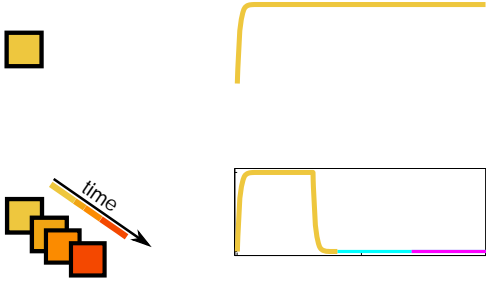


2012). In contrast, the temporal attributes of the stimuli -

Table 1 Variable and parameter with their default value

Symbol	Description
Variable	
I_j	Excitatory population j (at j)
u_j	Normalized firing rate of population j (at j) (at j , $u_j = 1$)
v	Normalized firing rate of inhibitory population (at $v = 1$)
p_j	Leak current of population j (at $p_j = 1$)
w_{jk}, w	Strength of connection from population k to population j
T_j, T	Decay time constant
Time scale (default value in the i)	
	Time scale of firing (10 ⁻⁶)
f	Time scale of fast excitatory (1 ⁻⁴)
w	Time scale of weight (150 ⁻¹)
a	Time scale of adaptation (400 ⁻⁵)
s	Time scale of synaptic time (50 ⁻⁶)
T_{cue}	Decay time constant of cue (50 ^{-2,3})
D	Decay time constant of excitatory (30 ⁻¹)
D'	Decay time constant of inhibitory (20 ⁻¹)
Other parameter (default value in the i)	
	Firing rate of excitatory (Heaviside function)
	Threshold of excitatory (0.5)
v	Threshold of inhibitory (0.5)
p_{max}	Maximum of fast excitatory (2)
Z_k	Strength of connection from population k to inhibitory (0.3)
L	Weight of inhibition (0.6)
b	Strength of adaptation (1)
M	Leak current of excitatory (1)
w_{max}	Maximum of synaptic weight (0.4852)
w'_{max}	Maximum of synaptic weight (4.1312)
w_{min}	Minimum of synaptic weight (1.3488)
d	Strength of LTD 6.4598999 194.03999328 369.368985f h hh

and ... ti ... ified the a a i, b t a t ece a



(Kerle et al. 1999; Pfeiffer 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 and gain is increased in 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 active. 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 the synaptic weight 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 synaptic 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 synaptic weight from synapse 1 to synapse 2, w_{21}^∞ (Sect. 2). For a given value of T_1 , LTD at gain, w_{21} (Fig. 2c). Hence,

is considered a mechanism for fine-tuning (Bassett et al. 2000; Drevets et al. 2003; Reiter et al. 2004; Kagan and Davidson 2007; Gao et al. 2009). With this change in connectivity, reduced activity in the dorsal attention network is observed, but if connectivity is able to be maintained.

For individual effects of connectivity, here activity of the first connectivity set is detailed (Fig. 3). This is if the analysis revealed that a particular region was significantly active. This activity is then detailed (Sect. 4.4). After this analysis is completed with a brief case, it is then detailed in the next section (Sect. 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 tead f h; t; .
 faci itai . I c; t; att the ca e f h; t; . faci itai ,
 ada tai 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 tai e e f ... ai j , a i
 the ti e ca e fa da tai , a d b i the ada tai 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 citai ($w_{jj}u_j$), a d
 a tic i t f; the; ... ai (s_j) hich e ed
 the ti e ca e s. N t 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 citai be; ee ... ai .
 The; he a ... ai bec e i acti e d e t ada -
 tai , 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 citai 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 addi a a ... ti that i ce w_{jj} e; e e ted 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 tai , $w_{11}(T_{tot})$, t the a tic; eigh t at
 the begi i g f the e e tai , $w_{11}(0)$:

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



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 network of brain regions that are active when the individual is at rest and not engaged in any task.

to occur. This article therefore provides a rigorous and
calibrates the evidence base for the use of
in the area of forensic child psychiatry.

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