produced by the brain's maturation of certain anatomical structures and of local functioning patterns in neuronal connections with special neurotransmitters (e.g., dopamine). We call each of these functional neuroanatomical utilities operators (**OP**) for two reasons. (**OP1**) They are functional mechanisms of brain "hardware" that actively operate on schemes (e.g., boost, inhibit, functionally coordinate, and create them). (**OP2**) They are defined as molar procedures whose computational and anatomical details are left unspecified (being defined only by releasing conditions and their effects on schemes and performance). Psychologically speaking, the brain operators apply on schemes to constrain them to synthesize truly novel performances, or be inhibited, or change and produce new schemes, and so on. These operators are *hidden* because they lack explicit content-specific markers in performance and experience, markers that schemes clearly have (such as perceptual, motor, representational, and other aspects of experience). Instead, these organismic operators express purely relational functional constraints of the brain, which cause surprising patterns or "anomalies" (exhibited under specific empirical circumstances) that a pure theory of schemes alone cannot explain (such as general-developmental cognitive stages, holistic/Gestaltist effects, or even automatic or associative versus effortful learning).

Operators express and formulate (as explicit functional constructs within a psychological theory) key organismic constraints (specific regulations) that the brain's cortical architecture imposes on psychological processes and behavior. Table 7.1 summarizes eleven hidden operators that we currently consider. These eleven (often compound) categories of hidden operators are ordered in table 7.1 according to their likely evolutionary emergence, as we critically speculate.

As this table shows, operators intervening in automatic attention, discussed in the previous chapter, appear first in the phylogenetic ladder. The first two operators to appear should be *A* (pure *affect*—appetitive or aversive dispositions and their biological regulations) and *C* (*content* learning and substantive-content schemes); most animals would have these two, intertwined or distinct. The third operator to appear phylogenetically may be *F*. As mentioned before, this is the tendency of the brain to effortlessly integrate performances following a simplicity (mini-max *F*) rule, which (in conjunction with *SOP* principle) causes the active schemes to overdetermine a minimal-complexity (mental or overt) performance. The right-hand column of this table gives, for humans, some regions of the brain from which the operators in question may primordially come. Next, in our evolutionary ladder, we find strong associative learning, that is, our *LC* (*logical-content*, or content-based structural) learning, possibly available in birds and mammals (see also chapters 5 and 6).

Then, at least in mammals, the *S*-operator (causing effortless relations-of-coexistence—such as *spatial* relations) and the *T*-operator (causing effortless *temporal/fluent* sequences) appear. These two operators, very important for automatic attention, expand considerably the power of associative (*LC*) learning. This *S*-and-*T* expansion may potentiate coordinations of affect (*A*-operator) with associative learning to enable frequent emergence of affective-and-cognitive, psychosocial, sociocultural schemes. We call the complex affective-learning psychosocial processes the *B*-operator to emphasize that these

Table 7.1
TCO's hidden operators listed in order of their likely evolutionary emergence

Operator	Description	Main Brain Region
A	Set of **affective** processes that intervene in motivation and attentive arousal.	Brainstem, hypothalamus, extended amygdala, limbic system
C	Both the process of **content** learning and the schemes derived from associative content learning.	Thalamus; Brodmann primary and secondary areas
F *(SOP)*	The **field** operator, which acts as a binding mechanism in the brain and brings closure to mental representations in a neo-Gestaltist manner. It often functions intertwined with the principle of Schemes' Overdetermination of Performance (SOP)	All areas
LC	The process of automatized **logical-structural** learning derived from ***C*-learning** through overpractice	Right hemisphere (RH)
T	**Temporarily** and effortlessly collates **sequences** of figurative schemes, thus facilitating the coordination that constitutes distal objects	Hippocampal complex, occipito-temporal cortex
S	Effortlessly coordinates relations of coexistence among activated schemes, during operative activity (praxis). It, thereby, facilitates emergence of **spatial** schemes or schemas	Hippocampal complex, occipito-parietal cortex
LA, B, LB	**Psychosocial and self-schemas** (*B*). **Logical-structural** learning primed by strong **affects** *(LA)*, or by the personal **being** preferences—including emotions (*LB*).	Limbic system, orbito- and medial prefrontal, inferotemporal, medial parietal cortex
I	The attentional **interrupt**, which corresponds to the power of central active inhibition of unwanted schemes activated in the situation.	Prefrontal, RH-medial cortex, dorsolateral cortex, basal ganglia, thalamus
M	**Mental** attentional capacity of the individual.	Prefrontal, lateral, and dorsolateral cortex; basal ganglia; thalamus
LM	**Logical-structural learning** caused by the effortful use of **mental** attentional capacity	Left hemisphere tertiary areas, polymodal
E	**Executive** schemes in the person's repertoire, for the task at hand	Prefrontal, lateral, dorsolateral, and frontopolar areas

Adapted from Pascual-Leone, J., & Johnson, J. (2005). A dialectical constructivist view of developmental intelligence. In O. Wilhelm & R. W. Engle (Eds.), *Handbook of understanding and measuring intelligence* (p. 181). Sage. Copyright 2005 by Sage.

processes (which possibly have innate/instinctual roots) causally determine the social being of animals.

An unwelcome consequence of this increasing power of associative learning, however, is that it becomes progressively harder for animals to control overlearned habits and automatisms (both attentional and action automatisms) when they are unsuitable for the task at hand. To reduce unwanted consequences of such overlearned functional "armour" of habits, evolution has endowed high mammals with the power of a "central" attentional inhibition or *interruption* (*I*-operator—Pascual-Leone 1984; Howard, Johnson, & Pascual-Leone, 2014) to enable fast and flexible inhibition of habits (i.e., overlearned automatized schemes). Inhibition alone is not enough, however. To boost low-activated but task-relevant schemes, otherwise suppressed by stronger task-irrelevant schemes, evolution had to create a mental *scheme-activation booster* controlled by affective processes and executives. This is the *M-capacity* operator (Pascual-Leone, 1970; Pascual-Leone & Johnson, 2005, 2011), a key maturational component of working memory that, in our view, tacitly underlies Cowan's (2016), Engle's (2002, 2018), Case's (1998), Halford et al.'s (Halford, Wilson, Andrews, & Phillips, 2014), and Demetriou's (Demetriou & Spanoudis, 2018) concepts of working memory.

Because the neurotrophic resource *M*-capacity appears empirically with a developmental stagewise pattern of growth, in normal children it *relates the highest task complexity* a child can handle *to his or her chronological age*. This is most noticeable when the child first solves a problem without specialized training. As we parametrically increase the number of aspects (essential notes) to be entertained simultaneously for coping with a task, the age of children capable of passing this task increases predictably. This pattern indexes endogenous growth of *M*-capacity in an age-bound manner till adolescence (e.g., Case, 1998; Johnson, Fabian, & Pascual-Leone, 1989; Pascual-Leone, 1970, 1987; Pascual-Leone & Baillargeon, 1994).

Our data and theoretical analyses indicate that *M*-capacity already is manifest in human infants during the second month of age, driven/activated by affect (*A*-operator) and motivation. This maturational graded-growth of *M* limits relational complexity of sensorimotor tasks a child can cope with (see chapter 3). At about 18 months, with a *sensorimotor* (*Me*) *M*-capacity of five, babies are capable of subjective consciousness. This is Damasio's (2012) core consciousness, which allows the child to pass the mirror test of self-recognition (to notice in the mirror a red mark on his or her own face—Gallup's [1982] test). This test is also passed by other animals high in the evolutionary ladder (e.g., primates, dolphins, and perhaps also elephants or parrots). According to our task analysis (chapter 3), this test demands from the subject a capacity to keep in mind simultaneously no fewer than five sensorimotor schemes (Pascual-Leone, 2000a, 2006). At about 26 months the child can simultaneously attend mentally to six sensorimotor schemes. Finally, at 35 months of age (3 years) children can simultaneously activate seven sensorimotor schemes, which enables truly mental symbolic processing (mentation with symbols of symbols). Mental-attentional complexity in primates' problem-solving behavior (in chimpanzees, bonobos, gorillas, and orangutans) suggests that they can match the capacity of 26-month-old humans, and at times that of 35-month-olds (Pascual-Leone, 2006). Beyond this age, humans appear to be alone across species in their developmental growth of mental (*M*-) capacity, which keeps growing after 3 years up to the ages of 15 or 16 years in healthy people. Note that the *M*-capacity growth in infants up to 3 years (sensorimotor *M* or *Me* capacity) is graded in a much smaller amounts than for older children (with symbolic *M* or *Mk* capacity), as explained in detail in chapter 3.

As table 7.1 shows, *LM*- and *E*-operators follow on the emergence of the *M*-operator. The compound operator *LM* emerges when *M*-capacity is used to synthesize new performances, leading to effortful (*M*-driven) logical-structural learning, which we call *LM* learning. *LM* learning in turn becomes automatized into *LCLM* complex schemes, which no longer need *M*-capacity to be activated (this is a complex operational *chunk* of information). Such power to form complex logical-relational *LM*-schemes permits creation of operative/procedural schemes that stand for generic plans, controls, and task organizers. These are *executive* schemes. We call *E-operator*—"the executive"—the set of highly activated and relevant executive schemes in a given task or situation. Executive schemes are essential to plan analytically into the future, something that also requires use of the other hidden operators. Finally, when affect (*A*) and cognitive learning processes (*C, L, LC, T, S, I, M, LM, E*) become coordinated in the psychosocial and social-group domains (*LA, LB*), they produce *personal/emotion schemes*, whose repertoire we call *B*-operator (a complex affective-and-cognitive, existential, and social schemes' coordination, with human being affect-related beliefs and biases—the individual person schemas). These *B*-schemes, more or less complex hybrid (affective and cognitive) schemas, are learned during psychosocial, or self-existential and sociocultural experiences.

Figure 1.1 complements table 7.1, showing symbolically that the hidden operators can influence performance by regulating activation or bringing change to the schemes of the person. In fact, figure 1.1 symbolically stands for what we call the metasubject (the brain's "psychological organism" as represented in a gist manner by our theory, the TCO). This metasubject includes as a functional part an operative self (William James' I-self) with its conative (unconscious self-agency) propensities and its conscious Will that may drive decision making. So defined, the metasubject is functionally close to what Demetriou (Demetriou & Spanoudis, 2018) called *cognizance*—the partly conscious self-agency and intentional control processes of the subject.

Model of Endogenous Mental Attention

Mental attention (<*E, M, I, F*>, as explained below) is endogenous, active, effortful, voluntary, executive attention. Often called working memory, this is better seen as a key aspect of the working mind. *M* (power or capacity) is an operator constituent of mental attention, which stands for the limited "mental energy" or "cortical activation tone" of task-relevant processes in the cortex if the person is vigilant. In some sense, Janet (1889), James (1892/1961), Spearman (1927), Freud (Rapaport, 1960), Luria (1973), and many others have had intuitions of this endogenous, limited-energy resource that we call *M*. We call this form of attention *mental*, and not executive attention, as it is often called, for three reasons mentioned in previous chapters. (1) Mental attention can be recognized in children after 2 months of age (see chapter 3), but executive schemes cannot be found until after 12 months. (2) It is mobilized/driven not just by executives but also by affective and emotional schemes. (3) It is used to boost activation of all sorts of schemes, not just executives.

Mental attention can join forces with automatic attention within facilitating situations, as in "flow" situations mentioned in chapter 6. In misleading situations, however, mental attention is in competition with automatic attention. Misleading situations induce strong, prepotent responses (strongly activated by often unconscious shadow schemes) contradicting what the person wants to do. Salient cues exist in such situations that lead to error, and these dynamic error-factor schemes cannot be ignored, because they are intertwined with task-relevant cues or schemes. Examples of such misleading contexts can be found shopping in supermarkets or pharmacies. Products often are placed inside excessively large packaging to create the illusion of containing more product; this is a misleading factor when appraising the relative cost.

By their very nature, problem-solving tasks involve misleading situations (as the wine and water problem illustrates). The need to suppress misleading schemes (i.e., unwanted activated neural circuits) forces use of mental attention to inhibit the "bad" schemes and concurrently boost task-relevant ones. Mental capacity is estimated by the number of separate task-essential schemes that can be activated simultaneously by mental attention to solve a task: we call such measure *mental (M-) power*. *M*-power increases with age up to adolescence. This growth of *M*-power enables transition across developmental stages (Pascual-Leone, 1970; Pascual-Leone & Johnson, 2005, 2011; Pascual-Leone et al., 2010).

We symbolize mental attention (often abbreviated as *Matt*) as a *searchlight model*, constituted by a dynamic system of four brain operators in coordination: Matt=<*E, M, I, F*>, key operators that we described before. The *field factor F* (related to lateral inhibition in layer 4 of the cortex; e.g., Edelman, 1987; see chapters 10 and 11) and the inhibition factor *I* help to produce closure in performance by inhibiting schemes that are outside the "beam of attention" and not relevant.

The beam of attention is symbolized in figure 7.1. Operators *E, M,* and *I* are expressed in the prefrontal lobe, and their coordinated application to action schemes produces the *M-centration* (mental centration). This is the inner ellipse. Notice that in figure 7.1 we call H the repertoire of habitual, well-learned schemes (part of long-term memory) found within *M*-centration and call H′ the set of schemes in long-term memory but outside *M*-centration. The outer ellipse symbolizes the field of more or less activated schemes (*field of activation*) in the repertoire or long-term memory. The middle ellipse symbolizes the field of all hyperactivated schemes, which corresponds to the full attention (i.e., working memory). When hyperactivation of schemes is done exclusively with *M*-capacity, these *M*-centrated schemes constitute the *M-centration* or *focus of attention,* different from, but included into, full attention or working memory. Some schemes in full attentional centration may be hyperactivated by factors other than *M*-capacity boosting. Their high activation may be caused by associative content learning (*C*), logical-content learning (*LC*), effortful logical-structural learning (*LM*; notice that *LM*-schemes are effortful because, unlike *LC,* they still require use of *M*-boosting to fully apply), perceptual salience (*F*, *C*), affect (*A*), and so forth. Task-irrelevant hyperactivated schemes from outside *M*-centration tend to be automatically (perhaps also effortfully, I_e) interrupted/inhibited to some degree with each new act of *M*-centration (Howard et al., 2014; Im-Bolter, Johnson, Ling, & Pascual-Leone, 2015; Morra, 2000; Romero Escobar, 2006). This is a distinct variant of attentional inhibition (*I*), the automatic inhibition/interruption (I_{au}), different from effortful inhibition (I_e).

Note that we equate working memory or full attention with the field of hyperactivation (i.e., middle ellipse) which includes schemes being boosted by *M*-capacity (*M*-centration—inner ellipse) as well as schemes boosted instead by other organismic factors (e.g., hidden operators *C, LC, A, F*). In the case of misleading situations, highly activated misleading schemes are in full attention (working memory) and so executive processes (*E*-operator) must inhibit (*I*-operator) them to cope with the task. As a result, hyperactivated schemes placed outside *M*-centration should become inhibited, eliminating the middle ellipse and reducing full attention to *M*-centration (i.e., the inner ellipse; Pascual-Leone, 1984; Pascual-Leone & Johnson, 2005). This account of misleading situations is consistent with Engle, Tuholski, Laughlin, and Conway (1999),

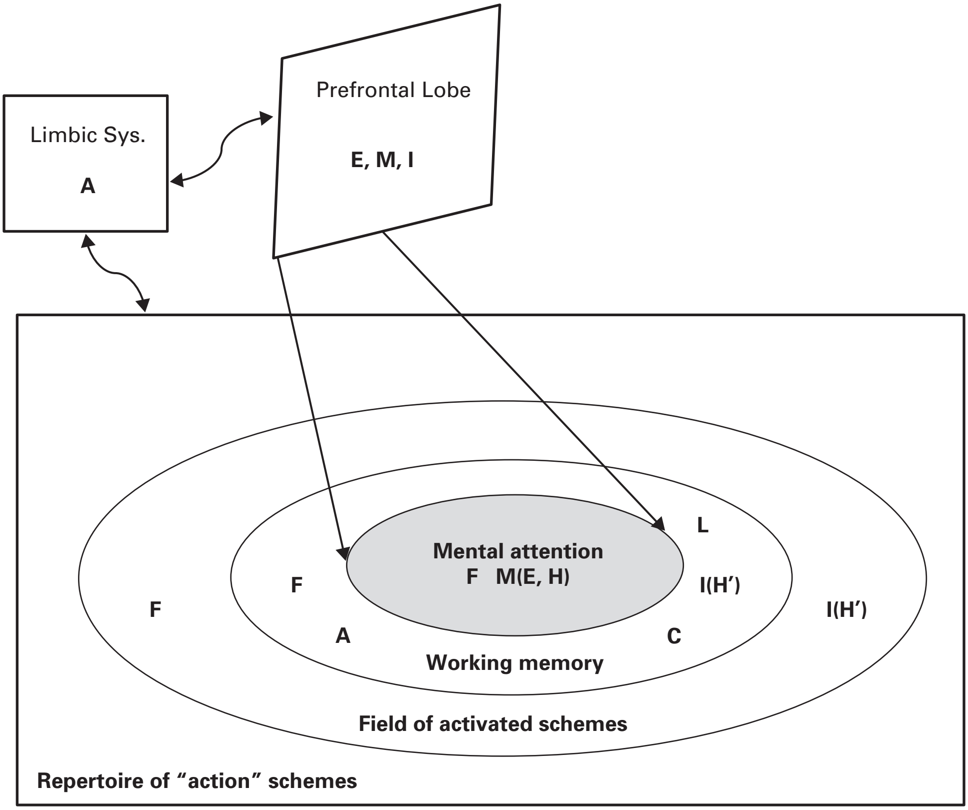

Figure 7.1
The TCO model of endogenous mental attention. (Adapted from Pascual-Leone, J., & Baillargeon, R. [1994]. Developmental measurement of mental attention. *International Journal of Behavioral Development, 17*[1], 169. Copyright 1994 by the International Society for the Study of Behavioral Development.)

among others. This is in part why misleading situations make better tasks for estimating *M*-demand via task analysis (Pascual-Leone et al., 2000). Notice that in our general theory (TCO), and in the model of figure 7.1, Matt is driven by the metasubject, which includes high-level personal schemes and developmentally evolving operative-self schemes (*self.1, self2.1, self2.2, self2.3, self2.4, self2.5, self2.6, self2.7*—see chapter 3).

Maturational Growth of *M*-Capacity in Humans

Mental attention increases during normal child development from early months of life to adolescence. This increment indexes the *power* of *M-capacity* (*Mp*), or maximum number of distinct schemes that can be boosted by *M* within an *M*-centration. Every maturationally achieved *M*-capacity level enables transition from one constructive-developmental stage to the next, if necessary learning has already taken place (Johnson et al., 1989; Pascual-Leone, 1970, 1987, 2000a; Pascual-Leone & Baillargeon, 1994; Pascual-Leone & Johnson, 1999, 2005; Pascual-Leone et al., 2000).

Table 3.1 gives Piaget's substages of cognitive-development during the sensorimotor period from birth to 35 months, along with the associated sensorimotor *Me*-stages; we do not discuss it further. Table 7.2 shows Piaget's substages of cognitive development from three years of age onward, with corresponding expected *M*-capacity values available for the *Mk*-scale (i.e., mental-symbolic processing). The parameter e (from the scale *Me*; see chapter 3) is the maximum *M*-capacity found during the sensorimotor period, that is, number of sensorimotor schemes that normal 26-month-olds can simultaneously boost with mental attention. This max-*Me* capacity functions during symbolic mental processing as a parameter or constant e ($M = e + k$). In the symbolic-processing years (up to and beyond adolescence) this amount e serves, we believe, to activate task-relevant *executive* schemes. In contrast, the value k expresses the progressively growing number of symbolic/action schemes that can be boosted by *M* during elementary school and high school years. At the end of this developmental *M*-growth, in late adolescence, the value of k can be as much as seven—the "magical" number seven of George Miller (1956).

Our task analyses and considerable data that cannot be reviewed here support this causal model (e.g., Arsalidou & Im-Bolter, 2017; Arsalidou, Pascual-Leone, & Johnson, 2010; Burtis, 1982; Johnson et al., 1989; Morra, 2000; Pascual-Leone & Baillargeon, 1994; Pascual-Leone & Johnson, 2005, 2011, 2017; Pascual-Leone et al., 2010). Participants

Table 7.2
Predicted *M*-capacity values as a function of age and their correspondence to Piagetian substage sequence

M-capacity ($e+k$)	Piagetian substage	Normative chronological age
$e+1$	Low preoperations	3–4 years
$e+2$	High preoperations	5–6 years
$e+3$	Low concrete operations	7–8 years
$e+4$	High concrete operations	9–10 years
$e+5$	Transition to formal operations	11–12 years
$e+6$	Low formal operations	13–14 years
$e+7$	High formal operations	15 years to adult

often do not mobilize all the *M*-capacity they have available (Pascual-Leone, 1970; Pascual-Leone & Johnson, 2011). There is a lower bound or *functional M*-capacity often used by subjects, which is equal to four or five *k*-units in adults, and there is an upper bound or *M-reserve* (the structural *M*-capacity, Pascual-Leone, 1970), which is their max-*Mk*. This *M*-reserve is often used only under very high mental activation. It is equal to seven in adolescents (15 to 16 years) and adults, decreasing in old age (Arsalidou & Im-Bolter, 2017; Arsalidou et al., 2010; Arsalidou, Pascual-Leone, Johnson, Morris, & Taylor, 2013; Jedrzkiewicz, 1983; Pascual-Leone, 1970, 1983). Our estimates come from many tasks and much data, some of which we briefly summarize below. These estimates of *Mk* are probabilistic, idealized averages or estimates for normal children, which can be modified by causal variables such as alertness, vigilance, fatigue, state of health, and so on.

M, whose behavioral measure is *M*-power, is a hidden construct, hidden because one must vary conjointly participants' expected *M*-power and the tasks' *M*-demand to obtain measured estimates of the participants' *M*-capacity (i.e., *Mp*) or the tasks' *M*-demand (*Md*). This is a purely relational invariant found in the data. The need to conjointly vary the two estimated organismic variables, *M*-power and *M*-demand, suggests that *M*, as empirical construct, exhibits what Bohm (1980) called an "implicate order." In our case, this is a complex, purely relational system of constraints (i.e., resistances to the subject from the task, aspects to be considered concurrently) binding together brain processing complexity and task complexity. *M* is the sort of latent variable that Bohm and many others call a *hidden variable*. This key characteristic appears in *M* as a purely relational invariant expressing trade-off between participants' *Mp* and tasks' *Md* (items are passed only when *Mp* is equal to or greater than *Md*). We have repeatedly tested empirically this *Mp*/*Md trade-off* and its relationship to participants' cognitive style (e.g., Arsalidou et al., 2010; Arsalidou, Pawliw-Levac, Sadeghi, & Pascual-Leone, 2018; Raymond Baillargeon, Pascual-Leone, & Roncadin, 1998; Pascual-Leone, 1970, 1978, 1989; Pascual-Leone & Baillargeon, 1994; Pascual-Leone & Johnson, 2011). Tasks assessing *Mp*/*Md* trade-off tend to show increase in performance level at the ages when *M*-operator capacity increases developmentally in normal children, that is, with Piaget's substages and Case's stages.

Staircase Model: Another Comparison of *M*-Capacity Levels with Developmental Stages

Piaget knew that an organismic general process, different from learning, was at work in cognitive development. He ambiguously called this general process "regulations" (Pascual-Leone, 2012a; see chapter 1). He also knew that a growing mobility and scope of decentration (flexibly changing the content/schemes within mental centration—focusing and re-focusing on different chosen schemes) were a major indicator of cognitive growth. This is what we now call executive-function factors such as updating, shifting, and so on. For Piaget, regulations were the cognitive processes that cause mental decentration. Reflective abstraction was his unexplicated mechanism of emergence, via constructivist learning, of schemes/schemas characteristic in developmental stages (i.e., sensorimotor, preoperational, concrete operational, formal operational) and substages within them (Piaget, 1975/1985).

Figure 7.2 (Pascual-Leone & Johnson, 2005; Pascual-Leone et al., 2010) presents the *staircase model* of stages put forward by Robbie Case (1985, 1992, 1998), modified by us to demonstrate correspondence between Piaget's substages (Case's stages) and *M*-operator levels. The initiative to change the causal significance from Piaget's developmental stages to his substages was taken first by Pascual-Leone, after inferring that

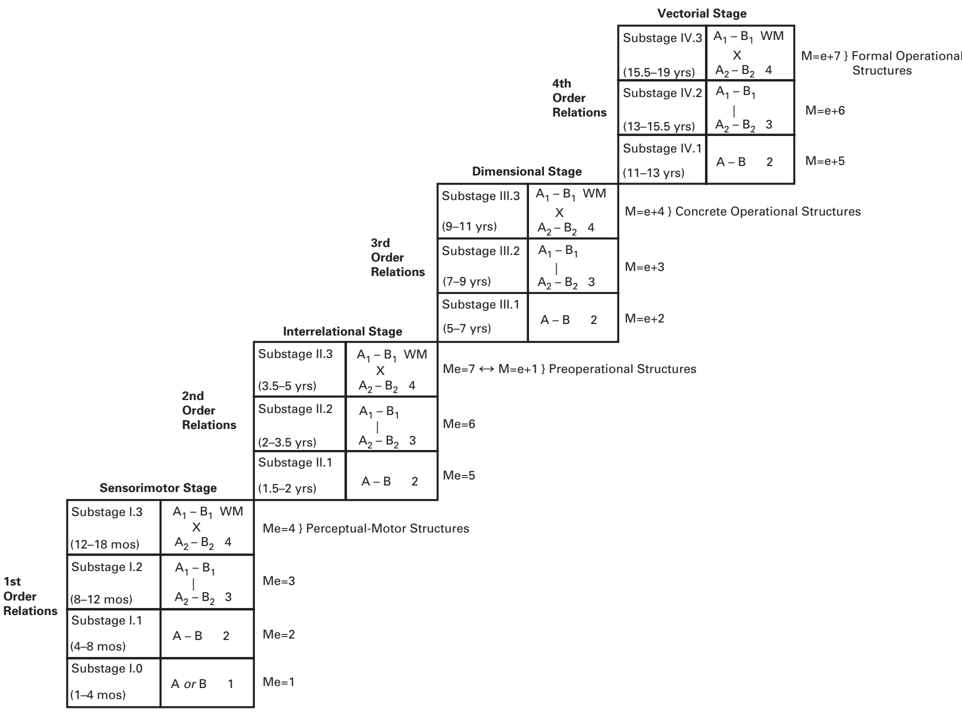

Figure 7.2

Case's staircase model of developmental stages integrated with the TCO model of *M*-capacity growth. (From Pascual-Leone, J., & Johnson, J. [2005]. A dialectical constructivist view of developmental intelligence. In O. Wilhelm & R. W. Engle [Eds.], *Handbook of understanding and measuring intelligence* [p. 184]. Sage. Copyright 2005 by Sage.)

mental-attentional capacity (the *M*-operator) was a determinant of stages. He did this empirically, via task analyses of Piaget and others' data (Pascual-Leone, 1969, 1970; Pascual-Leone & Smith, 1969; Stewart & Pascual-Leone, 1992).

In the neo-Piagetian staircase model (see figure 7.2), substages are given along with the empirically confirmed estimates of *M*-capacity (on the right side of the staircase blocks). Notice that in our view stable stages appear only within misleading situations: only these situations clearly exhibit *M*-demand constraints (because few facilitating schemes are available). Because familiarity or practice may transform (via learning) misleading situations into facilitating ones, any developmental stage could in principle be changed, with practice, in its local expression. That is, maturational development and learning maintain with each other a dialectical relation of complementarity: both are jointly needed, but each tends to obscure the clear manifestation of the other (which may justify the use of cross-sectional research in investigating developmental stages).

Children grow cognitively by moving from one developmental stage to another: from sensorimotor to pre-operational (Case's interrelational), to concrete-operational (Case's dimensional), and formal-operational (Case's vectorial). As they pass through these stages, they shift their focus of interest from one level of thinking/mentation to the next, although these levels are complementary and cumulative. As they do, children's concern moves from the here-and-now present (this is sensorial perception/action, sensorimotor); to the present inferred via some analysis, synthesis, and interpretation (this is intelligent perception/action, preoperations); to the empirically inferred future (this is intellection/action, concrete operations); to the possible future, inferred not from experience but from rational analysis of noncontradictory possibilities (this is intellectual processing or reason, formal operations). In table 5.3 we named these levels of "phenomenological" processing, giving the corresponding developmental stages and basic brain areas.

Within each Piagetian stage there are substages, each of which uses as bootstraps the maturational growth of mental attention, our Matt system of hidden operators. In it, at least constituents *M* and *I* grow maturationally in a concurrent manner with age, up to adolescence. This growth impacts on a child's ability to learn. A mental-processing *M*-unit is a quantum of *M*-capacity needed to maximally activate ("hyperactivate") learned, but not automatized, schemes.

As discussed in chapter 3, it is reasonable to assume that units of *M*-capacity are acquired cumulatively with maturation, possibly developing at a constant rate (so that time taken to acquire a given amount could be used as an indirect estimate of this amount). Initially, during the first two years of life, transition from one *M*-level to the next occurs about every four (first year) or eight months (second year). However, stage transitions after 3 years of age occur only every twenty-four months. This change in rate of stage transition suggests that sensorimotor *M*-units (the *Me* scale) may be about three to six times smaller than the symbolic *M*-units (Mk scale). Thus, sensorimotor (*Me*-) units and symbolic (*Mk*-) units cannot be combined or interchanged, because the mental (*k*) units are much larger.

We assess *M*-units behaviorally by counting, within suitably misleading tasks, the maximum number of distinct schemes that *M* would have to boost simultaneously to solve the task; thus, the need for task analysis "from within" (e.g., Pascual-Leone, 1970, 2013; Pascual-Leone & Baillargeon, 1994; Pascual-Leone et al., 2012; Pascual-Leone & Johnson, 1991, 1999, 2005, 2011, 2017; Pascual-Leone et al., 2010). In figure 7.2, we follow Case's (1992) model to indicate for each Piagetian stage (I, II, III, IV) and substage (0, 1, 2, 3) the average age at which the substage in question normally occurs. We symbolize, using repeatedly the letters A and B with a developmentally changing concrete meaning, the emergence of different sorts of integrative functional structures (schemes or schemas) at the end of each stage. This succession illustrates graphically reflective abstraction (Piaget, 1975/1985)—the levels of abstraction that Karmiloff-Smith tacitly adapted within cognitive science under the name of *representational redescription* model (Elman et al., 1996; Karmiloff-Smith, 1992). Such renaming is misleading, however. It ignores that these levels are found equally well (as Piaget asserted, e.g., Piaget & Garcia, 1983) in operative procedures and in figurative representations, when proper task analyses are done.

The theory-estimated complexity (*M*-demand) of tasks or items, and the person's quantitative levels of *M*-capacity (which *M*-power, *Mp,* assesses) are general constructs, in principle applicable across all content-domains (based on organismic processing assumptions). This is in line with both Vygotsky's concept of internalization (R. Miller, 2011; Kozulin, 1990) and with a decentralized, situated construal of Piaget's reflective abstraction process (Pascual-Leone, 1995, 1996b; Pascual-Leone et al., 2012; Pascual-Leone & Johnson, 1999, 2011; Piaget, 1975/1985). Content (*C*) learning and relational or logical-structural (*L*) learning are epistemically reflective because they internalize experiential/ecological resistances to agency/praxis that the person has encountered. Both forms of learning express the contingencies or "causal texture" of the actual environment (Pascual-Leone & Irwin, 1998; Pascual-Leone & Johnson, 2005, 2011; Tolman & Brunswik, 1935).

Developmental data supporting our claims on mental attention were presented among others by Pascual-Leone (1970, 1978, 1987, 1995, 1996b, 2000a, 2000b); Pascual-Leone and Sparkman (1980); Pascual-Leone and Johnson (2005, 2011); Pascual-Leone et al. (2010); Johnson et al. (1989); Arsalidou et al. (2013), and more. Complementary data and discussions of this mental-attention model, in particular about *M*- and *I*-resources, appear in Arsalidou et al. (2010); Howard et al. (2014); Im-Bolter, Johnson, and Pascual-Leone (2006); Johnson, Im-Bolter, and Pascual-Leone (2003); Pascual-Leone and Baillargeon (1994); Pascual-Leone and Goodman (1979); Pascual-Leone and Morra (1991). Chapters of this book, in particular chapters 3, 8, and 9, give task analyses illustrating how mental-attentional demand of tasks can be estimated across content domains. Morra, Gobbo, Marini, and Sheese (2008) and Troadec and Martinot (2003) each offer a chapter with good overviews of our *M*-theory and TCO.

Is *M*-Capacity a Maturational General Resource of Developmental Intelligence?

Data supporting the construct validity of *M* as a measure of developmental intelligence are many. We will limit ourselves in this section to summarize three types of evidence.

1 Relationship between *M*-Task Performance and Standardized Ability Score

The discussion that follows is adapted from Pascual-Leone and Johnson (2017). Pascual-Leone, Johnson, and Calvo (2004; Calvo, 2004) sought to demonstrate the general and content-free characteristics of mental-attentional capacity, by treating it as a constructivist-developmental measure causally related to Gf (fluid intelligence, the functional core of *g*, which may have as key organismic causal determinant a developmental growth of *M* and *I*). We studied 1,148 grade-four children (9 to 10 years old), from twenty-one Toronto-area schools. Children completed the figural intersections task (FIT) measure of *M*-capacity (Arsalidou & Im-Bolter, 2017; Pascual-Leone & Baillargeon, 1994; Pascual-Leone & Johnson, 2005, 2011). FIT items ask one to find the area of intersection of a variable number of geometric shapes (from two to eight). The *M*-capacity estimate is the maximum number of shapes the child can reliably intersect in his or her item responses, theoretically interpreted as maximal number of task-relevant schemes a subject can hold in mind together while solving items (FIT *M*k-score). The percentile scores on the school-administered *Canadian Cognitive Abilities Test* (*CCAT,* 1998)—a standardized measure of cognitive ability with verbal, nonverbal, and quantitative subscales—were available for 1,052 of the children. Average FIT score for the sample was 3.92 ($SD = 1.34$), matching the theoretical prediction that 9- to 10-year-olds have an *M*-capacity of four symbolic schemes simultaneously coordinated (Pascual-Leone, 1970; Pascual-Leone & Johnson, 2005). Mean percentile score on CCAT ($M = 54.96$, $SD = 26.22$) was as expected from age norms.

FIT correlated strongly with total CCAT score, $r(1050) = .59$, $p < .0001$. We also computed mean test scores for each of the twenty-one schools and ran correlations on the school means. Again FIT was highly related to CCAT, $r(19) = .73$, $p < .01$. We partialed out the percentage of ESL (English as second language) students at each school and average family income of the census tracts (neighborhoods) where the schools were located (obtained from 2001 Census of Canada data). FIT remained strongly associated with CCAT, partial $r(17) = .74$, $p < .01$. We can infer that variance due to *M* is strong and likely distinct from the variance as a result of sociocultural learning/experience.

To examine more closely the pattern of covariation between FIT and CCAT, we grouped participants in terms of deciles in CCAT percentile score and computed the mean FIT and CCAT score for children falling into each CCAT decile group. Figure 7.3 shows the covariation of mean FIT and CCAT. Up to the 81st to 90th percentile group, mean FIT score increases linearly with CCAT score. However, in the highest percentile group (91 to 100), mean FIT score abruptly increases, breaking the linear pattern. Within age, linear growth of FIT scores with the CCAT percentiles is likely to be due to constructivist learning: children's available *M* and growth in sociocultural experience and school learning, moderated by individual differences in *M*-capacity. However, the spurt in FIT scores after the 90th percentile is unlikely to be due to sociocultural and

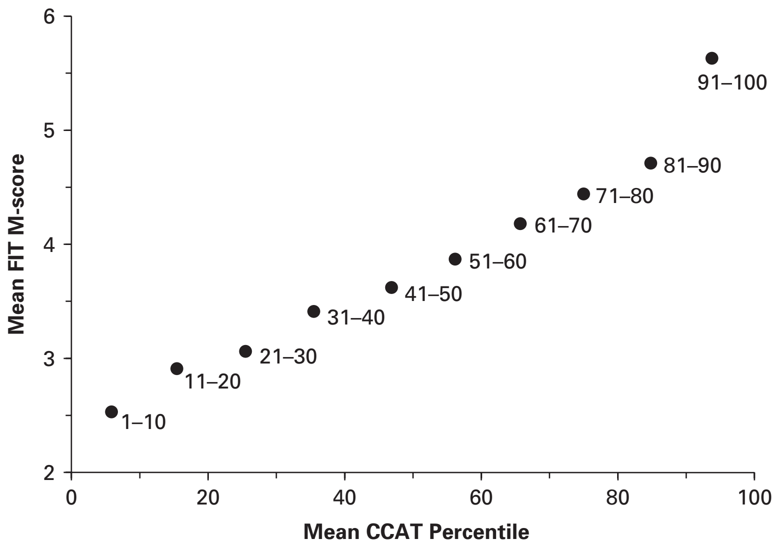

Figure 7.3
Pascual-Leone et al. (2004) sample divided into ten groups according to CCAT percentile score (1–10, 11–20, etc.). For each group, mean CCAT is plotted against mean FIT *M*-score. (From Pascual-Leone, J., & Johnson, J. [2017]. Organismic-causal models "from within" clarify developmental change and stages. In N. Budwig, E. Turiel, & P. Zelazo [Eds.], *New perspectives on human development* [p. 77]. Cambridge University Press. Copyright 2017 by Cambridge University Press.)

school learning or experience, because it does not follow the age-bound linear growth characteristic of learning factors. Performance at the highest level in general ability is likely to express mostly a higher maturational *M*-capacity for children in the last CCAT percentile, perhaps a sign of true cognitive giftedness.

There is a way to appraise whether the variance boosting FIT score in the 91st to 100th CCAT-percentile corresponds mostly to sociocultural learning versus maturational *M*-capacity. Because the average 9-to-10-year-old has (in our well-supported developmental model) an *M*-capacity that can coordinate easily no more than four symbolic schemes, FIT items with more than five figures should be hard for this sample. Success on hard items may rely on learned perceptual strategies, such as guessing that the correct response is likely to fall in an area with high density of intersecting lines. If learning enhances performance on hard items, we thus may expect these items to exhibit higher correlation with CCAT in the very high percentiles. However, if learning is not an important factor in FIT performance for the highest percentile CCAT subsample, we should expect higher correlation between CCAT and the easier FIT items that children's *M*-capacity can handle. We, therefore, split the FIT test into two subtests: FIT-easy items (with two to five overlapping shapes) and FIT-hard items (with six to eight shapes). Children of this age should be able to solve the FIT-easy items using only *M*-capacity. In FIT-hard items, however, they must use both *M* and learned perceptual strategies.

We then correlated scores of the two types of FIT items with the CCAT score. For the total sample, the correlation was [$r(1050) = .57$] for FIT-easy versus [$r(1050) = .53$] for FIT-hard—a statistically significant ($p < .05$) difference. We then examined correlations for just the group in the 91st-plus CCAT-percentile group. Because of reduced variance, correlations were lower, but they maintained the same pattern: [$r(93) = .26$, $p < .05$] with FIT-easy and [$r(93) = .19$, $p > .05$] with FIT-hard. This finding adds credence to our claim that the abnormally high FIT score in the highest CCAT-percentile group was due to the factor *M*, a general-purpose maturational (not learning) constituent of Spearman's *g* (fluid intelligence, to be precise).

2 Individual-Difference Intelligence versus Developmental Intelligence

The question of whether these are causally two distinct forms of intelligence, raised by Pascual-Leone and Johnson (2005), is relevant here, because main organismic-causal determinants of ID-intelligence (the individual's intelligence variation) may be distinctly different from, albeit complementary with, developmental intelligence (the age-bound, maturational, normal growth in intelligence). Given the universality of Piagetian and neo-Piagetian stages/cycles, the component of general intelligence corresponding to developmental intelligence may be largely due to the portion of intelligence variance known to be maturational. Janet, James, Spearman, Freud, Luria, and other researchers called mental "energy" this maturational cause of intelligence (as Pascual-Leone, 1970, assumed for *M*-capacity). Thus, if maturational growth of mental attention exists, two distinct causal sources of general intelligence should exist that are independent.

General intelligence, as measured in individuals, is a complex functional probabilistic-invariant found across cognitive content domains. It subsumes both ID-intelligence (individuals' intelligence variation mainly due to learning) and developmental intelligence (maturational, age-bound variation). Factor scores of the *g* factor, often expressed by Gf (fluid general intelligence), are good individual evaluations of this compounded general intelligence. It was always assumed without proof that ID-intelligence is the same as developmental intelligence studied by Piaget and many others, but is it causally so? The discussion of CSMS and FIT data below is adapted with permission from Pascual-Leone (2019).

Figure 7.4, provided by Dr. Michael Shayer and based on research by Adey and Shayer (1994; see also Demetriou & Spanoudis, 2018; Shayer, Demetriou, & Pervez, 1988), presents these two causally distinct aspects of intelligence: one is the mean average score in Piagetian intelligence performance within every given degree of competence, exhibiting the ID variation (assessed by means of all different percentile-level samples from 12,000 children). Second is the age-bound mean developmental growth in children of Shayer's excellent Piaget tasks' point scale. The two aspects appear respectively as ordinate and abscissa of figure 7.4. The range in ID variation in intelligence may in part be innate, but it often should be due to variation in prior intellective or intellectual learning experiences, as figure 7.3 already suggested.

Shayer's CSMS survey data (1975–1978) on 12,000 students from 9 to 16 years of age (Adey & Shayer, 1994; Shayer et al. 1988) used a carefully designed stage-level scaling similar to our *M*-measures, but using only Piagetian Reasoning tasks—a unified scale based on three major Piagetian tasks (spatial relations, volume and weight conservations, and pendulum). The three tasks were given on three different occasions and covered every substage/level of development from Piaget's early concrete to mature formal operations. Point scores like those of *M*-measures were assigned to the obtained Piaget's substages in all tasks and then averaged to generate individual scores. A striking feature of Shayer's data, previously known, is the wide variability of the children's competence level in Piagetian tasks at any given age (range of variation in the ordinate of figure 7.4). In this figure the curves express, across age groups, overall performance levels for each of seven different percentile samples (graded from low to high competence levels, from the average).

All percentile samples exhibit similar patterns in their age-bound developmental growth. This growth is estimated from the substage-levels passed. The curves maintain

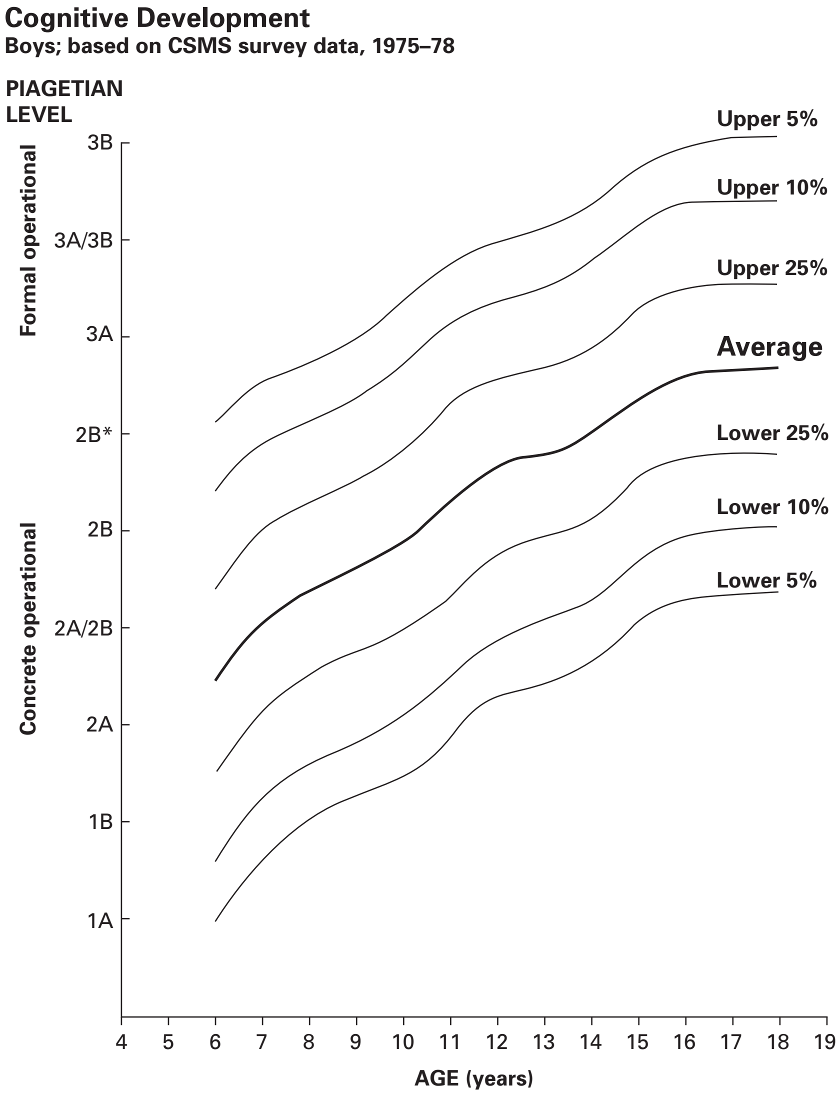

Figure 7.4

Adey and Shayer's (1994) Piagetian tasks' substage point-scale scores, within each level-of-competence sample ($N = 12{,}000$). Note that percentage curves are based on performance on Piagetian tasks. (Reprinted from *Intelligence, 72,* J. Pascual-Leone, Growing Minds Have a Maturing Mental Attention: A Review of Demetriou and Spandoudis [2018], p. 63. Copyright 2018, with permission from Elsevier.)

the same unique pattern across all percentile-sample levels of performance, all collinear and nearly parallel. In every curve, performance level keeps increasing with age, equally across percentile samples. This finding suggests that the variance in performance is similar across levels and ages. The key causal variables of ID intelligence score and of developmental growth (*M* or Matt) appear to be statistically independent from one another, and they combine (additively) to produce the empirical general-intelligence capacity of each individual. Note that if these causal variables would have interacted (been interdependent) and the slope in the ordinate values would have increased or decreased in magnitude as a function of the abscissa values, percentile curves may have spread as a fan, because children's competence level would then result from a multiplicative combination of individual-difference variation and age, relative to this Piagetian scale (e.g., N. Anderson, 1981). Notice what these data mean: learning-based causes of intelligence (i.e., ID intelligence), often appraised by IQ-like tests, are distinct and independent from the maturation-based causes of intelligence (i.e., developmental intelligence) that Piaget's scales or our *M*-measures evaluate. These learning and maturational causes vary with individuals, but they are two independent sources of variability, as figure 7.4, and also figure 7.3, suggests. General intelligence as measured (usually with I.Q. tests) combines the two sources indiscriminately.

The additive combination (the parallel-curves result in figure 7.4) is possibly caused by *M*-capacity measures (here represented by Shayer's Piagetian scale) that assess the average processing-complexity demand (*Md*) of items, relative to the children's mental power (*Mp*), a power assessed independently from the individuals' range of variation in learning-based causes of intelligence. Thus *if* the hidden-process variable of individual differences (ID) in intelligence is distinct and independent from the age-bound developmental growth in *M* (Matt assessed via a Piagetian derived *M*-scale), *then* the ID intelligence learning-based causes (assessed with IQ tests or Gf measures) versus the causes of developmental intelligence should be largely produced by distinctly independent processes of the brain (which combine to produce empirical mental age or general intelligence). The literature often conflates these two causal aspects of intelligence (Pascual-Leone & Johnson, 2005). Such conclusion contradicts experimental researchers and psychometric developmentalists like Demetriou and Spanoudis (2018), who would explain developmental intelligence by appealing only to constructivist learning. Notice further that this causal separation of subjects' learning-based response variability (the ordinate) and the maturational developmental growth in *M*-capacity was postulated by Pascual-Leone in 1970 ("Thus it seems that any attempt to save the general-stages construct must account *separately* for the general structural invariants and for the response variability," p. 304).

Figure 7.5 shows a similar pattern of relative independence between variability in *M*-competence levels and children's cumulative *M*-score (k +, i.e., k or more) as a function of age. This figure was produced by Dr. Shayer, using data on the FIT from our Developmental Processes Lab at York University. These FIT data were collected over several years from 2,684 participants of various ages. FIT is a key *M*-measure, and the figure shows cumulative *M*-scores for age groups 7 to 14, and 17-and-over (i.e., young adults). For example, the curve for *M*-level 4+ shows proportion of participants at each age level obtaining a score of four or above. Note that subsamples defined by cumulative *M*-score levels are epistemologically equivalent to the percentile-passing-score samples of figure 7.4. Figure 7.5 shows that when we exclude the extreme *M*-competence levels two (well within the competence of all age samples) and seven (beyond the capacity of most participants), all other cumulative *M*-levels (three, four, five, and six) show curves that approximate parallel lines, suggesting that growth of the *M* variable with age is relatively independent from *M*-score variability within and across age groups—as found already in figure 7.4 for Shayer's Piagetian-derived *"M" scoring*.

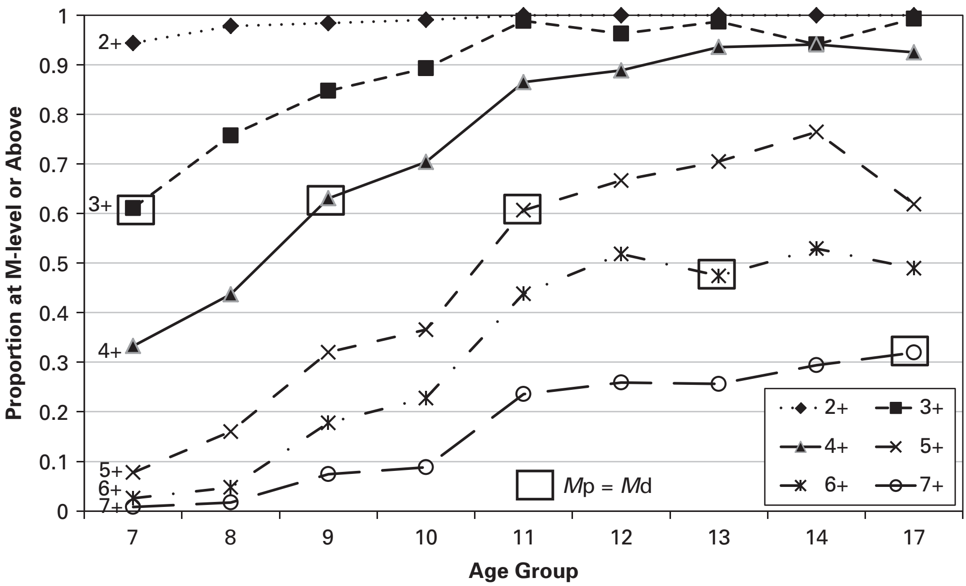

Figure 7.5
Proportion of age samples performing at different *M*-levels or above on figural intersections task (N=2,684). (Reprinted from *Intelligence, 72*, J. Pascual-Leone, Growing Minds Have a Maturing Mental Attention: A Review of Demetriou and Spandoudis [2018], p. 64. Copyright 2018, with permission from Elsevier.)

Notice further that data points in figure 7.5 marked by a small square are those in which children's theoretical *Mp* and items' *Md* are matched (*Mp*=*Md*). In our theory, when *Mp* and *Md* are equal, the subject's task difficulty should be the same, across these items, irrespective of absolute values of *Mp* and *Md*; it is their value difference that regulates task difficulty in *M*-measures (Arsalidou et al., 2010; Pascual-Leone, 1970; Pascual-Leone & Johnson, 2011). Thus square-marked points should be aligned horizontally as they are in figure 7.5, because at these points *Mp*=*Md,* provided that the *M*-measure constitutes, or at least approximates, an interval-scale within a measurement structure (Krantz, Luce, Suppes, & Tversky, 1971; Pascual-Leone & Baillargeon, 1994; Pascual-Leone & Johnson, 2011). The square-marked values are horizontally aligned from 7 to 11 years of age. Beyond this age they adopt a softly descending line, possibly because in late adolescence cognitive motivation decreases, perhaps because of hormonal changes. Such functional change in late adolescence has been found in brain waves (Uhlhaas et al., 2009).

As mentioned, the developmental growth scores plotted on the abscissa of figures 7.4 and 7.5 are likely expressing a maturation causal factor, independent from the learning causal factor that in both figures is plotted in their ordinate dimension. If these two causal factors are independent and the developmental intelligence factor is largely maturational, we should expect that a similar result can be obtained in infancy. Figure 7.6, derived from figure 3.3, shows that it can. These data (see chapter 3) come from analysis of a sample of 1,336 mothers in Brazil who completed the *Dimensional Inventory for Child Development Assessment* (IDADI; *Inventário Dimensional de Avaliação do Desenvolvimento Infantil;* Silva, Mendonça Filho, & Bandeira, 2019, in press). This scale assesses infant development (using mothers' report of their children's developmental level). Figure 3.3 showed a scatterplot of cognitive-development Rasch scores against the children's chronological age. Figure 7.6 presents normative developmental curves for the same sample, now split in subsamples corresponding to different percentiles of the cognitive-development performance score (a rescaling of the Rasch score). Thus, the ordinate dimension expresses how these different percentiles evolve throughout early development, from 4 to 72 months of age. What we wish to highlight is that growth curves of these percentile subsamples are parallel and similar to patterns exhibited by older children in figure 7.4. Thus, developmental growth with age, throughout infancy and childhood, is largely caused by maturation, in relative independence from the learned experience expressed in the figures' ordinate dimension.

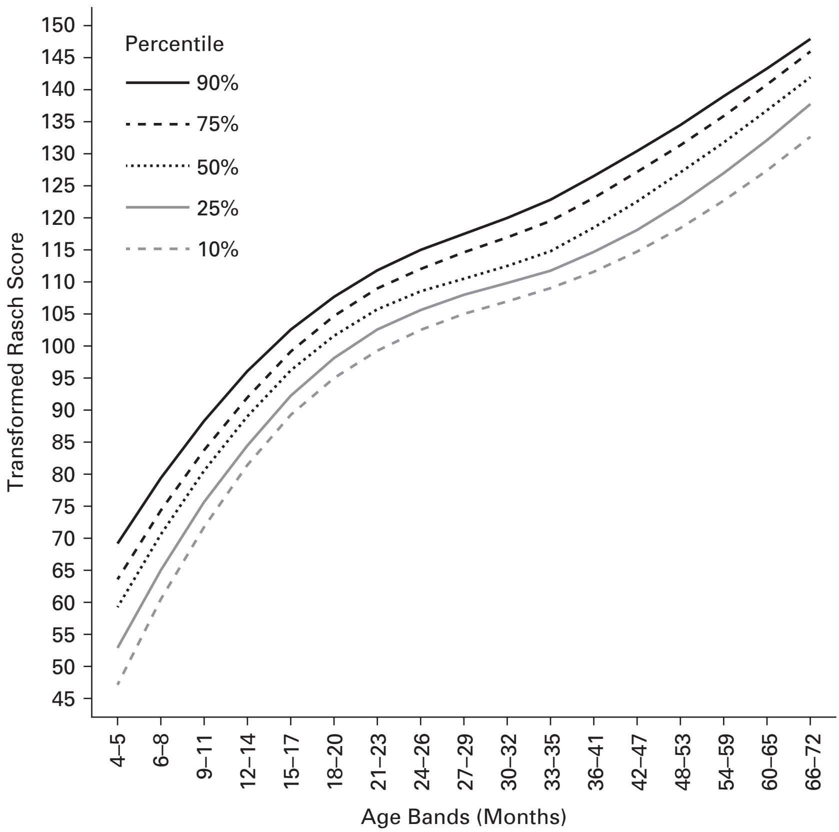

Figure 7.6

Normative cognitive-developmental curves for various percentile levels on the Dimensional Inventory for Child Development Assessment. (Adapted from Silva, M. A., de Mendonça Filho, E. J. & Bandeira, D. R. [in press]. *Inventário Dimensional de Avaliação do Desenvolvimento Infantil* [Dimensional Inventory for Child Development Assessment]. São Paulo, Brazil: Vetor Editora. With permission of the authors and the Publisher. See color plate 2.)

3 Correspondence of *M* (Matt) with the Developmental *g* Factor

This section is adapted with permission from Pascual-Leone (2019). Demetriou and Spanoudis (2018) found that the ID general-intelligence factor *g* did not capture all developmental variance in their data. This led them to adopt a *developmental g* score, based on a scoring method proposed by Tucker-Drob (2009). They obtained individual factor scores for *g* and multiplied them by the chronological age of individual children. Because this developmental *g* score is semantically/epistemologically congruent with our definition of *M*-power, we asked Andreas Demetriou to send his data, which

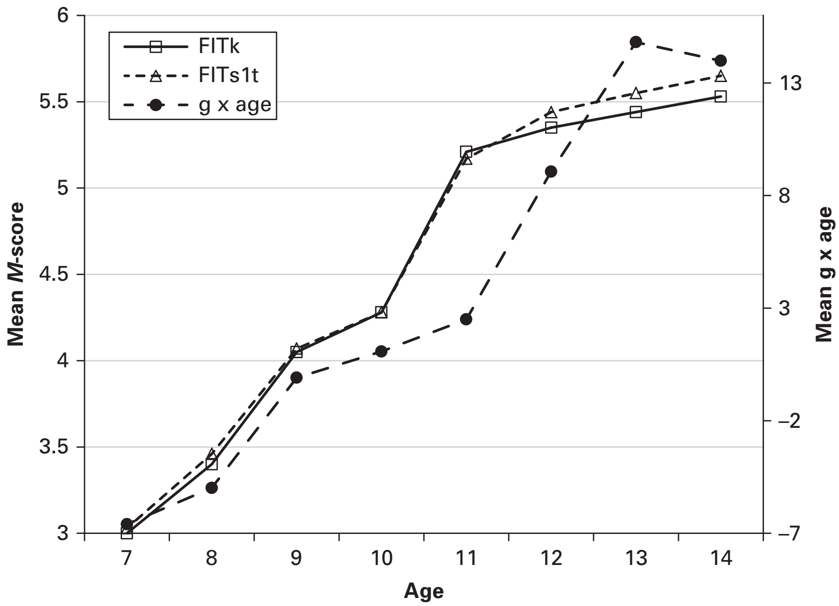

Figure 7.7
Mean FIT *M*-scores (*N*=2567) plotted against Demetriou and Spanoudis' (2018) developmental g scores (g×age; *N*=506), as a function of age. (Reprinted from *Intelligence, 72*, J. Pascual-Leone, Growing Minds Have a Maturing Mental Attention: A Review of Demetriou and Spandoudis [2018], p. 64. Copyright 2018, with permission from Elsevier.)

we used to plot figure 7.7. It compares Demetriou's developmental *g* scores (*N*=506) with developmental scores from our FIT. FIT data came from multiple studies and ages varied from 7 to 14 years (*N*=2,567). Demetriou and Spanoudis' developmental *g* score (*g times age,* i.e., g×age) is very close indeed to the two complementary FIT *M*-scores plotted in figure 7.7: FIT k-score (i.e., item class with highest number of relevant shapes that the person can conjointly intersect) and FIT s1t-score (i.e., the total number of items passed rescaled to the theoretical *M*-distribution).

The only point at which the curves diverge is at 11 years of age, where g×age falls below FIT *M*-score. According to our mental attention (Matt) theory, growth of *Mp* occurs every two years after 3 years of age (Arsalidou et al., 2010; Pascual-Leone & Baillargeon, 1994; Pascual-Leone & Johnson, 2011). Thus, all contiguous odd-even years after three theoretically have the same *M*-capacity (e.g., 7 and 8, 9 and 10, 11 and 12, 13 and 14). FIT is a single visuospatial task designed to measure *M*. In contrast, Demetriou's *g* factor score is calculated over a diverse multiplicity of tasks, across content domains, which often have considerable executive and knowledge demands. Thus, we could expect that in the first year of every *M*-level stage (i.e., in the odd years of participants' age) performance increments with age in FIT could already be manifested, whereas in the *g* factor omnibus task one may have to wait until the even years to observe effects of developmental *M*-growth in the data. This predicted contrast explains the anomalous departure of FIT versus g×age curve at age eleven. As expected, FIT's upsurge of *M* occurs between 10 and 11 years, whereas sharp increase in g×age occurs between 11 and 12 years, but, in these two *M*-capacity performances (FIT at 11 years and g×age at 12 years), the respective values are very close; thus, FIT *M*-measure is very close to the g×age developmental-general-intelligence variable, confirming the construct validity of *M* as a measurement of developmental intelligence.

M-Measures Are Not Just Working Memory Measures

M is the brain resource or specific regulation (hidden operator) that allows simultaneous holding in mind of *k* task-relevant symbolic schemes ($M=e+k$) within misleading tasks. By task design, *M* is measured in terms of Matt (Matt=<*E, M, I, F*>), parametrically increasing the *M*-demand across item classes (homogeneous scales) while holding constant across classes the demands of *E, I,* and *F.* This *M*-measurement is a new form of behavioral measurement, modeled from-within a person's mental process (Pascual-Leone & Johnson, 2017) and indexing the trade-off between the subject's *M*-power and the task/item's *M*-demand. This is a "from-within"/organismic form of *fundamental measurement* (Krantz et al., 1971).

Fundamental measurement occurs when numbers are assigned to objects/entities so that (1) real relations among objects can be mapped to relations among numbers and (2) this measure does not require prior measurement of other quantities. *Additive conjoint measurement* is a kind of fundamental measurement in which two distinct variables (in our case, the child's mental capacity, estimated from age, versus the task's mental demand, estimated from task analysis) combine to produce a single fundamental measurement scale. Our estimation of the two variables is based on modeling from-within the subjects' mental processes (metasubjective task analysis, MTA). With this MTA method the *M*-demand of tasks or test items are estimated using empirical developmental-experimental results. Then a scale of measurement is constructed as indicated below.

When the *M*-measurement scale (*M*-scale) has been empirically validated with results such as those illustrated below, using developmental *M*-scales created in different content-domains (e.g., visuospatial, verbal, visual, attentional memory), we are in a position to define average *M*-capacity of an age group. Our estimate of a group or individual child's current *M*-capacity (expressing his or her *M*-power or energy of attention) is the highest *M*-demand that the child or age group can master to solve *M*-task classes (each with a different *M*-demand) of items. Once empirically validated, the task analyses on items in each class (a homogeneous scale because its items all have the same *M*-demand) warrant the value estimates for the task's *M*-demand.

Thus, an *M-measure* is characterized by six points (Pascual-Leone et al., 2000). **(Mm1)** *M*-measures have classes of items, each presenting one level of *M*-demand, obtained via developmentally verified MTA. **(Mm2)** All possible levels of *M*-capacity are represented in the complete *M*-scale. **(Mm3)** Other aspects that can affect performance (such as executive task/item demand, prior learning or familiarity, perceptual field *F*-factors, whether facilitating or misleading) are held constant across classes of items. **(Mm4)** Items within the total scale may be randomly ordered or ordered from easier to difficult across classes, and item executive processes involved are basically constant across items and classes, so executive procedures can be learned in easy items and transferred to harder *M*-demand items without difficulty. **(Mm5)** Because *M*-measurement characteristics are structural and not content bound, we can obtain equivalent *M*-measures across very different content-domains, and these *domain-different M-scales* exhibit predictable same (or very similar) average quantitative scores, validated across ages (preserving predicted relations in *M*-growth with increasing age) and across populations (e.g., Arsalidou & Im-Bolter, 2017; Pascual-Leone et al., 2000). Some illustrative data are given below. Such predicted scale/score invariance is not mathematically possible without having an interval scale of measurement. Yaremko, Harari, Harrison, and Lynn (1982) define an interval scale as one in which the units are equal (constant) throughout, but which lack an absolute zero point. Our units are equal on the basis of metasubjective task analysis and the *M*-theory, and they empirically behave as such. **(Mm6)** In these measures the person's *M*-score (his or her *M*-capacity) is the *M*-demand of the highest item class that he or she can pass.

Notice that this empirically found invariance of *M*-scales across different content-domains and populations (and across human development) gives validity to our task-analytical method—metasubjective task analysis (MTA). It does because MTA is used to establish score values for the two conjoint variables (i.e., *M*-capacity versus *M*-demand) for the "from within"/organismic fundamental measurement procedure (we discuss the MTA method in detail in chapters 8 and 9). In conclusion, *M*-tasks assess trade-off between mental demand of task items and the mental capacity of a child. In contrast, working memory (WM) tasks lack distinct item classes of theoretically estimated mental demand, and test developers use only their refined common sense to decide on the mental demand of the few items, with validity often insufficient because of a lack in process-analytical theory. Other aspects or factors intervening on the WM item (e.g., executive demand, learning, perceptual field factors) often are not constant across items or not controlled. WM tasks often yield ordinal or perhaps metric ordinal scales, but not interval scales.

Invariance of *M*-Scores across Content Domains and Populations

Our average estimates of attentional *M*-capacity exhibit the characteristic (uncommon for a psychological measure) of having values reasonably (probabilistically) invariant across content domains and across populations, whenever task analysis and task construction are properly done. This quantitative invariance shows our *M*-measures to have the power of interval scales of (metasubjective) measurement (Pascual-Leone & Johnson, 2011, 2017). We briefly illustrate these important characteristics of *M* measurement using data from different studies in our lab.

Figure 7.8 shows the mean *M*-scores of twenty-six mainstream and twenty-six cognitively gifted 9- to 11-year-old children (gifted children identified by their school board) on three of our measures (Johnson, Pascual-Leone, Im-Bolter, & Verrilli, 2004; Pascual-Leone & Johnson, 2005, 2011). Mainstream peers were schoolmates who did not meet criteria for gifted programming. We originally hypothesized that gifted children (identified on the basis of IQ and ability test scores), who possess a superior executive repertoire relative to mainstream children, may not necessarily have superior *M* (Johnson et al., 2003; Pascual-Leone et al., 2000).

M tasks were the figural intersections test (FIT), the mental attention memory (MAM) task, and the direction-following task (DFT). As described above, FIT asks children to find the one area of common intersection of two to eight overlapping geometric shapes. The MAM (Agostino, Johnson, & Pascual-Leone, 2010; Im-Bolter et al., 2006) is a novel WM task with low executive demand, and (as task analyses suggest) variable degree of misleadingness in its items, making it an *M*-measure that minimally taxes executive repertoire. Children read aloud sets of consonants arranged in a circular pattern and then recall the consonants under differing degrees of interference (i.e., simple free recall, dialing each letter recalled on a rotary phone, or responding to a Stroop item before voicing each recalled letter). *M*-score was the average number of consonants correctly recalled across items in each of the three conditions. The DFT involves verbal directions of increasing complexity that children must carry out (Cunning, 2003; Pascual-Leone & Johnson, 2011). These directions require placement of tokens (which vary in size, color, and shape) on locations that vary in size and color. *M*-demand of each complexity level (estimated via task analysis; Pascual-Leone & Johnson, 2011)

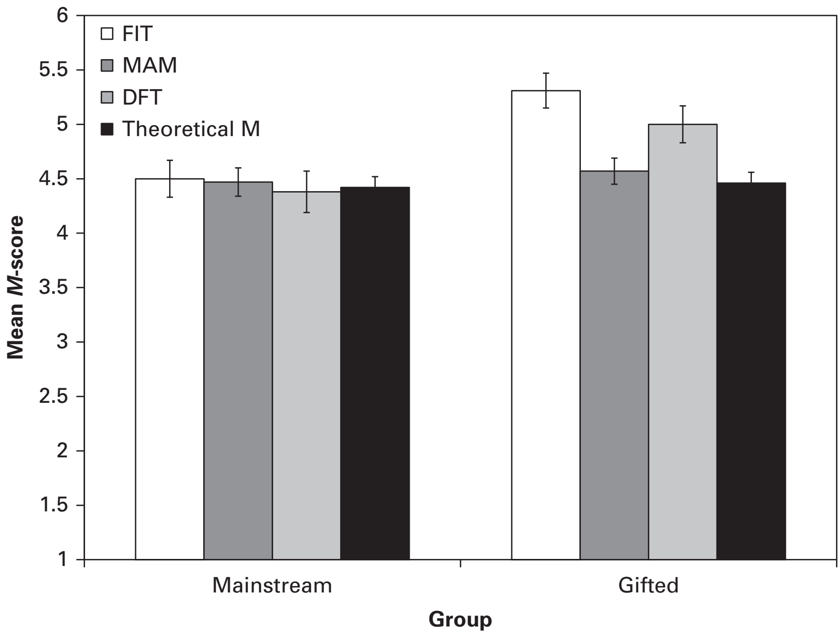

Figure 7.8
Mean *M*-scores on the figural intersections task (FIT), mental attention memory (MAM) task, and direction-following task (DFT) for age-matched gifted and mainstream children; bars show standard errors. (Adapted from Pascual-Leone, J., & Johnson, J. [2005]. A dialectical constructivist view of developmental intelligence. In O. Wilhelm & R. W. Engle [Eds.], *Handbook of understanding and measuring intelligence* [p. 196]. Sage. Copyright 2005 by Sage.)

varies with the number of objects or attributes specified in the instructions. *M*-score is the *M*-demand of the highest complexity level that the child can reliably enact.

Figure 7.8 shows mean *M*-scores, as a function of task and group, as well as expected theoretical mean *M*-score based on the children's ages. There is considerable group-mean invariance of *M*-scores across the content domains for the three *M*-tasks (visuo-spatial, verbal, and linguistic) in the mainstream sample. A mixed analysis of variance indicated that gifted children scored higher than mainstream children only on the FIT and DFT (which have greater executive demand than MAM), consistent with the common idea of giftedness. In other research we have demonstrated that FIT scores can be used to predict giftedness in children (Johnson et al., 2003; Pascual-Leone, Johnson, Calvo, & Verrilli, 2005; Pascual-Leone & Johnson, 2017). As described above (see figure 7.3), children with performance at the highest level of general cognitive ability (using the Canadian Cognitive Abilities Test, CCAT) tended to have a very high *M*-capacity for their age. Research is needed to investigate whether gifted children (as identified by school boards) have superior *M*-power independently from their executive know-how, which tends to be high (Johnson et al., 2003; Pascual-Leone et al., 2000).

Figure 7.9 shows (with the same samples) mean proportion pass on FIT and DFT, with items grouped by their predicted *M*-demands (*M*-complexity of the item classes; Johnson et al., 2004; Pascual-Leone & Johnson, 2011). Consistent with data in figure 7.8, gifted children perform better than mainstream children. However, within each sample, for each *M*-demand class of items, the proportion correct levels for FIT and DFT are almost identical.

Figure 7.10 shows the mean *M*-scores on FIT, DFT, and MAM of children with specific language impairment (7- to 12-year-olds) versus children with normal language. The

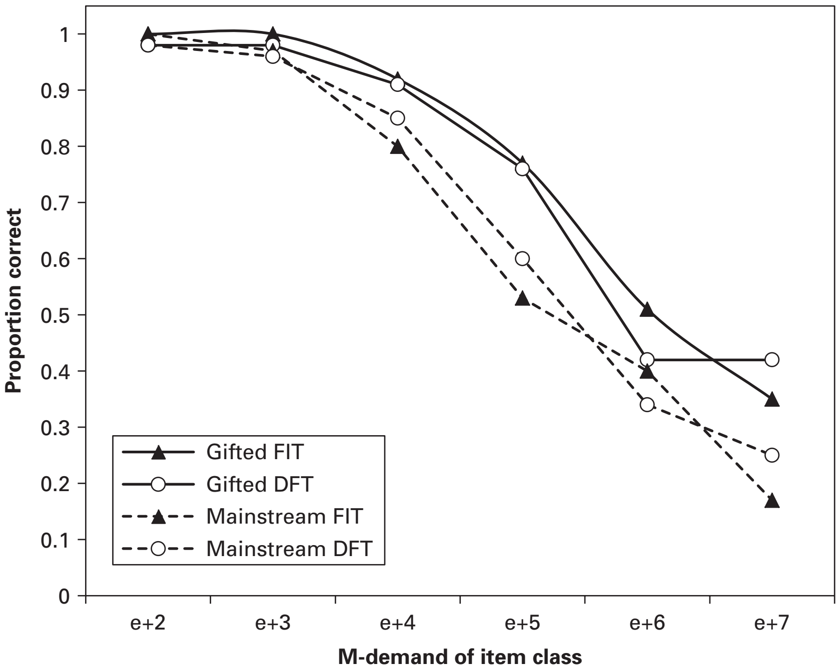

Figure 7.9
Mean proportion of items passed on figural intersections task (FIT) and direction-following task (DFT), as a function of items' *M*-demand. Samples are age-matched gifted and mainstream children. (From Pascual-Leone, J., & Johnson, J. [2011]. A developmental theory of mental attention: Its applications to measurement and task analysis. In P. Barrouillet & V. Gaillard [Eds.], *Cognitive development and working memory: A dialogue between neo-Piagetian and cognitive approaches* [p. 37]. Psychology Press. Copyright 2011 by Psychology Press.)

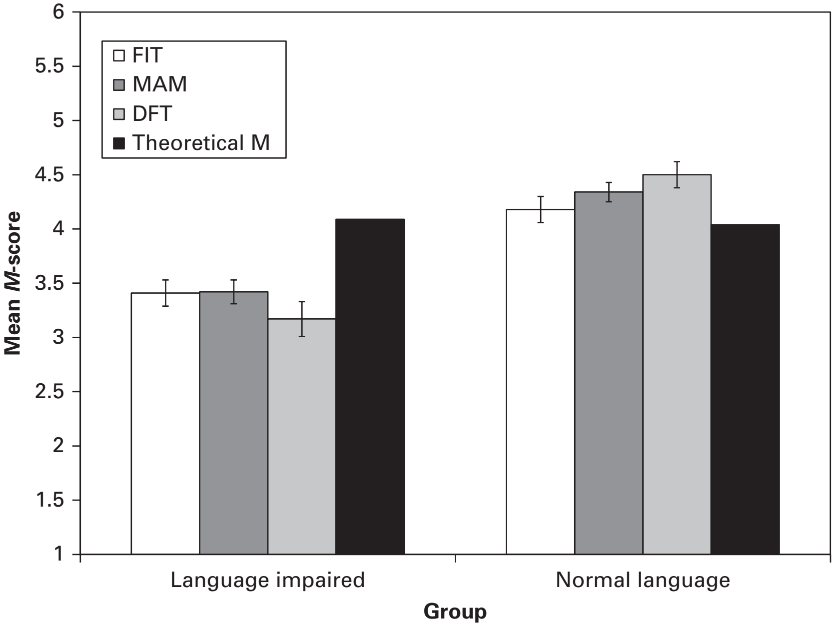

Figure 7.10
Mean *M*-scores on figural intersections task (FIT), mental attention memory (MAM) task, and direction-following task (DFT) for children with language impairment and normal language; bars show standard errors. (From Pascual-Leone, J., & Johnson, J. [2011]. A developmental theory of mental attention: Its applications to measurement and task analysis. In P. Barrouillet & V. Gaillard [Eds.], *Cognitive development and working memory: A dialogue between neo-Piagetian and cognitive approaches* [p. 38]. Psychology Press. Copyright 2011 by Psychology Press.)

samples ($n=45$ in each sample) were matched on age and performance-IQ (Im-Bolter et al., 2006; Pascual-Leone & Johnson, 2011). Children with language impairments underperformed significantly on *M*-measures relative to both their theoretical age-expected *M*-scores and the control sample. Notice that, despite the underperformance, the three *M*-measures exhibit, in each sample, invariance of mean scores over the three content-domain tasks. These and other results support construct validity of our *M*-measures and show that the scale of measurement behaves as an interval scale.

Upper Bound of *M*-Capacity in Adults

It often is claimed that the upper bound of WM in adults is about 4 (Cowan, 2005). The upper bound level of WM capacity is important, because we (e.g., Pascual-Leone, 1970) and others (Case, 1998; Cowan, 2005, 2016; Hansell et al., 2015) claim that endogenous attention is maturational during both the sensorimotor and symbolic-processing periods. After the sensorimotor period we claim that *M*-capacity has an upper bound of 7 (this is the adults' structural reserve of *M* or max *M*) but it also has a lower bound of 4 or 5 (adults' frequent functional *M*-level). Thus, we expect probabilistic oscillation of adults' measured *M*-capacity, often between the values 4 and 7 (Arsalidou et al., 2010, 2013; Pascual-Leone 1970).

Figure 7.11 shows as example the mean *M*-score obtained by young adult samples in five studies, using FIT, DFT, and MAM (Pascual-Leone & Johnson, 2011). The average *M*-score across tasks and samples is 6, consistent with our prediction (see also the 17+ sample in figure 7.5). Figure 7.12 shows data from four studies using the DFT with adults in Canada and Italy (Pascual-Leone & Johnson, 2011). Sample Canada-3 received DFT items in random order. Other samples received them in order of increasing complexity,

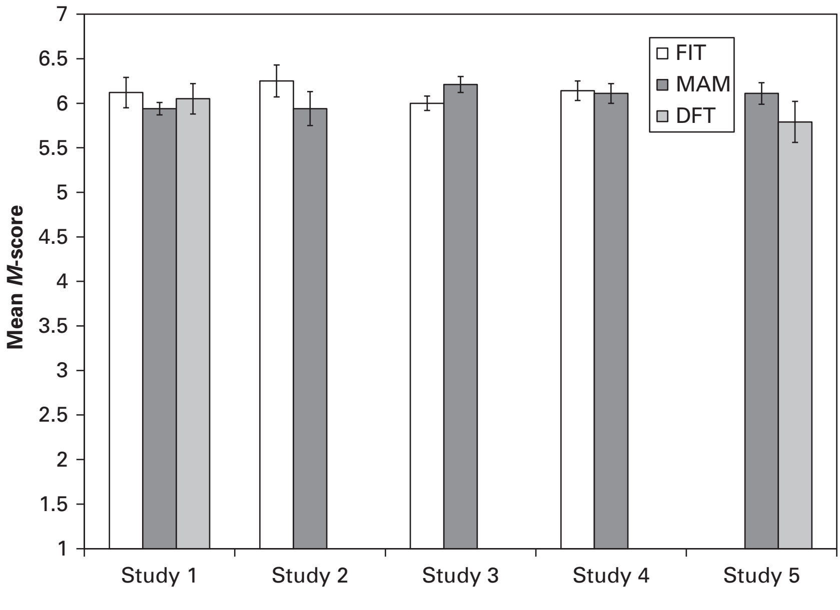

Figure 7.11
Mean *M*-scores on figural intersections task (FIT), mental attention memory (MAM) task, and direction-following task (DFT) from five studies with university-student samples; bars show standard errors. (From Pascual-Leone, J., & Johnson, J. [2011]. A developmental theory of mental attention: Its applications to measurement and task analysis. In P. Barrouillet & V. Gaillard [Eds.], *Cognitive development and working memory: A dialogue between neo-Piagetian and cognitive approaches* [p. 39]. Psychology Press. Copyright 2011 by Psychology Press.)

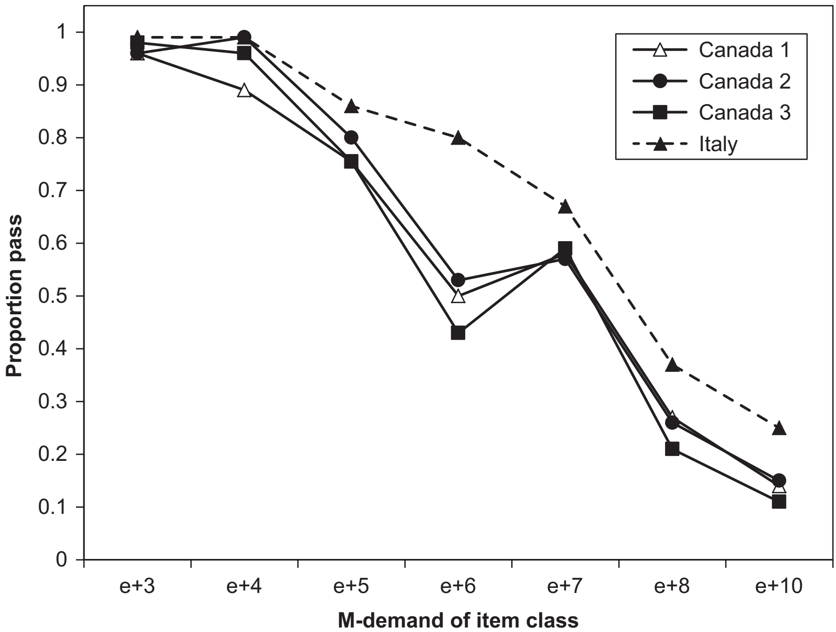

Figure 7.12

Mean proportion of items passed on direction-following task (DFT), as a function of items' *M*-demand for four adult samples from Canada and Italy. (From Pascual-Leone, J., & Johnson, J. [2011]. A developmental theory of mental attention: Its applications to measurement and task analysis. In P. Barrouillet & V. Gaillard [Eds.], *Cognitive development and working memory: A dialogue between neo-Piagetian and cognitive approaches* [p. 40]. Psychology Press. Copyright 2011 by Psychology Press.)

and random-versus-progressive order of items clearly does not affect results. The Italian data were collected by Sergio Morra in Genova (Morra, Camba, Calvini, & Bracco, 2013). All Canadian samples yield very similar performance patterns, with passing rate of 60% in adults for items with *M*-demand equal to 7 (although performance dips a bit for items of *M*-demand 6). All three Canadian samples obtain a mean *M*-score of about 6. Performance of adults tested in Italian parallels that of the Canadian samples tested in English, with an important exception: Italians maintain high performance on items with demand of 6, and their mean *M*-score is 7. Morra et al. (2013) suggested that this higher performance of the Italian sample is due to facilitating linguistic factors introduced by the Italian translation of the DFT items. Morra's linguistic interpretation, and his revised task analysis, were investigated and supported by research in our lab (Giuliano, Johnson, & Pascual-Leone, 2015; Johnson, Tsvetkov Kristen, & Pascual-Leone, 2014).

We return to this research in the next section, because it illustrates how situational/contextual factors can affect mental attentional (*M*) demand of tasks.

In all, the results support our prediction of an upper bound in *M* (often globally interpreted as working memory) equal to 7 symbolic schemes in adults. This result contradicts the majority view about adult WM capacity (a max-WM equal to 4 or 5).

Dynamic Context-Sensitive Character of Tasks' *M*-Demand

The current literature on WM research recognizes that a task's WM-demand (its *M*-demand when properly measured) is dynamically variable with contextual or organismic circumstances. Yet it is often not explicit why or how this is so. The key organismic factor in this regard may be task familiarity—familiarity with the repertoire of schemes that participants need in the task, including degree of automatization (habituation, chunking). Estimation of the *M*-units required in a task should count only the essential schemes that are distinct, that is, not already overlearned and chunked in their coordination (not *LC*-structured). Therefore, prior repeated experience with the task can change (decrease via schemes' learning and *LCLM* coordination) the task's actual *M*-demand. Part of the current problem for quantifying reliably WM-demand of tasks may be related to neglect of this important structural/relational factor of prior learning. In chapter 5 we discussed learning from a constructivist (metasubjective) perspective, including the role of associative learning/chunking (*LC* learning); we do not discuss it further.

We address here instead another distinct factor, often neglected in the literature. We refer to the internal field factor, or *F*-operator, known as holistic or Gestaltist factor, stimulus-response (S-R) compatibility, minimum principle, simplicity principle, and so on (see chapters 1 and 6). We illustrate the function of this contextual *F*-operator factor as modulator of *M-power/M-demand* trade-off, using three examples.

1 Color-Matching Task (CMT)

Arsalidou et al. (2010) showed the role of this organismic *F*-factor interacting with both learning and mental (*M*-) processing. We constructed two tasks very similar in informational and executive-demand characteristics but radically different in the role (facilitating vs. misleading) played by the *F*-factor. Using suitable samples of children, we showed the *F* factor affecting task difficulty.

The CMT paradigm adapts an updating design known as 1-back task (e.g., Owen, McMillan, Laird, & Bullmore, 2005). In this timed paradigm, participants see (one item at a time) a set of figures (either a clown or a bunch of balloons, depending on task version). For each item they must indicate whether relevant features (or schemes) of the current figure match those of the immediately preceding figure. We varied number of features/schemes (concretely, relevant colors) needed to determine a match. Thus, while keeping executive demand constant (i.e., number and kind of operations needed), the *M*-demand was varied across classes of items by adjusting number of relevant colors. Number of relevant colors (varied from one to six) determined *M*-demand (basically, WM complexity level) of each item. Participants had to indicate whether the current (i.e., target) item had the same set of relevant colors as the previous (i.e., criterion) item, irrespective of color location. Blue and green were colors to be ignored (irrelevant), as were colors in the clown's face. Presented in different item blocks were classes of items that varied in difficulty level in terms of *M*-demand. These levels spanned the expected *M*-capacity of our participants (children from 7 to 14 years, and adults).

To examine contextual influences, we contrasted a task with items having a set of balloons (CMT-balloon) with one whose items had the single integral figure of a clown (CMT-clown). CMT-balloon is facilitating, because task relevant features (i.e., colors) of the stimuli are salient, being part of segregated shapes (balloons) with relatively constant form and size, shapes best identified by their color. The bundle of distinct balloons was not salient as an integral whole. In contrast, CMT-clown is a misleading task: it contains in each item an attractive integral whole, the clown itself, very salient but irrelevant to the task—a "frame" in which relevant colors are embedded. Further, the costume parts (e.g., shoes, hat, patch) are attractive distractors, variable in shape and size, contiguous, and task irrelevant, which make the search for colors in the holistic Gestalt of the clown mental-attentionally demanding (because of *F*-misleadingness, because the holistic-clown Gestalt and the irrelevant distractors must be overcome and inhibited). These contextual differences should influence *M*-demand at every item level of the two CMT versions. We estimated this demand using our method of metasubjective task analysis.

Let us now examine some summary results from Arsalidou et al. (2010). One hundred forty-nine participants completed the CMT, covering age groups that represented five levels of *M*-growth: 7 to 8 years, 9 to 10 years, 11 to 12 years, 13 to 14 years, and adults (18 and older). The CMT *M*-score corresponds to the *M*-demand of the highest level of items passed. Metasubjective task analyses of these tasks, presented in chapter 9, showed that *M*-demand of each class of items is equal to the number of relevant colors to be matched plus two. This added value of two corresponds to needed operative and parameter schemes.

Arsalidou et al. (2010, table 1) found that performance for each age group on CMT-clown was high whenever the estimated *M*-demand (*Md*) of the item's class was less than or equal to the predicted *M*-capacity (*Mp*) of the age group in question. That is to say: For as long as $Mp \geq Md$, participants exhibited a very high probability of passing the item; when $Mp < Md$, participants had very low probability of succeeding. Furthermore, Arsalidou et al. (2010, table 3) used an equivalence test, that is, a test that directly examines whether means are statistically indistinguishable (Wellek, 2003), to compare CMT-clown mean *M*-score with the expected theoretical *Mp* for the age group. The mean values in all ages were close to the theoretically predicted, and in three of them (for samples 7 to 8 years, 9 to 10 years, and young adults of 18 years or more) equivalence vis-à-vis the theoretical prediction was found. Qualitatively and quantitatively our predicted *Mp/Md* trade-off was confirmed for CMT-clown.

In contrast, this was not so for the facilitating task CMT-balloon, which tended to show subjects passing item classes with *Md* one unit beyond the predicted *Mp*. In addition, Wellek test for the balloon task showed equivalence only for 13 to 14 years and adults. To conclude, a suitably chosen context-misleadingness (a negative *F*-factor), as found in CMT-clown, facilitates fitness to predictions for developmental *M*-theory. In contrast, congruently with the theory, a facilitating context makes estimation of *M*-capacity unstable (Pascual-Leone et al., 2000). In chapter 10, we briefly summarize two fMRI studies that used the CMT-clown. Results with adults show activity in the dorsal attention network that increases in a graded manner with increasing demand of CMT-clown items. This is congruent with the developmental *M*-power (participants) versus *M*-demand (tasks) trade-off, which we have discussed in this chapter.

2 Linguistic "Italian" DFT Effect

The DFT (Pascual-Leone & Johnson, 2011) is an excellent verbal/linguistic measure of *M*-capacity (see figures 7.8–7.10). It is composed of a series of increasingly complex verbal commands to move shapes on the lower part of a task board to spaces on the upper part of the board (e.g., "Place a green circle on a yellow space," "Place a red square and a white circle on a small yellow space"). Task analysis was used to estimate the *M*-demand of each complexity level in the DFT. Research with English-speaking participants has supported DFT's validity as a measure of *M*-capacity (Agostino et al., 2010; Balioussis, Johnson, & Pascual-Leone, 2012; Im-Bolter et al., 2006; Pascual-Leone & Johnson, 2011).

Morra et al. (2013) translated the DFT into Italian and found that performance of adult and child Italian samples paralleled that of our English Canadian subjects (see figure 7.12). However, the Italian version appeared to carry one unit less of *M*-demand. In Italian, the adjective often is placed after the noun (equivalent to "Place a circle green on a space yellow"). Morra et al. reasoned that Italian word order may create a *recency effect* (an *F*-factor effect) that would facilitate DFT performance, because the final word (e.g., "yellow") may remain sufficiently active and not require *M*-boosting. Note that in English the final word of a DFT instruction always is "space," which is not informative. Johnson et al. (2014) tested this hypothesis, using an English DFT version with "Italian" phrasing (e.g., "Place a green circle on a space that's yellow"). English-speaking adults were randomly assigned to complete the standard DFT or a DFT that used English instructions with "Italian" word order. They also received the FIT *M*-measure and counting span—a commonly used WM task (e.g., Conway et al., 2005). They found that mean DFT *M*-score was higher in the "Italian" condition, exceeding DFT *M*-score in the standard condition (between groups) as well as FIT *M*-score (within-subjects). As predicted, performance on the "Italian" version exhibited the recency effect but only at higher *M*-demand levels. Both DFT versions correlated significantly with FIT and counting span.

Results support Morra et al.'s (2013) findings: Italian word order facilitates DFT performance and appears to reduce *M*-demand of the task by one unit. This effect is seen only at the *M*-demand levels that approach the expected *M*-capacity of the age sample, as one would expect if performance were expression of an *Mp*/*Md* trade-off. Giuliano et al. (2015) have replicated these findings by testing adult Spanish-English bilingual participants with both Spanish and English DFT versions (Spanish has word order similar to Italian). Thus, word order and other linguistic aspects that may affect *M*-demand should be considered when task-analyzing or translating verbal *M*-measures (or WM tasks).

3 Simon Effect and the Joint Simon Effect

There are other ways in which characteristics of the situation (particularly the context and the participant's affective/emotional mood) can change task performance. Indeed, because *F*-factor (whether facilitating or misleading) applies within the focus of attention (i.e., *M*-centration), if the content (the activated schemes) of this attentional focus changes, so could the task's *M*-demand. Motives also could change with the task construal. Consider as examples the Simon task and its derivative, the joint Simon task.

In the standard Simon task, the child sits before a monitor and has two response buttons (Left vs. Right). Stimuli appear one at a time, on the left or right side of screen. The task is to press the right button when a given stimulus (e.g., a frog) appears; and press the left button when another stimulus (e.g., a butterfly) appears. The joint Simon

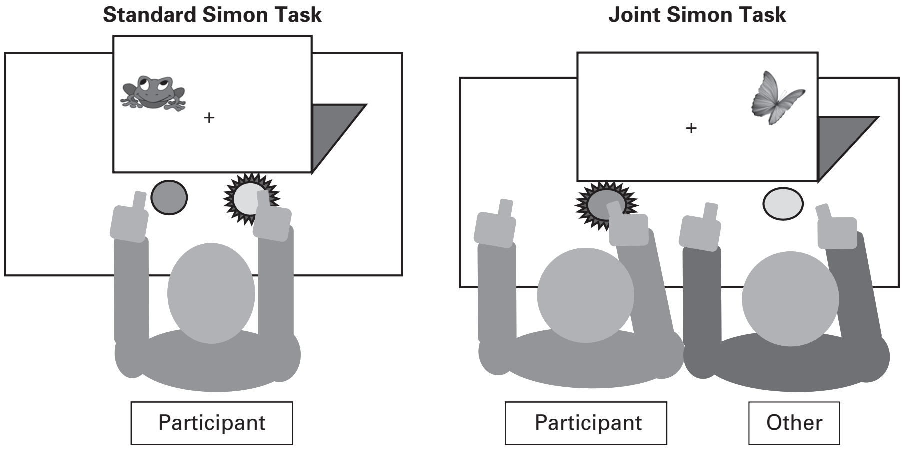

Figure 7.13
Diagram of Simon and joint Simon tasks.

task (e.g., Saby, Bouquet, & Marshall, 2014) is a variation in which two participants sit side by side and play concurrently, each responding to a different stimulus (e.g., either frog or butterfly, not both). Figure 7.13 illustrates both tasks. The *Simon effect* is the tendency of participants to respond faster, and with fewer errors, when the stimulus appears on the same side of the screen (right or left) as the appropriate response button. This is an S-R compatibility effect produced by the *F*-factor. It can facilitate fast and accurate performance on spatially compatible trials, but becomes a misleading factor on spatially incompatible trials. A metasubjective analysis of the Simon task is presented in chapter 9. At this point, we just remark that players know (via task instructions) that they must respond to butterfly, for example, by pressing the left button and respond to frog by pressing the right button. Similar rules are followed in the joint Simon task, but now one player responds only to the frog and the other only to the butterfly.

To respond correctly, participants must synthesize a response by suitably coordinating two symbolic schemes, which require the boosting power of *M*-capacity: (1) a PRESS-the-button scheme that already has chunked to it the operative actions of LOCATE the stimulus that appears and IDENTIFY it (as being a frog or butterfly) and (2) an operative parameter to PRESS, which evaluates the response button to choose by appraising (in Simon task) identity of the present stimulus, OR (in joint Simon) deciding whether this is the stimulus one should respond to. In the joint Simon task, if subjects construe the other player as participating in the same game (so that they experience the other's play as part of their own activity), parameter (2) is replaced by one reminding players of their own player-to-stimulus assignment (i.e., who, subject or other, should respond to frog vs. butterfly).

The Simon effect also occurs in the joint Simon task when the other player is friendly, and the subject identifies with this other. Players tend to respond faster when their stimulus appears on their side, but slower when it appears on the side of the other, although by rule the other player cannot respond to the subject's present stimulus. Remarkably, in adults, such joint-task Simon effect only occurs when participants have with one another good interdependence and achieve cordial collaboration. The effect is absent when participants compete or are hostile (Hommel, Colzato, & va der Wildenberg, 2009). This surprising finding becomes theoretically clear when we realize that participants attend only to schemes relevant to the task at hand, that is, tend automatically to exclude (automatic attentional inhibition) presently irrelevant schemes they are not attending to. When the other player is experienced emotionally as a cordial collaborator, both the schemes of the other and the subject's own schemes for the task are construed as task relevant and so are automatically included in the task's field of centration. Thus, as a result, the schemes are attended to, and interact dynamically with one another (prompted by the *F*-factor), which prompts the Simon effect. In contrast, if the other is hostile or unfriendly, and thus is not construed as being part of the subject's own task, schemes of the other are not task relevant and not *M*-centrated and would be automatically inhibited, preventing a joint Simon effect.

How Mental Attention Is Expressed in Tests of Intelligence

William Stern (1914/1977), contemporary of Binet and inventor of the IQ concept, defined intelligence as the person's skill in successfully coping with novel problem situations. This coping synthesizes or constructs performance by composing previously acquired processes (schemes) in novel ways. Thus, Burt, according to Stankov, defined intelligence as "the 'integrative function of the mind' that encompasses processes at *all* levels" (Stankov, 2002, p. 25). Other definitions have been offered, often less apt, but all assume that intelligence increases with age in normal persons, up to adulthood. They all assume that this growth with age is due to learning and maturation (in that order), and they do not differentiate between individual-differences (ID) intelligence and developmental intelligence, as we do. In spite of its beginning (in Binet's and Spearman's work), current conceptions of intelligence often suffer from lack of integration with cognitive-developmental research. Ever since Reuchlin (1962, 1964), researchers have recognized the need to integrate constructivist developmental (e.g., Piagetian or neo-Piagetian) theory with ID conceptions of intelligence (e.g., Case, Demetriou, Platsidou, & Kazi, 2001;

Demetriou & Spanoudis, 2018; Pascual-Leone, 1969, 1970; Pascual-Leone & Goodman, 1979; Pascual-Leone & Johnson, 2005, 2011; Pascual-Leone et al., 2012). The hope is that developmental theory and its empirical methods can help to create theory-based measures that can be used at all ages. This goal has not yet been met.

A good enough organismic-causal theory must explain these two sorts of measures: intelligence task/tests mostly rooted in individual differences other than age (our ID causal organismic factors) and those mostly rooted in developmental age (due to developmental growth in mental attention within relatively misleading problem-solving situations). Although these two aspects of intelligence were traditionally considered to have the same organismic causes, we suggest that they may in part have different causes: those of *individual-difference intelligence* (indexed by cognitive tests scaled with reference to across-age *reference groups*, or "populations") and those of *developmental intelligence* (which evaluates from a within-the-subject perspective, effective complexity of tasks/tests, by *using the age when ordinary children can first cope*, without special training, with the task/item in question). Both causal sources of intelligence empirically combine to form general intelligence, as usually measured. Some form of endogenous mental attention was pioneered under various names by many classics (e.g., Janet, James, Freud, Binet, Spearman, Jung, Luria). For them it was a mental energy or volitional effort used during acts of judgment or problem solving (perhaps as part of a self that includes voluntary/mental attention and preconscious or conscious plans).

In contrast to developmental intelligence, ID intelligence stems mostly from the study of adults using the correlational method and factor analysis. Factor analysis is a descriptive, abstracting tool, a way of condensing relational structures found in the data across tasks (e.g., Deary, 2000; Reuchlin, 1962; Spearman, 1927). Other approaches, like development and neuroscience, anchor and clarify constructively these intelligence causal factors (e.g., Arsalidou & Pascual-Leone, 2016; Horn, 1998; Horn & Noll, 1994; Reuchlin, 1964).

In table 7.3 we summarize correlations of the FIT and DFT *M*-tasks with various ID intelligence or IQ measures. Of these cognitive ID tasks, Otis-Lennon, OLSAT (Otis-Lennon School Ability Test), and WASI IQ (Wechsler Abbreviated Scale of Intelligence) are recognized general ability measures. Ravens Matrices is the known standard for fluid intelligence measurement, and Matrix Analogies (Naglieri, 1985) is a closely related test. The CCAT (Canadian Cognitive Abilities Test) and CAT-3 (Canadian Achievement Test) provide excellent assessments of ability and school achievement, respectively. All correlations are significantly different from zero, and most are $r = .50$ and above. *M*-measures also correlate with standard complex WM tasks. For instance, correlations from our lab for 7-to-12-year-olds: backward digit span with FIT, $r(45) = .54$, $p < .05$; sentence span with FIT,

Table 7.3
Correlations of FIT and DFT *M*-scores with standardized ability measures

Ability Test	Figural Intersections Task (FIT)		Direction-Following Task (DFT)		Sample
CCAT percentile		**.59****			*N* = 1000, 9 years
CAT-3 percentile		**.51****			*N* = 1000, 9 years
CCAT percentile		**.52****		**.60****	*N* = 156, FIT & DFT at 7 years; CCAT at 9 years
CAT-3 percentile		**.53****		**.58****	*N* = 156, FIT & DFT at 7 years; CAT-3 at 9 years
WASI IQ		**.45****		**.50****	*N* = 156, 7 years
OL mental age	.71**	**.40****			*N* = 161, 6–12 years
OLSAT raw score	.37**	**.39****			*N* = 80, 9–13 years
Ravens total score	.40**	**.36***			*N* = 80, 9–13 years
Matrix Analogies	.55**	**.36****	.45**	**.28****	*N* = 175, 7–12 years

Note: CCAT = Canadian Abilities Test; CAT-3 = Canadian Achievement Test; WASI = Wechsler Abbreviated Scale of Intelligence; OL = Otis Lennon; OLSAT = Otis-Lennon School Ability Test. **Bolded *r's*** are without age variance; non-bolded *r*'s are with age variance.
**$p < .001$. *$p < .01$.

$r(173) = .40$, $p < .01$, and with DFT $r(173) = .52$, $p < .01$; running span with FIT, $r(104) = .40$, $p < .01$, and DFT $r(104) = .50$, $p < .01$; counting span with FIT, $r(104) = .48$, $p < .01$.

We (Arsalidou & Pascual-Leone, 2016; Arsalidou et al., 2010; Pascual-Leone & Goodman, 1979; Pascual-Leone & Johnson, 2005, 2011) have a process-causal interpretation of organismic factors traditionally seen to underlie intelligence (e.g., Wilhelm & Engle, 2005). Clearly (see the last epigraph) there are multiple distinct factors (in our theory, different schemes and multiple hidden-resource operators) that help to configure *mental strategy formulas* for organismic functioning. Using task analysis, we can characterize formulas for different tasks and types of paradigms, such as those that assess fluid intelligence (Gf). These formulas describe demands in cognitive-processing strategy raised by tasks (or types of tasks/tests) or situations, when subjects pursue intended goals. Individual-differences in intelligence correspond to the quality and degree of availability in individuals of the resources and schemes required by these formulas.

From such theoretical perspective, psychometric factors can be explained semantically and process-causally. For instance, Gf (Horn & Hofer, 1992; Horn & Noll, 1994), the *fluid intelligence* factor, would have as main causal-organismic determinants the resource-operators and executive schemes of mental attention (Matt = <*E, M, I, F*>), together with learned effortful schemes (*LM* learning) that may be automatized (*LCLM* learning) in part (Pascual-Leone, 1995; Pascual-Leone & Goodman, 1979; Pascual-Leone & Johnson, 2005). In addition, tasks indexing Gf present a mental strategy formula that involves *intellective convergent* problems (problems with an explicit unique solution) in the context of misleading situations, usually tapping the participant's experiential (nonconceptual) domain—Piaget's infra-logical or our mereological processes. In contrast, Gc, *crystallized intelligence* (or acculturation knowledge) may have as a key determinant a good conceptual or logical knowledge (overlearned or automatized schemas from past effortful, analytical thinking—complex schemes' coordinations that we call *LCLM* structures). This knowledge is well exhibited in tasks that use mental attention within *facilitating* situations (see chapter 6).

In general, the nine psychometric second-order factors of Horn (1998), and of other psychometricians, are descriptively congenial to our approach. For instance, visual processing factor (Gv) may have as key resource determinants the *S*- and *T*-operators, in addition to the operators of mental attention (*E, M, I, F*) and schemes needed for coping with misleading situations. In contrast, the auditory processing factor (Ga), as well as language, may have the *T*-operator as a dominant constituent, often within facilitating tasks involving the auditory domain.

Our theory of constructive operators also can contribute to four other research enterprises: (1) developmental theories of neo-Piagetians (e.g., Case, 1998; Case et al., 2001; Demetriou et al., 2018; Demetriou & Spanoudis, 2018), (2) theories of WM (e.g., Cowan, 2005, 2016; Engle, 2002, 2018), (3) issues involving the working mind such as Matt and *M*-capacity measurement, briefly discussed in this book, and (4) helping to understand metasubjectively developmental changes that occur with aging, that is, the "mechanics" of normal human intelligence change during the later years (Baltes, Lindenberger, & Staudinger, 2006; Lövdén & Lindenberger, 2005; Pascual-Leone, 1983, 1990a, 1990b).

Mental Attention and Consciousness: Relation, Similarities, and Differences

What is consciousness? As suggested in chapter 3, it is a special representational state. According to Damasio (2012), "consciousness is a *state of mind in which there is* [conceptual and experiential] *knowledge of one's own existence and of the existence of surroundings*" (p. 167). Neuroscientific formulations of consciousness are offered by Damasio (2012), Dehaene (2014), and many others, but this vast literature is not reviewed here. To comprehend consciousness, we need a clear understanding of *representation* (Pascual-Leone, 1976a, 1976b, 1983, 1990b, 2000a; Pascual-Leone & Johnson, 1999; Pascual-Leone &

Irwin, 1998). As Bickhard (2015a) and others have emphasized, representation is not a passive *presentation* of what is given in experience. Bickhard (2015b) says that "interactive representation is anticipatory, and the anticipations of interactive potentialities may be true or may be false" (p. 64). A similar descriptive conception of representation, cast in very different language, was offered by Husserl (e.g., 1970, 1973). If we concretize this abstract formulation causally and use our own language (Pascual-Leone & Johnson, 1999), representation appears to be a subject's own creative dynamic synthesis of more or less conceptualized experience (issues, states of affairs). This dynamic synthesis emerges by way of competitive coordination (overdetermination) among clusters of highly activated compatible schemes of all sorts, present in the subject's field of activation.

Bickhard emphasized four key characteristics of representations. (**RE1**) They are *emergent*, that is, they result from (perhaps conscious) creative dynamic syntheses of distinct activated schemes. (**RE2**) All representations point to the future with tacit or explicit anticipations of plausible outcomes, and consequences that express both semiotic intentionality and a cognitive/affective "horizon" (i.e., expectancies that aim to some future or possible goals or outcomes, evoking other related schemes; Husserl, 1973). (**RE3**) Representations may carry a truth value (a true-versus-false evaluation criterion for anticipations, expectancies, and outcomes), so errors (false evaluations) can be recognized and changed by the psychological organism, whether consciously or not. (**RE4**) The truth value of a representation is knowable or accessible to the subject's metasubject and often can become conscious. Thus, a representation should not be defined from an observer's perspective, but from within the subject's own processes as we have defined these terms (i.e., a metasubjective perspective).

To complete our characterization of a symbolic or interactive representation, we must add two other key conditions. (**RE5**) Although Bickhard does not address this important issue, representations (and consciousness) can also involve operative schemes, which express transformations, and so representations can also carry what may be called deliberate, willful or conative, *intentions* (i.e., conscious or unconscious goals to do such or such). In this case, new figurative states and truth values appear when figurative schemes apply to characterize the newly transformed state-of-affairs produced by application of operative schemes. (**RE6**) Affective schemes (pure affects) or affective-and-cognitive schemes, such as emotions or other personal (psycho-cultural) schemes, may not carry truth values by themselves but carry instead vital (evolutionary, bio- and sociocultural) values. Both semantic-pragmatic facets (i.e., deliberate intentions and vital values) could be expressed, tacitly or consciously, in any representation.

Ordinary consciousness is the aptitude of a metasubject (the subject's inner organization, both operative and figurative self) to have a distinct representation of some constituents of its own thinking (perception, cognition), feeling (affects and emotions), or willing (deliberate intentions). As consciousness emerges, self-schemes differentiate that produce the *ego* (which for us is the *outer* self or *persona*—as Jung called it), the inner *self* (operative and figurative), the *Will*, and self-conscious reflective representations. Demetriou's (Demetriou et al. 2018; Demetriou & Spanoudis, 2018) construct of "cognizance" resembles considerably this sort of developmentally advanced metasubject; a metasubject that is representation driven, often conscious, and with a conative self-agency (an *operative self*) that can produce a Will function.

Ordinary subjective experience may not be a true representational experience. Ordinary low-level perception may not qualify as a deep-enough consciousness, because experiences in low-level perception are not distinct, not organized in distinct sorts or levels of knowing; they are holistic. Therefore Husserl, Piaget, and others talked in this case of "presentation" (presentational processes), which they contrasted with "re-presentation" (see Pascual-Leone & Johnson, 1999). From this developmental perspective we have emphasized (Pascual-Leone, 2000a; chapter 3), independently but converging with Damasio's (1999, 2012) neuroscience perspective, that consciousness emerges in the child, and in the brain, in a sequence of constructivist stages: from a level of sentience that in humans Damasio calls *protoself* to various intermediate levels that culminate in a personal, social-and-historical self-consciousness that Damasio calls *autobiographical self*. The agent who does this representation (the knower or knowing self) first appears in child development at the end of infancy (Legerstee, 1998). At about 35 months a reflective/conceptual self-consciousness has begun its developmental run (in chapter 3 we called it *self2.1*—for us the precursor stage of Damasio's autobiographical self). Consciousness of any real-life situation involves many distinct, different schemes, most of which are not automatized and cannot by themselves be hyperactivated. "Hardware" exists in the brain, monitored by executive schemes, that brings about this hyperactivation. In our view, a major "hardware" mechanism is endogenous *mental attention*.