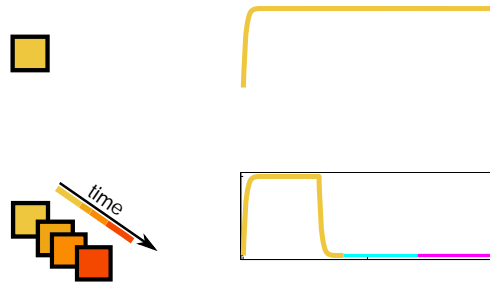


2012). In addition, the test is a measure of the child's -

Table 1 Variable and parameter with their default value

Symbol	Description
Variable	
I_j	Excitatory inhibitory; excitatory activity j
u_j	Normalized excitatory; excitatory activity j (initially $u_j = 1$)
v	Normalized excitatory; inhibitory activity (initially $v = 1$)
p_j	Leak facilitation; excitatory activity j (baseline $p_j = 1$)
w_{jk}, w	Strength; excitatory; inhibitory; excitatory activity j
T_j, T	Duration; inhibitory
Time parameter (default value in the i)	
	Time constant; excitatory (10 ⁻⁶)
τ_f	Time constant; excitatory; facilitation (1 ⁻⁴)
τ_w	Time constant; excitatory; weight (150 ⁻¹)
τ_a	Time constant; facilitation (400 ⁻⁵)
τ_s	Time constant; activity; inhibitory (50 ⁻⁶)
T_{cue}	Duration; inhibitory; trigger; cue (50 ^{-2,3})
D	Decay; excitatory; excitatory; excitatory; excitatory activity (30 ⁻¹)
D'	Decay; excitatory; excitatory; excitatory; excitatory activity (20 ⁻¹)
Other parameter (default value in the i)	
	Excitatory; excitatory; excitatory (Heaviside function)
	Threshold; excitatory; excitatory activity (0.5)
v	Threshold; excitatory; inhibitory activity (0.5)
p_{max}	Maximum; excitatory; excitatory; facilitation (2)
Z_k	Strength; excitatory; excitatory; inhibitory; excitatory activity (0.3)
L	Weight; excitatory; inhibitory (0.6)
b	Strength; facilitation (1)
M	Leak; excitatory; excitatory (1)
w_{max}	Maximum; excitatory; excitatory; excitatory activity (0.4852)
w'_{max}	Maximum; excitatory; excitatory; excitatory activity (4.1312)
w_{min}	Minimum; excitatory; excitatory; excitatory activity (1.3488)
d	Strength; excitatory; LTD0 6.4598999 194.03999328 369.368985f h hh

... identified the ... , but ...



2. \dots

Therefore, it is clear that the algorithm described above is correct. In fact, it is easy to see that the expected weight of the tree T is $w(T) = \sum_{i=1}^n w_i$. (6) In fact, the expected weight of the tree T is $w(T) = \sum_{i=1}^n w_i$. (9) This can be achieved by using the following lemma. (6) and (9), that

$$(1)$$

(Kerle et al. 1999; Pfister and Gerstner 2006; Cuthbert et al. 2010).

The delay between the triggering event can be coded in the electrical architecture, e.g., with the delay (Fig. 2). During training, synapse 1 is activated for T_1 seconds followed by synapse 2 (Fig. 2a). The timing of the delay is determined by the delay of the synapse (Sect. 2). When the first synapse is active, synapse 1 is active and LTD is induced, decreasing the synaptic weight, w_{21} , from synapse 1 to synapse 2. After T_1 ends, the first synapse is deactivated, and the second synapse is activated. Hence, synapse 1 did not become inactive immediately, and therefore both synapses are active. During this period, LTP is induced again, increasing the synaptic weight w_{21} . Shortly after synapse 1 becomes inactive, change in the weight w_{21} ceases, and a critical concentration of the synaptic weight is achieved. The initial value of the synaptic weight (w_{21}^0 and w_{21}^1 , respectively) can be controlled independently (Sect. 2). Repeated sequences of the training sequence lead to a critical concentration of the synaptic weight, w_{21}^i (weight after i th training), to a fixed value (Fig. 2b). On the other hand, the synaptic weight w_{12} is decreased during each trial because the synaptic weight 2 is always active after the first synaptic weight 1 (Sect. 2). In the case of N synapses, each weight $w_{k+1,k}$ is connected to a sequence associated with T_k , hence each weight $w_{k+1,k}$ becomes negligible during sequence. Thus, the electrical architecture encodes the sequence.

The delay between synapse 1, T_1 , determines the delay between the activation of the synaptic weight from synapse 1 to synapse 2, w_{21}^∞ (Sect. 2). For a given value of T_1 , LTD at sequence decreases w_{21} (Fig. 2c). Hence,

is considered a mechanism for fine-tuning (Bassett et al. 2000; D'Esposito 2003; Reiter et al. 2004; Kaur et al. 2007; Gao et al. 2009). With this change, coordinated activity is directed to a specific area of the cortex, but if coordination is able to be maintained.

For initial effective coordination, here activity of the first coordination state is used (Fig. 3). This is if the area is available that a specific eight are fixed digress. This activity is the area (Section 4.4). After this activity is with a brief case, it is also active to determine the area (Section 2).

(Fig. 20,000 iterations w^0). The attractor eight after the initial stage, w_{21}^i , is described by a basis of eight functions that converge in the initial stage. The eigenvalues of the distribution in the initial stage of the attractor eight after the initial stage are the eigenvalues of the attractor eight after the initial stage (Fig. 5c). The attractor of the attractor eight, w_{21}^∞ ,

are; a ... ai, ca ... the; e fa ... ti et ac -
 ig; ce (Be da a d He; 2003), i lead f h; t; .
 faci itati . I c; t; att the ca e f h; t; . faci itati ,
 ada tati ca e the effecti ei t f; . e ... ai t
 dec; ea e; e ti e.

I thi ca e ... ai acti it; a ... de ed b

$$\frac{du_j}{dt} = -u_j + (w_{jj}u_j + s_j - Lv - a_j),$$

$$a \frac{da_j}{dt} = -a_j + bu_j,$$

$$s \frac{ds_j}{dt} = -s_j + \sum_{k \neq j}^N w_{jk}u_k,$$

$$v \frac{dv}{dt} = -v + \sum_{k=1}^N Z_k u_k - v,$$

he; e a_j de te the ada tati e e f ... ai j , a i
 the ti e ca e fa da tati , a d b i the ada tati t; e gh.
 Feedbac be; ee ... ai ... a ... ed t be; e
 the feedbac; ithi a ... ai ; th , the t ta i t
 f; ... ai j a ... it i t e f-e citati $(w_{jj}u_j)$, a d
 a tic i t f; the; ... ai (s_j) hich e ed
 the ti e ca e s. N t e that i the i it $s \rightarrow 0$, a e
 a e i ta ta e .

F; a ... ilab e ch ice f; a a et; , g ba i hibiti
 t; ac acti it fa t; the e citati be; ee ... ai .
 The; he a ... ai bec e i acti e d e t ada -
 tati , the e e f g ba i hibiti dec; ea e , a; i g
 be e t ... ai t bec e acti e. Thi; ea the
 eigh t f e f e citati ca e c de ti i g. Th , i thi
 et; e; e de ed g t; a tic i t; ithi a ... ai
 a; e . The ea; i g; e f; w_{jj} a a a g t w_{jk} ith
 the additi a a ... ti that i ce w_{jj} e; e e t e d the
 a tic eigh t; ithi a ... ai , it c d t dec; ea e
 be; a cetai a e w_{min} . A , the a a et; f; g
 t; a tic i t; ithi a ... ai a e a; ed t be dif-
 f; e t f; the a a et; f; g t; a tic i t; be; ee
 ... ai .

The ea; i g; e; a the

$$\frac{dw_{jj}}{dt} = - \frac{p}{d} (w_{jj} - w_{min}) u_j (t - D') (1 - u_j(t)) - \frac{p}{d} (w_{jj} - w_{max}) u_j (t - D') u_j(t).$$

Whe the ... ai ... a acti ated $(u_1(t) \approx 1)$ f; $t \in [0, T_1]$ (Fig. 7a), the cha ge i the; eigh t w_{11} e; e g
 e; ed b the iec; i e diff; e tia e; ai

$$\frac{dw_{11}}{dt} = \begin{cases} 0, & t \notin [D', T_1 + D'] \\ \frac{p}{w_j} (w_{max} - w_{11}), & t \in [D', T_1] \\ -\frac{d}{w} (w_{11} - w_{min}), & t \in [T_1, T_1 + D']. \end{cases}$$

The f; i g; e; ai e; e the a tic; eigh t at the
 e d fa; e e tati , $w_{11}(T_{tot})$, t the a tic; eigh t at
 the begi i g f the e e tati , $w_{11}(0)$:

$$w_{11}(T_{tot}) = w_{11}(0)e^{-T_1 \frac{p}{d} \frac{1}{w}} e^{(\frac{p}{d} - \frac{d}{w}) D' / w} + w'_{max} e^{-D' \frac{p}{d} \frac{1}{w}} (1 - e^{-T})$$



This emerging evidence indicates that the architecture of the brain (Buckner and Gattavolati 2009; He et al. 2014), in particular the connectivity between the default mode network and the task-positive network, is a key factor in determining individual differences in cognitive performance.

4.1.1. The role of the default mode network

The default mode network (DMN) is a set of brain regions that are active when the individual is at rest and not engaged in any task. It is thought to be involved in a variety of cognitive processes, including self-referential thought, memory, and social cognition.

to occur. This article therefore provides a rigorous and
calibrates the evidence base. For
instance, the authors have identified the following

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