***g*CODE Theory**

Far Transfer Brain Training for *g*

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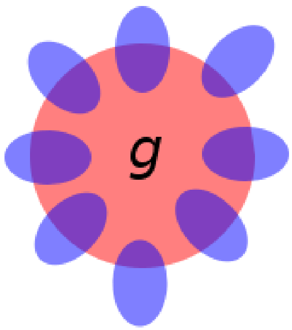


g – General Intelligence

Although there is still no standard definition of 'intelligence', there are strong similarities between informal definitions, and the psychometric construct *g* can be defined with precision. The following definitions are from Legg and Hutter (1).

The cognitive scientist Mike Anderson defines general intelligence as:

> *". . . that facet of mind underlying our capacity to think, to solve novel problems, to reason and to have knowledge of the world."*

An op-ed statement signed by fifty-two intelligence researchers extends this definition to include learning efficiency and being 'switched on' or having situational awareness:

> *"A very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience. It is not merely book learning, a narrow academic skill, or test-taking smarts. Rather, it reflects a broader and deeper capability for comprehending our surroundings — "catching on," "making sense" of things, or "figuring out" what to do."*

From an applied approach comes and emphasis on productivity, captured by:

> *"An intelligence is the ability to solve problems, or to create products, that are valued within one or more cultural settings."* H. Gardner

> *". . . I prefer to refer to it as 'successful intelligence.' And the reason is that the emphasis is on the use of your intelligence to achieve success in your life. So I define it as your skill in achieving whatever it is you want to attain in your life within your sociocultural context"* R. Sternberg

From the artificial intelligence (AI) movement comes an emphasis on efficient goal achievement, captured in these definitions:

> *"Achieving complex goals in complex environments."* B. Goertzel
>
> *"Intelligence is the ability to use optimally limited resources – including time – to achieve goals."* R. Kurzweil

General intelligence can also be defined as *g* - a statistical construct developed in psychometric testing to account for the positive correlations ('positive manifold') found between a broad range of cognitive tasks - from reasoning to general knowledge to processing speed to creativity, self-regulation and attention control (2) – not just those found in psychometric full scale IQ tests.

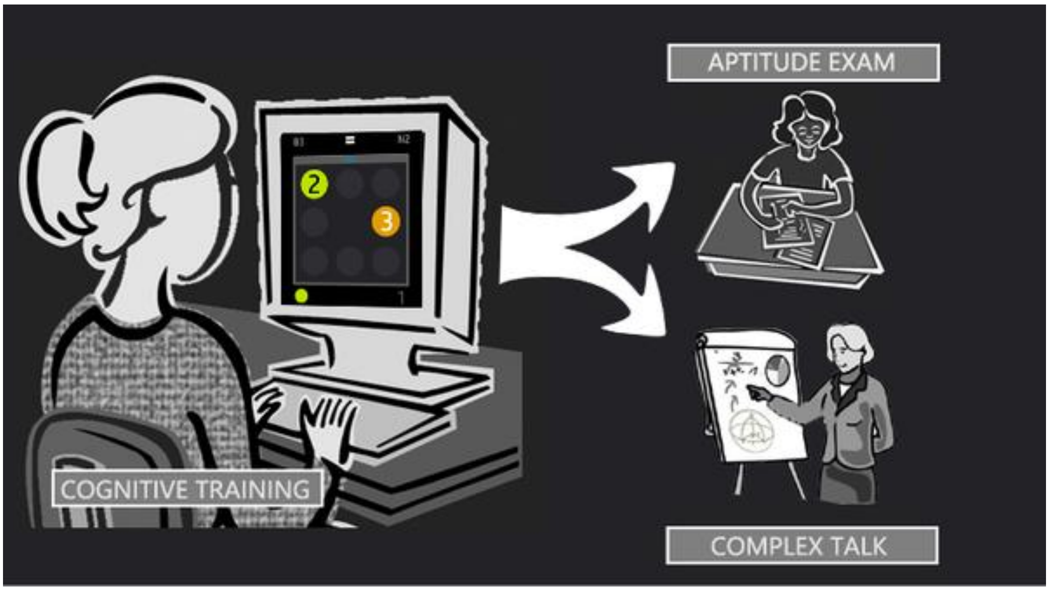
At Cambridge Mindware Lab we use *g* as our working definition for intelligence.

The Brain Training Goal: *Far Transfer to g*

Brain training apps developed by scientists are intended to result in the **transfer** of performance gains on the training exercise itself to *g*-related cognitive skills that are useful to you in real life.

This kind of transfer from training is called **far transfer**.

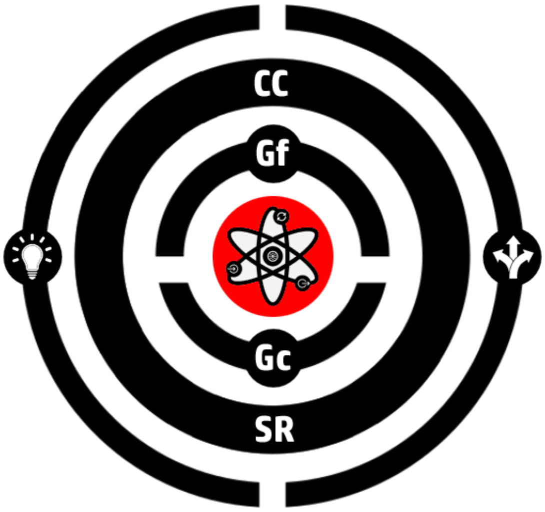
Many brain training apps on the market only result in **near transfer**: you improve skills specific to the exercises you train with, but this does not help you with more general-purpose *g*-related skills in everyday life.



Far transfer examples

Real World *g* Functions

Effective far transfer brain training can target any of the 5 types of *g*-related cognitive function shown in this figure:



i. Fluid Intelligence (Gf)

- Comprehending & understanding
- Problem solving & reasoning
- Strategic planning & decision-making
- Learning efficiency

ii. Crystallized Intelligence (Gc)

- Store of knowledge, skills strategies, & experience in long-term memory
- Ability to use the above in appropriate contexts

iii. Cognitive Control (CC) & Self-Regulation (SR)

- Attention focus & flexibility
- Will power
- Control and regulation of emotions
- Ability to conduct sustained practice & training
- Ability to establish new habits or break old ones
- Goal pursuit, choice-making and autonomy

iv. Creativity

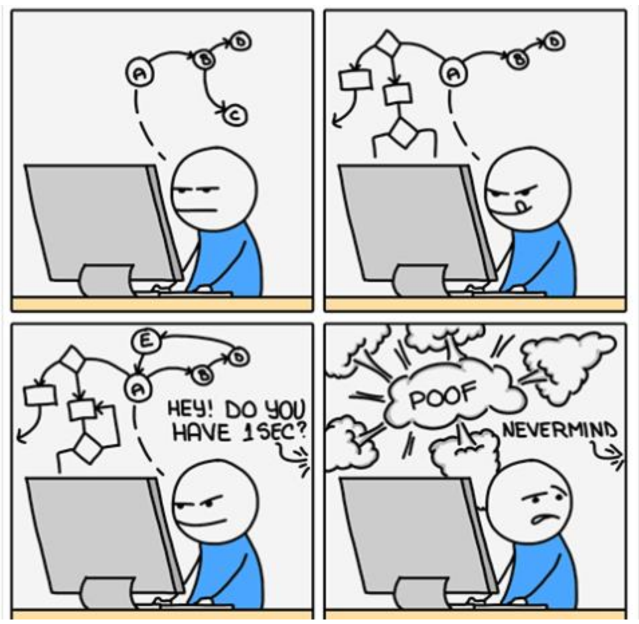
- Divergent thinking
- Creative problem solving
- Creative strategizing & decision-making
- Inventiveness / entrepreneurship

v. Flexibility, Adaptiveness & Situational Awareness

1) Attentional & cognitive flexibility
2) Situational awareness
3) Ability to disengage from goals, set switch and adapt to new environments
4) Ability to adapt strategies to face new and unexpected conditions.

Supporting these *g*-related functions, and playing a fundamental role in intelligence:

- **Working memory**: This is your 'mental workspace' that maintains the information you need for the current context and cognitive task – whether you are comprehending, reasoning, problem solving, learning or planning – while not losing track from distractions. Working memory is required to mentally relate, integrate, and recombine information. Following a conversation in a foreign language puts high demands on working memory, as does difficult mental arithmetic or planning the optimal route through a city during rush hour traffic. **WM capacity** (or span) is the 'bandwidth' of this workspace – like how much RAM a computer has.



- **Strategic metacognition**: This is your ability to manage your own 'cognitive resources' flexibly and adaptively to multi-task efficiently, to strategically change responses based on priorities, and make use of speed-accuracy and cost-benefit trade-offs, as well as to notice relevant contexts to apply your training or learning. It depends in part on your own self-awareness of your own cognition – called metacognition.

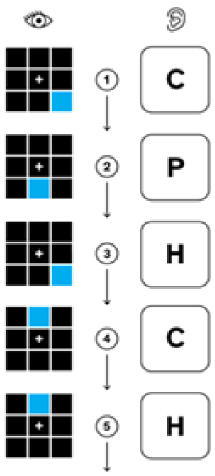
- **Cognitive resilience**: This is your ability to maintain optimal working memory, attention focus and intelligent cognition in the face of fatigue, stress or other emotional pressures.

Effective Brain Training

In published research you often hear about a brain training study showing a statistically ‘significant’ result. But significance alone doesn’t tell us about how **effective** the training is –how much of an impact it has on IQ test scores for example. For this we need the **effect size**.

The effect size is quantified in a statistic that can be converted to standardized points. An effect size of 1.0 = 15 standardized points. So a brain training program with an effect size of 1.0 is expected to result in a post-training gain of 15 points; a training program with an effect size of 0.5 results in a post-training gain of 0.5 x 15 = 7.5 standardized points.

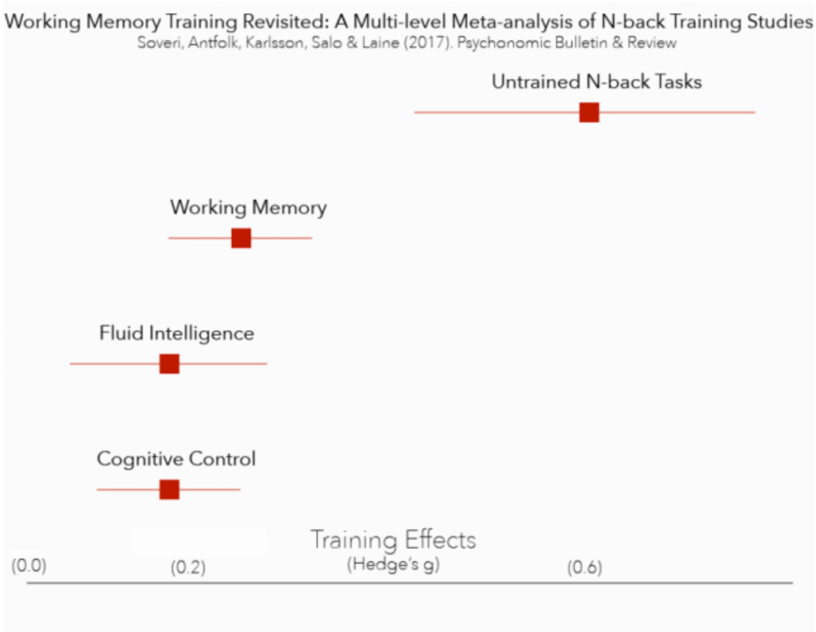
Effectiveness of the Dual N-Back Game



What is the scientific consensus on effect sizes for the most widely tested brain training games? One of these is the dual n-back (DNB) – a **working memory** brain training game.

The latest meta-analysis that combines the data of all 33 published, randomized, controlled DNB trials from independent labs around the world (3) reveals there are far-transfer training effects for:

- Working memory (Gwm)
- Fluid intelligence (Gf)
- Cognitive Control

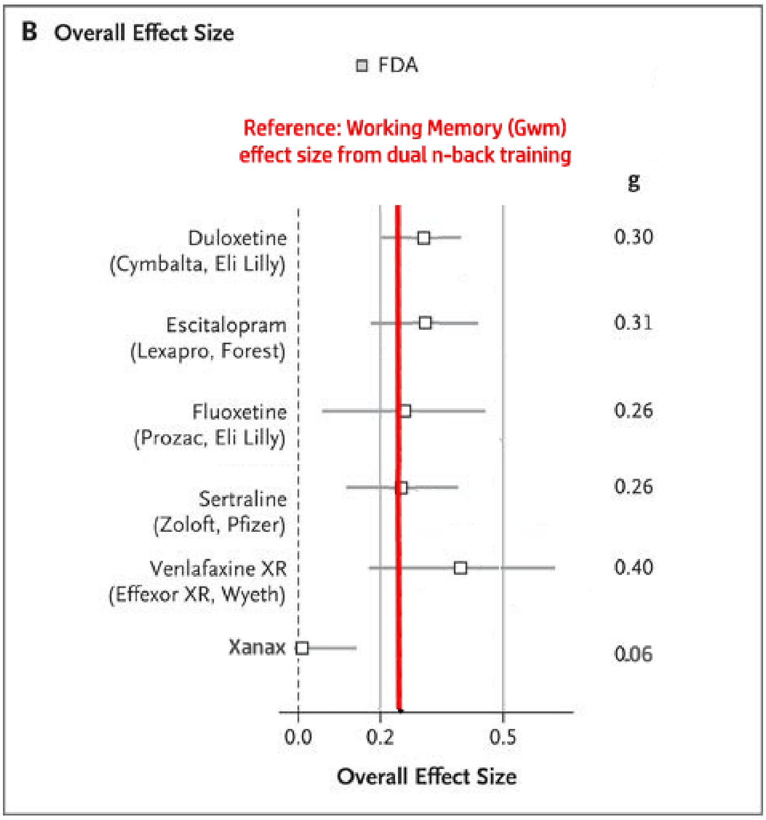


Effect size data from Soveri et al, 2017

Dr Au and colleagues' earlier 2015 meta-analysis also found the same effect size of DNB training on fluid reasoning (4). This team concluded:

> *"the results reported in this meta-analysis represent a low-end estimate of the true extent of improvement that n-back training can have on measures of fluid intelligence."*

Note: The DNB effect sizes for visuospatial fluid reasoning (Gf) and working memory (Gwm) – both measures of IQ - are approximately double what you get with *Lumosity* training for a similar duration (5).



How do these effect sizes compare with other well-known interventions? The effect size for working memory capacity (Gwm) is 0.24. This is the same effect size as that of commercial antidepressants such as Fluoxetine (Prozac) in treating depression (6).

Certainly a lot of money is invested into developing anti-depressants! If research reports far transfer effects of 0.2 or higher, this is worth your attention. Many pharmaceutical drugs have effect sizes in the 0.2 to 0.4 range.

But still, we are only looking at gains of 2 to 4 standardized points from DNB training! The effect sizes are small as conventionally understood:

Small effect = 0.2
Medium effect = 0.5
Large effect = 0.8

Traditional cognitive training just isn't resulting in the far transfer benefits for *g* that we are looking for. Brain training should be striving for effect sizes of 0.5 or higher – ideally at least 10 standardized points.

Enter the *g*CODE and *g*CODE+ training paradigm.

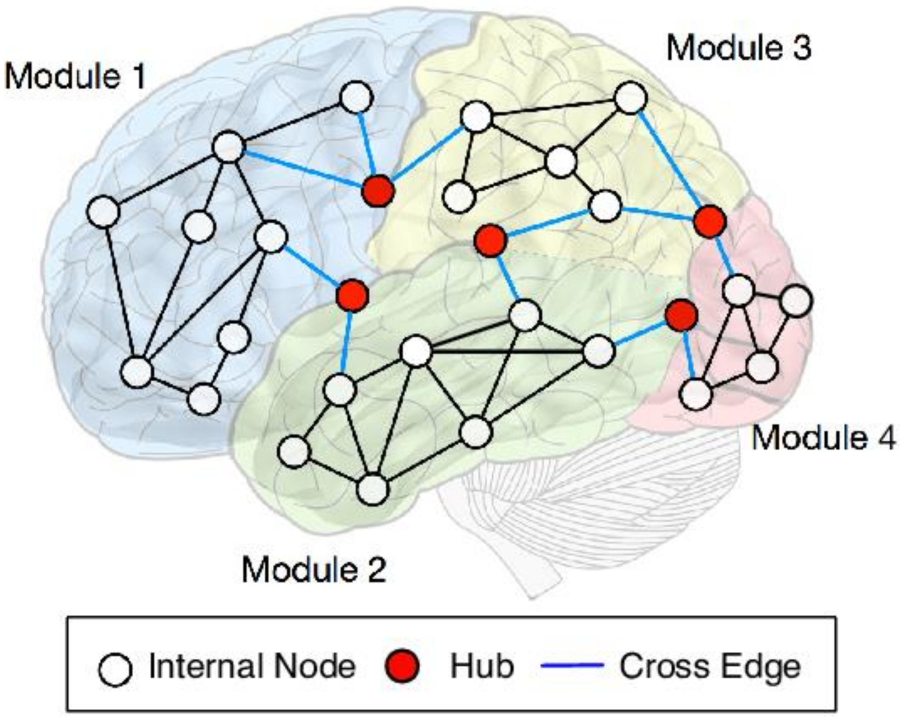
Paradigm Shift:
Key Training Principles

A paradigm shift is needed. We need a new set of principles around which to build brain training apps and programs in systematic ways to achieve medium to large effect sizes.

I have converged on a number of evidence-based principles that have emerged with good consistency in published research over recent years. The *g*CODE model for brain training is built from these key principles (P1 – P7):

P1. Network Hubs

Some brain regions are highly connected, acting as flexible network **hubs**. These have a central role in supporting integrated brain function. Domain general, integrated brain function is clearly needed far transfer (7). Thus, any effective brain training program needs to be designed to target the brain's network hubs. In this diagram, the 'modules' are the frontal, parietal, temporal and occipital cortical lobes of the brain. The nodes and edges are brain regions and their network connections. The red hubs are the types of regions brain training should target for far transfer.



From Guixiang Ma et al., 2017

P2. Executive Control Networks & Core Functions

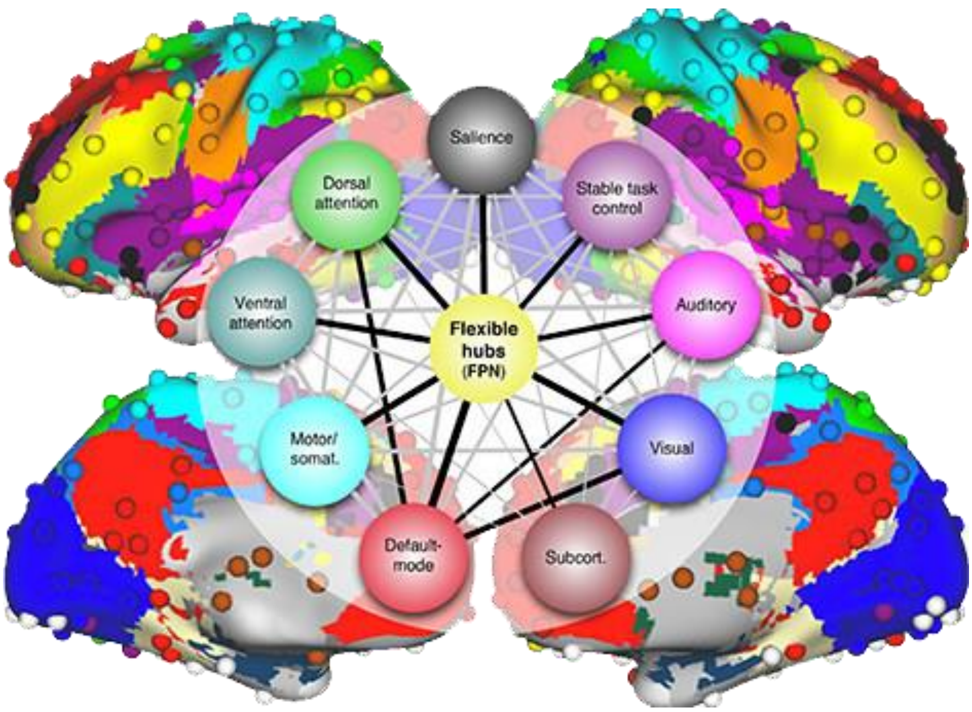
Humans have a unique ability to envision outcomes and carry out actions to achieve them. Our capacity to manage goal-directed behaviours, counter to habit or amidst competing action-choices, is termed **executive control**[1]. Executive control has a close dependency on the **frontal lobe** and its associated working memory networks (8, 9).

At Cambridge Mindware Lab we develop apps that target executive control networks and their associated executive functions (EFs).

> **Executive functions:** *a broad collection of higher-order cognitive functions that allow individuals to flexibly regulate their thoughts and actions in the service of adaptive, goal-directed behavior."* (10)

(i) Frontoparietal Networks: Attention Control & Working Memory Maintenance

The frontoparietal control network (FPCN) is a flexible hub that coordinates processing across other brain networks in an adaptive, goal-dependent way (11, 12).



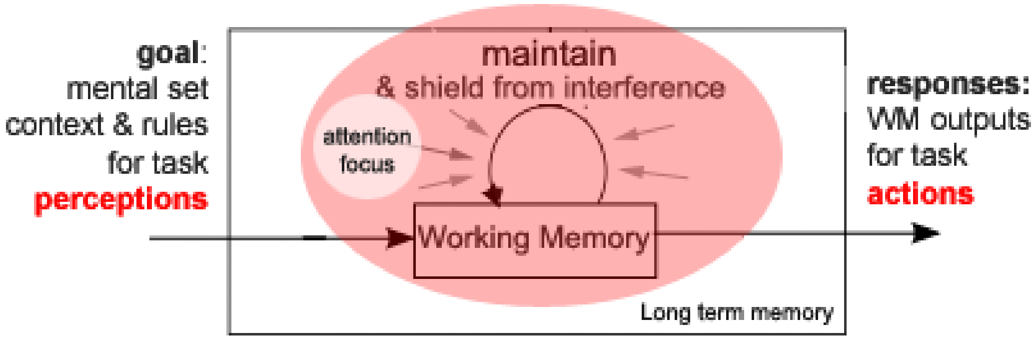
From the Cole and colleagues' Flexible Hubs model of the FPN

Different zones within this frontoparietal network fractionate into two attention and **working memory (WM) maintenance** networks, allowing us to temporarily

[1] Also known as 'cognitive control'.

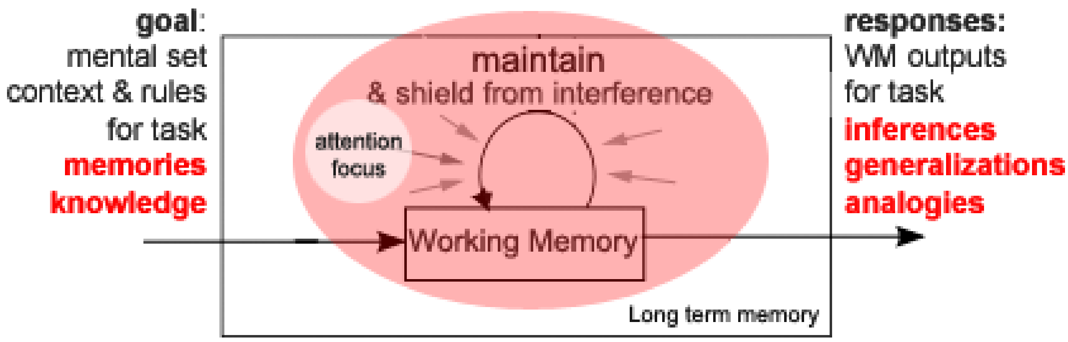
store task-relevant contextual information over time while inhibiting distractors or automatic responses ([13]):

Frontoparietal Control Network B (FPCNB): WM maintenance in moment-by-moment sensorimotor interactions with the environment. FPCNB is connected to the dorsal attention network (DAN) and contributes to cognitive control by flexibly encoding perception-action task rules and their relationship to expected reward outcomes in working memory. With top-down control over the DAN, FPCNB ensures that attention can shift between task-relevant information, rather than salient, yet irrelevant stimuli, or task-irrelevant thoughts.



Working Memory Maintenance for $FPCN_B$

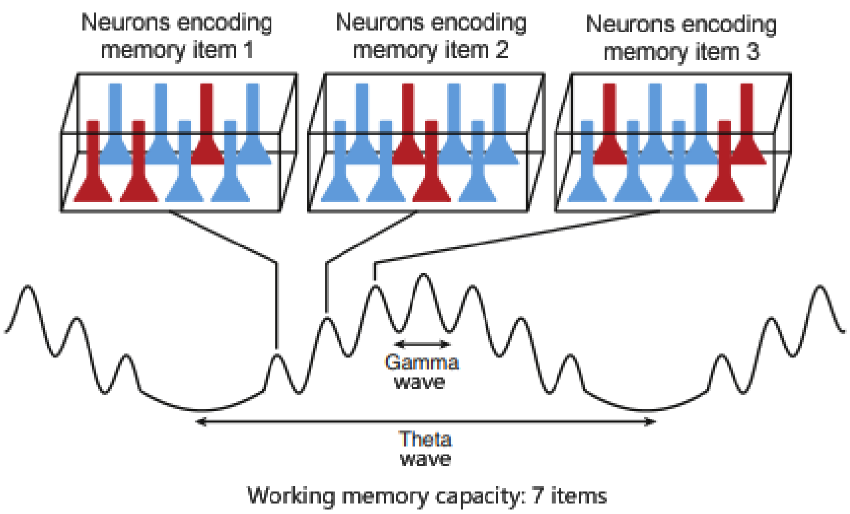
Frontparietal Control Network A (FPCNA): Working memory maintenance for the regulation of introspective 'offline' processes - free from sensorimotor interactions with the environment. It has strong links with the default mode network (DMN), hippocampus & parahippocampus. It plays a role in bringing conceptual–associative knowledge and episodic experience to bear on working memory. It is involved in metacognitive awareness, multitasking, mentalizing, temporal planning; also relational reasoning and abstract thinking.



Working Memory Maintenance for $FPCN_A$

In short, the FPCN$_B$ network is for online sensorimotor control (e.g. improvising with an instrument or playing sport), the FPCN$_A$ is for offline introspective/thought control (e.g. mathematical reasoning or planning).

WM maintenance in these frontoparietal networks may depend on **gamma wave** (35+ Hz) and **theta wave** (4-8 Hz) **synchronization** where circuits of neurons all oscillate together. Different memories items (e.g. perception-action rules) in WM may be encoded by gamma waves with different phases in the slower theta wave which keeps repeating itself during WM maintenance. Working memory capacity on this model is the number of distinct gamma-coded items in the theta wave (14, 15).



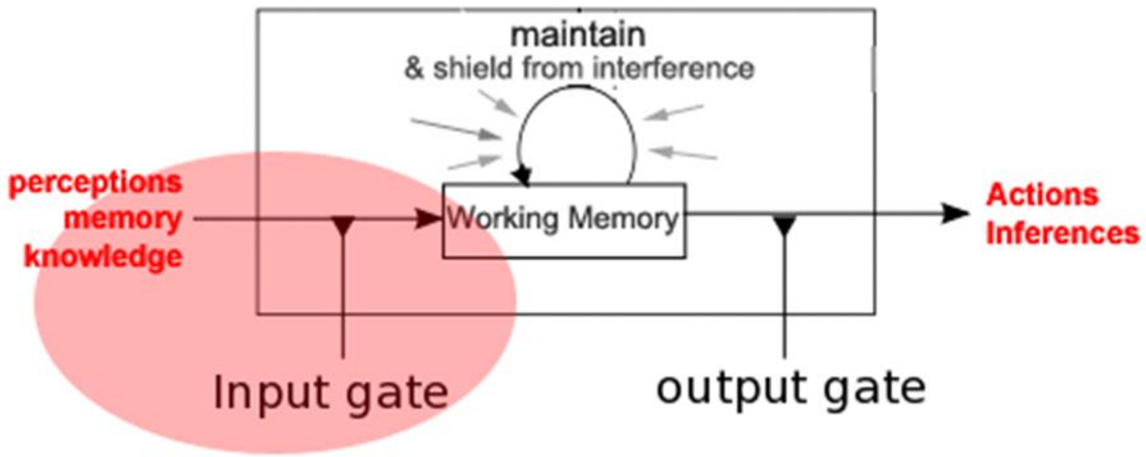
Adapted from Lisman, 2010

(ii) Corticostriatal Networks: Working Memory Input Gating (Updating) and Output Gating

Working memory needs both the ability to stably maintain information in the face of distractions, but also flexibly **select from** and **update** its contents (16).

Input gating

WM networks have **input gates** that enable context-sensitive updating. When these are open, newly relevant information can flow in; when these are closed, information is maintained and shielded from distraction. For example - if you are watching a movie and someone shouts that it's your turn to have a shower, you need to update the contents of your working memory (current scene, plot line, related to the movie) with a shower-related mental-set (what you need to do to have a shower and get clean). This updating of your current goal and mental set requires input gating.

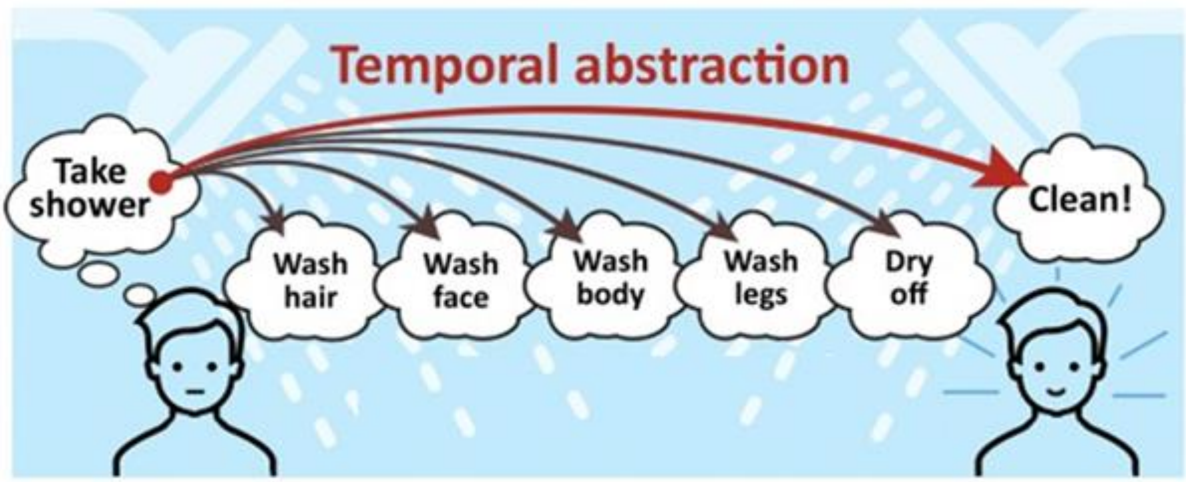


Working Memory Input Gating for Frontoparietal Networks

Professor Tod Braver (a fellow grad student) has shown that the input gate is opened via **dopamine signals** from the striatum (basal ganglia) to the **pre-frontal cortex** of the frontoparietal networks where the information is updated (17).

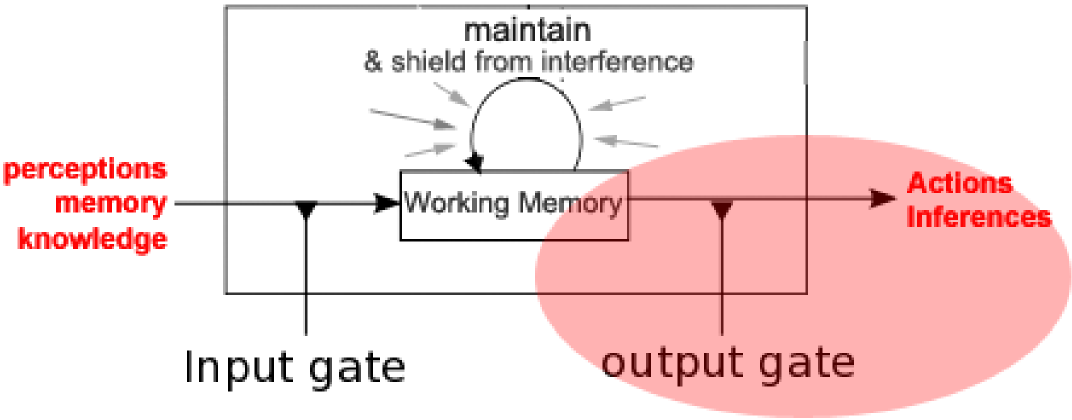
Output gating

Not all information that you are keeping in mind in the mental workspace of WM may be relevant to what you are currently need to do. For example, when showering you may have the long-range goal to get clean in mind, while also all the steps needed to get clean (wash hair, wash face, etc), but you only need deploy one step in WM at a time.



Adapted from Badre & Nee, 2018 (18)

This kind of selection and management of workspace information for 'downstream' processing depends on **output gating** from working memory (18).



Working Memory Output Gating for Frontoparietal Networks

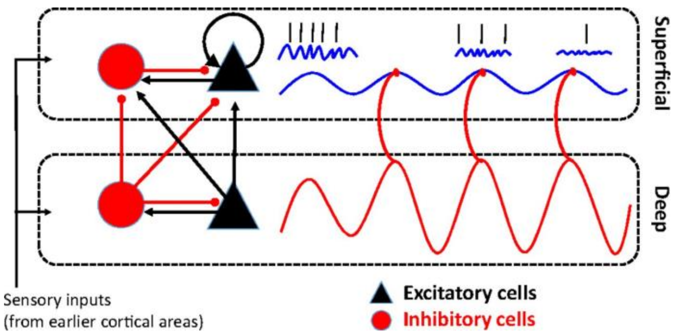
Output gating is important for both intelligent action selection via the $FPCN_B$ and for inference and abstraction of higher order rules and associations via the $FPCN_A$ (16, 19, 20, 21) needed for:

- Applying complex rules
- Decision making
- Planning
- Learning and generalization
- Complex reasoning

WM output gating is critical for fluid intelligence involving reasoning and concept abstraction.

Studies have shown that WM output gating depends on very similar cortico-striatal (dopamine-signalling) networks as WM input gating (19).

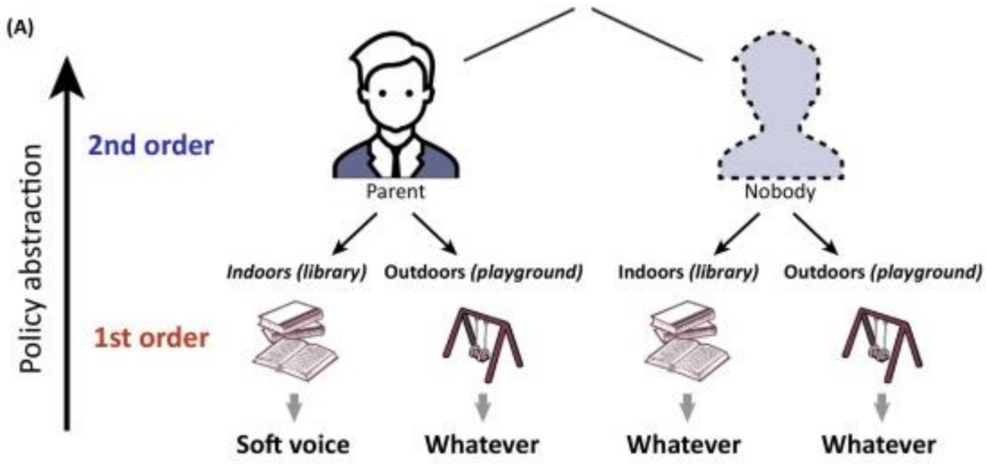
Input and output gating may depend on synchronized Alpha/Beta frequencies (8-35 Hz) in deeper layers of cortex, allowing information to enter or exit active maintenance in WM (35+ Hz Gamma frequencies) in more superficial layers cortex (15). Maintenance could also depend on slow wave theta waves as described above.



Bastos and colleagues' (2018) model of working memory (15)

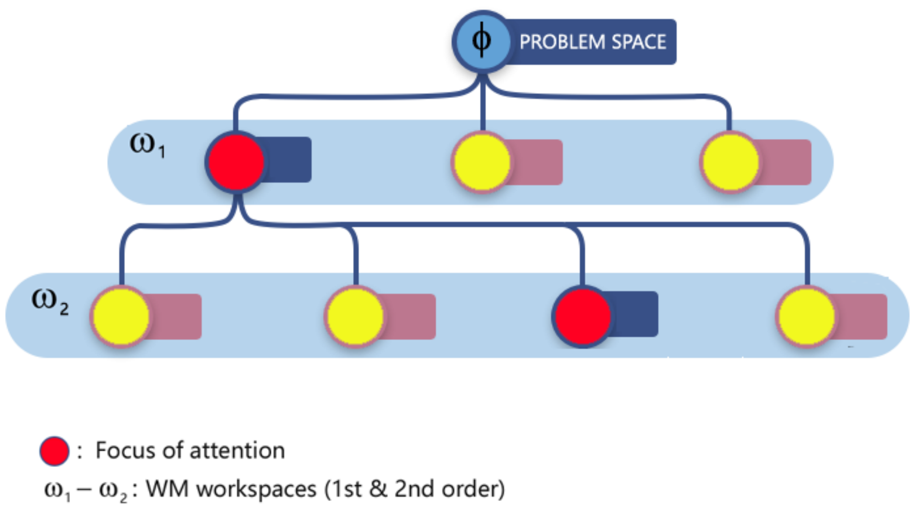
(iii) Multiple Cortico-Striatal Loops: Multiple WM Workspaces for Hierarchical Control

All intelligence-demanding tasks we do in everyday life have **a complex hierarchical structure** with multiple levels of goals over different timescales (18). Taking a shower involves holding a long-range abstract goal in mind (getting clean), while going through a number of concrete perception-action steps (wash hair, wash face) to get there. Analogously, a child can manage multiple rules like <library -> soft voice> and <playground -> whatever> (1st order abstraction) as well as multiple higher order contexts, such as <parent present> or <no parent present> (2nd order abstraction) that the lower order rules depend on, as shown in this figure:

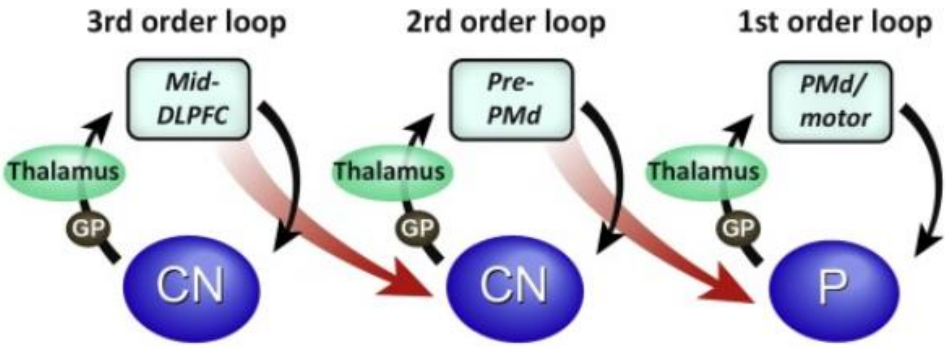


From Badre & Nee, 2018 (18)

Fluid intelligence demanding processing for problem solving, comprehension or decision-making typically involves shifting attention through some problem space with a hierarchical structure with different levels of 'policy abstraction' like this, as shown in this figure:



The research tells us that **multiple WM workspaces** can be input/output gated and maintained separately by different network hubs depending on (i) the type of control (sensory–motor or introspective) and (ii) the level of abstraction (1st or 2nd order abstraction) and (iii) modality (verbal/spatial/episodic) of content to be monitored. Generally, the more abstract and domain-independent the WM content, the more rostral (towards the front of the brain), and the more domain specific and concrete, the more caudal (towards more downstream regions of the brain) (18, 22, 23). Illustrated below is Badre and Nee's Corticostriatal Model for Hierarchical Control where you can see the nested look structure, enabling gating for multiple levels (18).



Badre & Nee's Corticostriatal Model for Hierarchical Control

Working memory capacity (WMC), as measured by complex span tasks, is thus a complex construct with multiple buffers or stores, each of which has limited capacity.

More rostral (prefrontal) higher order WM loops may be more continuous with semantic long-term memory, explaining why higher-level abstraction may aid in memory encoding or recall (24).

(iv) The Cingular-Opercular Network & Inferior Frontal Junction: Disengaging, Interference Control and Mental Set Shifting

The Cingular-Opercular Network (CON) – including an Anterior Cingulate Cortex network hub - interacting with the FPN networks via a common network hub called Inferior Frontal Junction (IFJ) enables us to shift between different task sets or rules without interference between them. It functions to prevent **proactive interference** (mental stickiness) by disengaging from previous rule-sets, associations and memories that are no longer relevant to the task. (25, 26). Neural mechanisms of interference control underlie the relationship between fluid intelligence and working memory capacity (27).

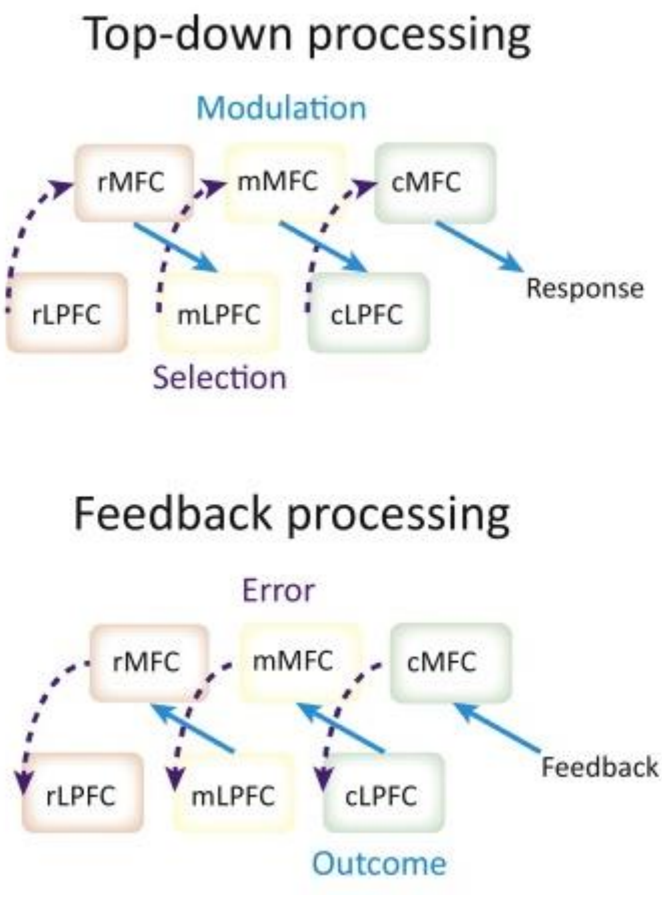
(v) Dorsomedial Salience Network: Mapping What's Important for WM

There is a lateral-medial (towards the side - towards the middle) organization in cortex, with lateral networks involved in working memory **content** and medial networks involved in **motivation** and **emotion** (18). The lateral frontoparietal networks ($FPCN_A$ and $FPCN_B$) interact strongly with medial prefrontal cortex -

specifically the Salience Network with hubs including the dorsal anterior (upper-frontal) cingulate cortex (dACC), the pre-Supplementary Motor Area (pSMA), the anterior insular cortex and the amygdala (28).

This medial network maps **information that is important** for working memory, and is sensitive to motivational signals, rewards/penalties, conflict monitoring and error signals. These signals modulate the intensity of control by the lateral frontal zones (29).

A fundamental function of this network may be to learn to **predict outcomes** (e.g. action-outcomes in FPCN$_B$) given the representations maintained in working memory networks. This could happen in a hierarchical way, with a 'diagonal' cascade of rostral-to-caudal ('top down') signals between embedded WM workspaces (see above) and their adjacent medial saliency/motivation zones. Conversely, 'bottom up' performance feedback reverses these dynamics with prediction errors motivationally updating WM content and dorsomedial PFC outcome predictions in the opposite direction (30, 31).



Alexander & Brown (2015) (31)

These 5 Principles and their associated brain networks and executive functions are the basis of the cognitive training apps that are being developed at Cambridge Mindware Lab.

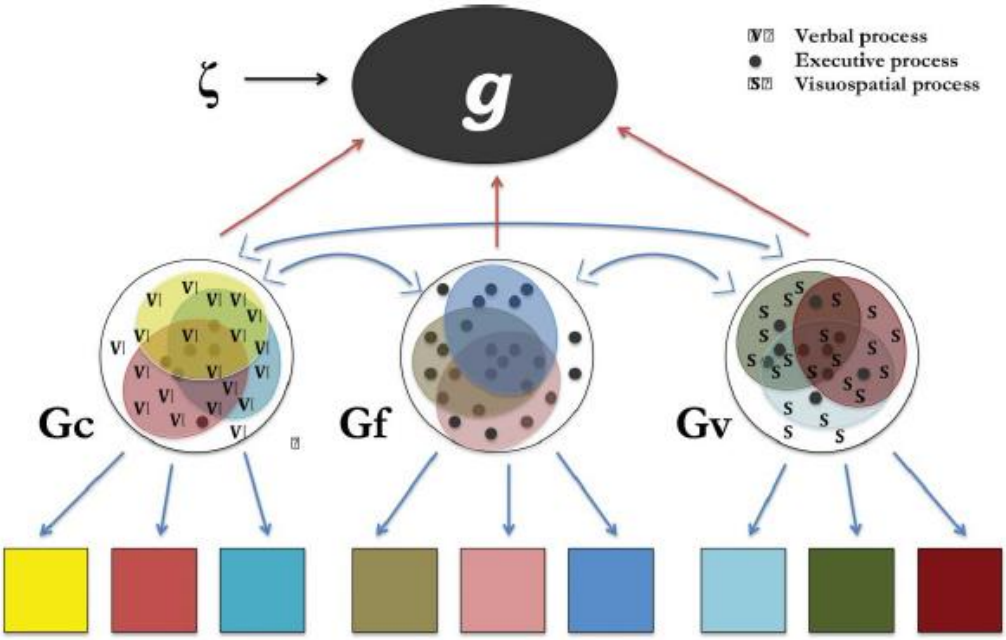
P3. Executive Processes = *g*

The frontoparietal networks have a 'multiple-demand network' architecture (32) supporting diverse cognitive demands associated with standard tests of fluid intelligence (G*f*) as well as working memory (WM).

Numerous factor analytic studies have demonstrated a strong association between individual differences in WM ability and G*f* (33, 34, 35).

In understanding how to train general intelligence (*g*), we build on the The Parietal-Frontal Integration Theory of Intelligence (P-FIT) (36) and Kovacs & Conway's (2016) Process Overlap Theory (POT) of general intelligence (37). According to the P-FIT model, information processing within this network during IQ demanding tasks is directly related to individual differences in general intelligence (*g*). Differences in the functioning of this network underlie differences in IQ test scores.

According to POT intelligence (*g*) is explained by an interaction of **domain general executive processes** (represented by the black dots in the model below), as well as domain specific processes such as visuospatial ('S's), verbal ('V's).



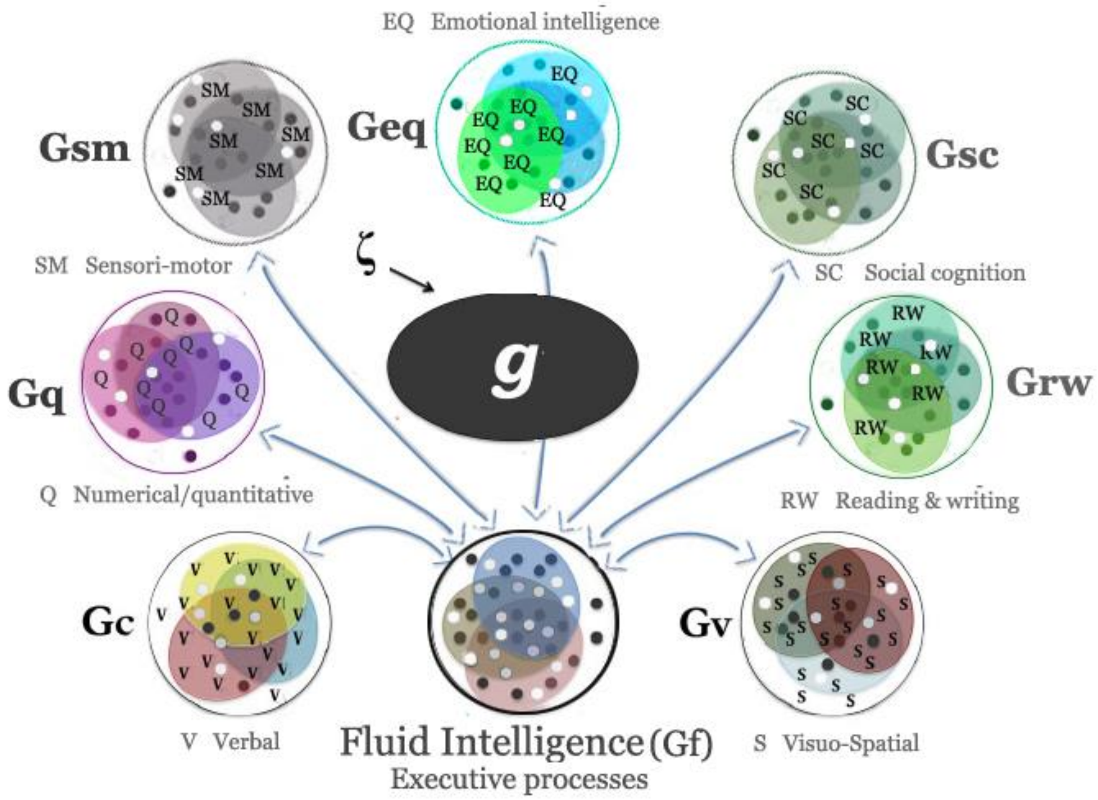
Process Overlap Theory (POT)

It is the **overlap** of the same executive processes (the dots) that explains the positive correlations between all the different 'broad abilities' (or subfactors) of intelligence that we statistically abstract as general intelligence (*g*). Hence 'process overlap' theory. Tests of different broad abilities (verbal, visuospatial, etc) measure these executive processes and their interactions with domain-specific processes.

POT theory claims that combinations of executive processes are in fact *the same as* **fluid intelligence (G*f*)** when they are applied to solving complex and novel cognitive as defined above. Our fluid intelligence is the most general-purpose, adaptive function of our cognition and it is very strongly correlated with general intelligence (*g*) measured by full scale IQ tests.

> *Fluid intelligence (Gf):* the ability to reason, problem solve, and to see patterns or relations among items. It includes both inductive and deductive logical reasoning. It involves being able to figure out the abstract relations underlying analogies.

The POT model can be expanded to incorporate numerous broad factors of *g* as shown here:



Extended POT model of *g*

Both the P-FIT and POT theories of general intelligence imply that if brain training works, it should target executive processes to augment IQ. There is no general-intelligence specific network that it should target, separate from executive processes such as frontoparietal working memory networks, updating/output gating or interference control networks.

This conception of general intelligence is also largely consistent with Schneider and McGrew's information processing theory of intelligence (38) as shown in the model below that also emphasizes the central role of working memory. This model is based on the well-established taxonomy of the underlying broad abilities of general intelligence called the CHC theory (39, 40).

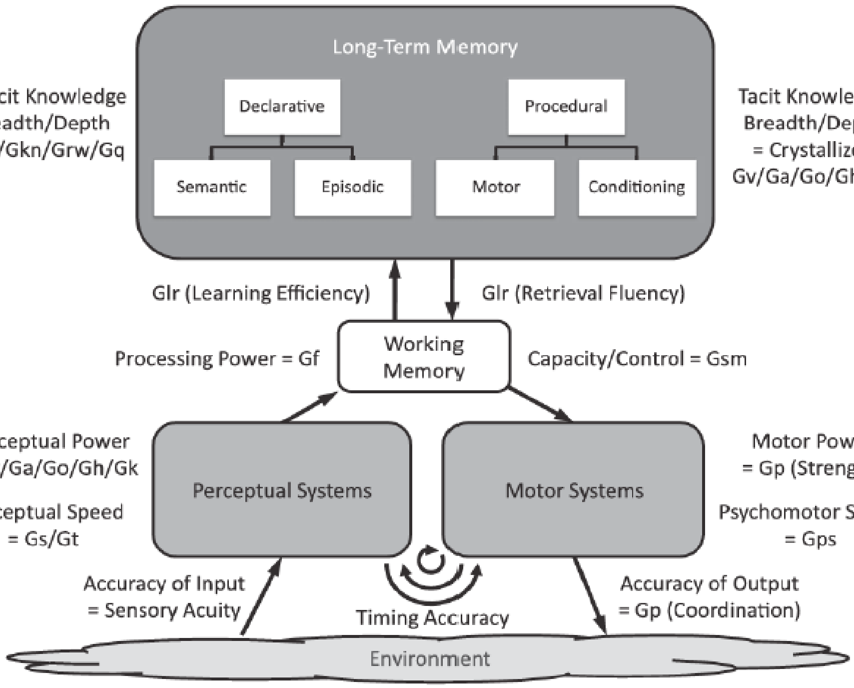
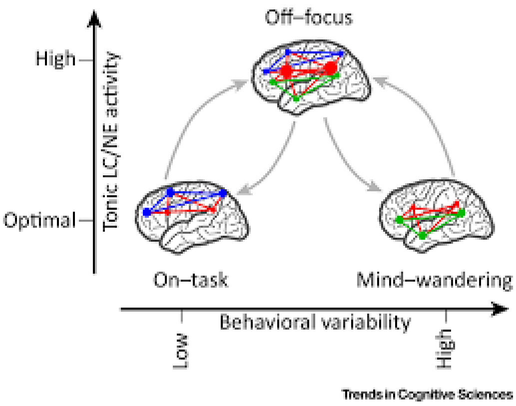


FIGURE 4.8. CHC abilities as parameters of information processing.

I also extend the scope of general intelligence (*g*) beyond the CHC taxonomy and typical psychometric tests of IQ I to include other executive control functions such as cognitive control and flexibility.

P4. Skill Specificity Principle



Effective far-transfer cognitive training depends on the acquisition of novel cognitive routines akin to **learning a new skill**. These cognitive routines will depend on appropriate executive functions and their combinations (or 'policies') for particular types of cognitive function (41, 42). Fluid intelligence, crystallized intelligence, cognitive control, creativity, and so on, each has its own far-transfer enabling executive processing policies. This is the **skill specificity** principle.

Just as core strength or functional movement training in the gym depends on specific combinations of exercises in the gym to far-transfer to actual skills in sports contexts, the neural networks you train while brain training and the 'policies' that determine how they coordinate together need to be 'fit for purpose' in terms of the cognitive functions you want to target with training. And they need to be trained at the right level of abstraction for far transfer.

A problem with classic dual n-back training that it only targets a limited number of executive function policies (involving maintaining and input gating), but not others (output gating and disengaging/shifting).

Well-designed brain training apps such as our IQ Mindware apps selectively target the appropriate executive function policies depending on the type of far transfer you want.

P5. Cross-Modal Training

A problem with classic dual n-back training is that after a few sessions you become familiar with the task and develop *game-specific* strategies to help you improve your scores. For the DNB, these strategies may involve 'tricks' like *chunking* where you group letters or positions in the dual n-back into higher level 'units' thus reducing the demands you put on your limited working memory capacity. But this can defeat the purpose of dual n-back training where your aim is to expand working memory.

Also classic dual n-back typically trains only specific types of sensory input (e.g. letter sounds). What is needed for more effective far transfer is to train multiple sensory modalities with the same domain-general (non-modality specific) executive functions associated with the prefrontal cortex as we have reviewed above.

To triangulate on domain general executive process skills for far transfer training needs to switch between multiple games, where each game has very different sensory properties which are more peripheral to the underlying executive functions themselves (43). This results in more powerful far transfer effects to IQ and cognitive control. This is illustrated here for dual n-back training.

Triangulating on domain-general executive function skills

P6. Cognitive Resilience Training

In addition to cross-modal training, IQ Mindware apps incorporate cognitive resilience training for the executive function skills that are trained.

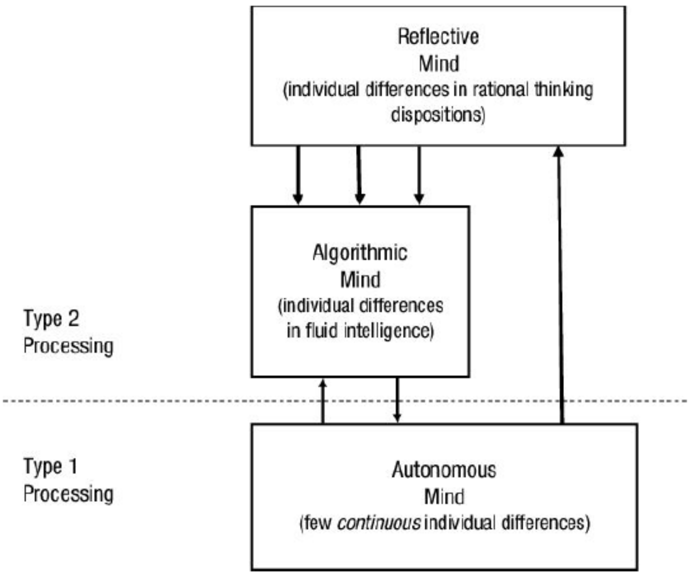
It is known that stress impairs executive functioning – and thus cognitive control and intelligence (44, 45, 46). A recent meta-analysis of relevant studies concludes: "A growing body of research has suggested that acute stress may impair core executive functions. ... We found that stress impaired working memory and cognitive flexibility, [and] nuanced effects on inhibition"

Our Cambridge Mindware Lab apps train cognitive resilience in the face of three types of stressors: (1) emotional threat that may be salient with anxiety, burnout or depression; (2) tiredness from sustained focus and effort; and (3) performance concerns relating to time-pressure, error-rates, or competitive environments.

P7. Metacognitive Monitoring & Strategic Control

For the importance of metacognitive monitoring and regulation I draw from Stanovich's Tripartite Theory of Mind (47, 48), and Zelato's Iterative Reprocessing (IR) Model of executive function development (49).

According to the Tripartite Theory of Mind, cognition can be classified as either Type 1 – automatic, effortless processing; or Type 2 – controlled, effortful processing. This is a common distinction found throughout cognitive psychology (System 1 vs System 2, Fast vs Slow, etc). Type 2 processing is further subdivided into the Algorithmic Mind measured by G*f* tests, and the Reflective Mind involving metacognition.



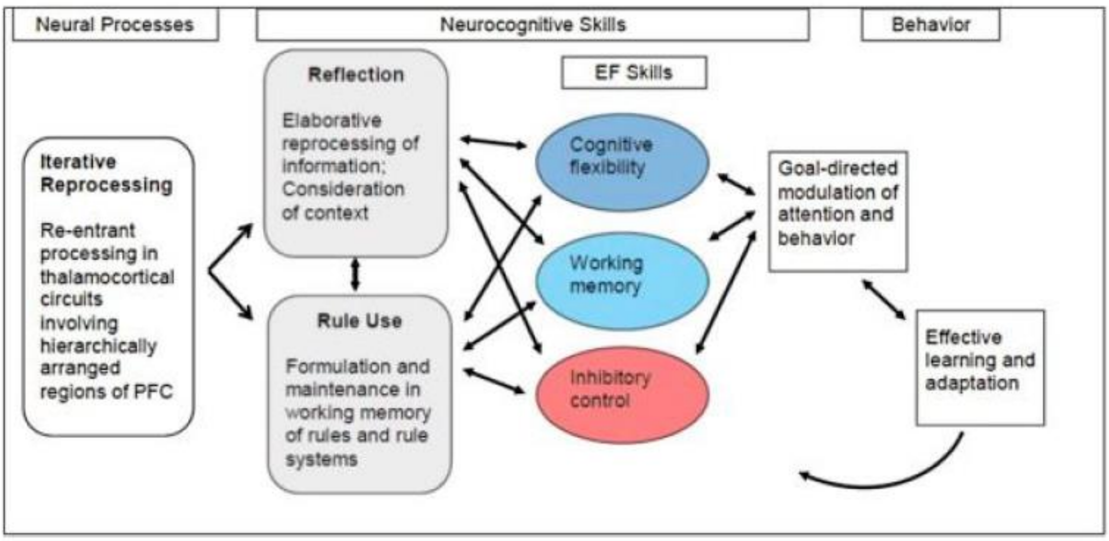
Stanovich's Tripartite Model of Mind

Processing efficiency of the Algorithmic Mind in the absence of metacognition functions well enough for well-defined problems in both academic settings and IQ tests. But many open-ended problems, require the metacognition of the Reflective Mind – for instance, in identifying that an automatic (Type 1) response is inappropriate in a certain context and having the executive capacity to inhibit such a response, as well as apply the Algorithmic Mind using relevant knowledge, strategies or rules.

Metacognition has both monitoring and strategic control functions that can be dissociated in brain imaging studies (50). The former may involve conflict or uncertainty monitoring and have close links with the Dorsomedial Salience Network (see above). The latter includes goal prioritization, cost-benefit trade-offs (explicitly weighing pros and cons), and epistemic regulation concerning e.g. how much information to collect before coming to a making a decision, how extensively to think about a problem before coming to a conclusion, how to calibrate the degree of strength of one's opinion to the degree of evidence available, and so on. These functions in the Tripartite Model relate psychometric IQ to the broader constructs of rationality and critical thinking.

I apply the principles underlying this Tripartite Model to identifying relevant far-transfer contexts, inhibiting automatic responses, as well as managing cognitive resources to optimize goal satisfaction under time, cost-benefit, etc, constraints. The Reflective Mind enables us to *satisfice* in 'bounded' rational ways, when perfect optimized solutions may not be possible! (51, 52).

According to Zelato's Iterative Reprocessing (IR) model, the reflective reprocessing of information provides a foundation for executive function development. For example, the reflective reprocessing of information prior to responding, provides a foundation for the control of attention, flexibly over time. Moreover, the goal-directed modulation of attention benefits from verbal guidance and the formulation and maintenance in working memory of explicit action-oriented rules (49).



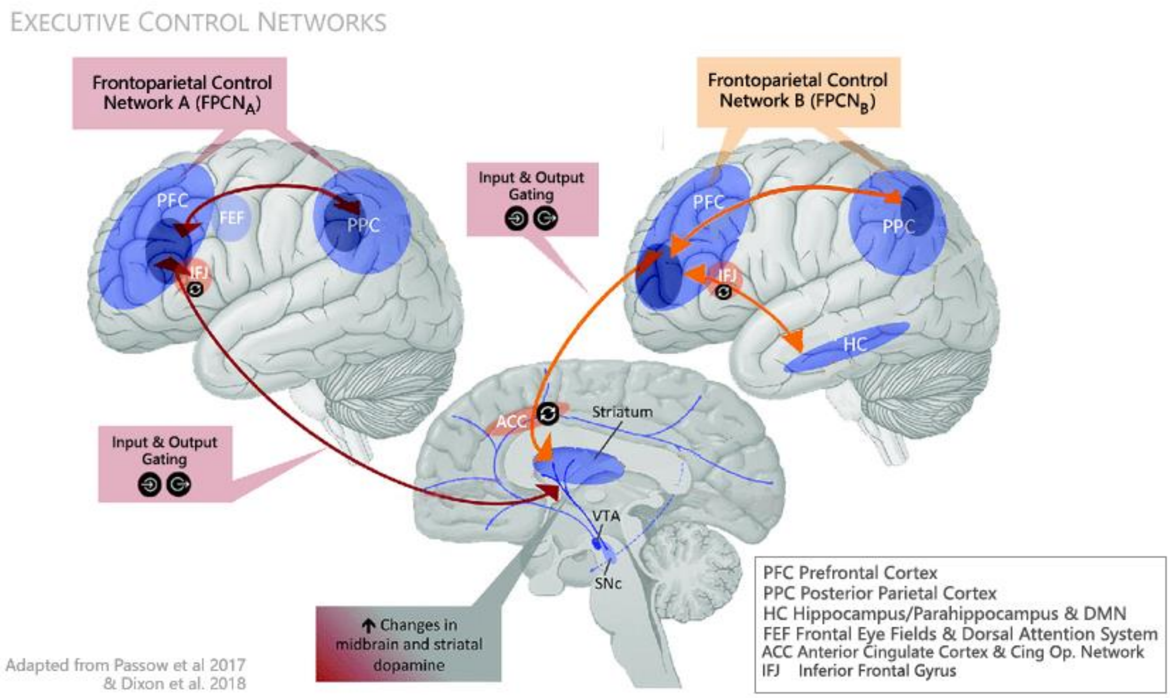
Zelato's Iterative Reprocessing Model of Higher Cognition

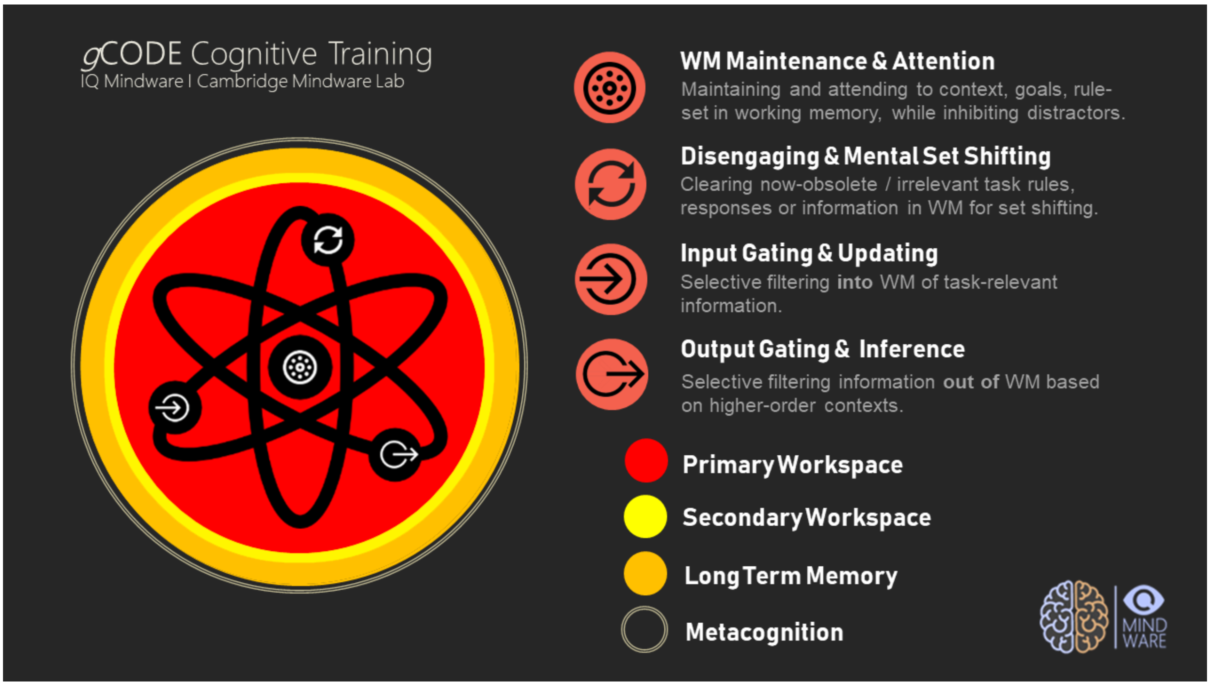
Through development, this kind of metacognitive processing allows for increases in the **hierarchical complexity** of the rules that can be used to characterize problems and select context-appropriate rules for responding – thus relating the IR model to the principles of hierarchical executive control discussed above in the context of input and output gating WM circuits.

I apply the principles underlying this IR Model of executive function to far transfer cognitive training in terms of developing higher-order executive function policies for a wide range of contexts.

The *g*CODE

Based on the brain training principles reviewed above, at Cambridge Mindware Lab I have developed an integrated paradigm for far-transfer cognitive training. I call this new paradigm ***g*CODE** cognitive training.





The gCODE Model (above & below), Mark Ashton Smith, 2019

When *g*CODE Training for Far Transfer Works Best

Assuming the Principles of cognitive training outlined above are implemented, the effectiveness of the training is most enhanced in the following conditions (37):

1) **Task complexity**

   g loads more highly on complex tasks. *g*CODE training will have more far transfer training effects when the cognitive challenges are complex and novel - i.e. more fluid intelligence (G*f*) demanding.

2) **Differential far transfer effects**

   *g*CODE brain training will have greater far transfer effects across **all** cognitive abilities that tap the shared executive processes underlying G*f* for relatively lower levels of cognitive ability (e.g. lower than 100 on a full-scale IQ test). For higher levels of ability, transfer effects will be more apparent when tasks are more complex and novel (such as G*f* subtests).

3) **Multiple bottlenecks and non-additivity of executive processes**

   Executive functioning acts as a bottleneck, and may mask individual differences in specific abilities. Each *g*CODE executive function (EF) has its own bottleneck, and each EF has to be functioning at an appropriate level to perform a cognitive task. Poor cognitive performance is often due to not being able to cope with the executive demands of a task, regardless of any domain-specific knowledge or skill (G*c*). Thus, by targeting a pre-identified EF bottleneck, there may be rapid gains in terms of deployment of skill-sets or knowledge.

4) **Worst performance improvement**

*g*CODE training will have most impact on improving worst performances (e.g. mistakes, interference errors, lapses concentration) rather than best performances. It is slip-ups during many tasks that largely differentiate lower vs higher IQ cognitive performance.

II

***g*CODE+**

*g*CODE Support Training

*g*CODE+ Framework

In addition to *g*CODE core computerized cognitive training, at Cambridge Mindware Lab we have identified a number of evidence-based supporting brain training strategies, depicted here in our ***g*CODE+ Framework**.

1. 'Mindware' (Strategy) Training

Stanovich defines "mindware" as "a generic label for the rules, knowledge, procedures, and strategies that a person can retrieve from memory in order to aid decision making and problem solving" (53).

Rapid instructed task learning (RITL) is the ability to quickly perform novel instructed procedures. It depends on a transfer process from **FPCN$_B$** to **FPCN$_B$**: first through perception-action rule representations in dorsolateral PFC (dlPFC) before more abstract 'task set' representations in anterior PFC (aPFC). Practiced task preparation inverts this process: higher-level rules and strategies ('mindware') recalled from long-term memory, in aPFC before lower-level perception-action rules in dlPFC (54).

RITL is implemented in the brain via a 'flexible hub' mechanism in which top-down influences from the frontoparietal control networks reroute pathways among procedure-implementing brain areas: perceptual and motor areas (55); as reviewed above, frontoparietal regions are hubs and their functional connections are flexible across task contexts - allows for **compositional coding** – i.e. rapid reconfiguration of information flow across multiple task-relevant networks via reuse of previously learned sets of connectivity patterns (11, 12).

Based on this research I propose the following hypotheses that guide Cambridge Mindware Labs brain training programs:

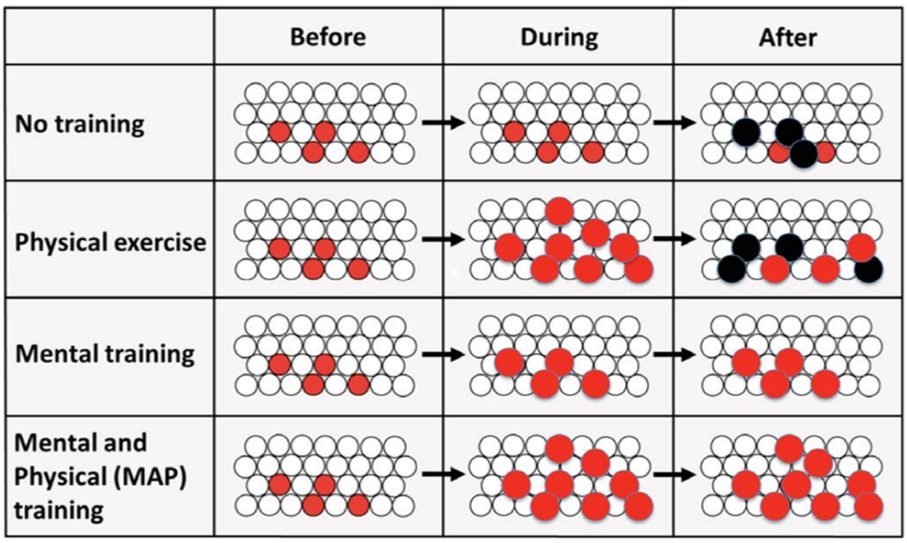
1. Compositional coding via frontoparietal flexible hubs can be interpreted as the brain basis of Gollwitzer's **implementation intentions** for goal-pursuit and self-regulation. Implementation intentions are of the form 'if cue x occurs I shall do y' (56).
2. Compositional coding set at high enough levels of **abstraction** (see Zelato's Iterative Reprocessing Model reviewed above) can aid **far transfer** between distal contexts.
3. This insight provides a basis for **combining** executive function (EF) training with strategic implementation intention (mindware) training to better facilitate far transfer.

The cognitive training programs I am developing at Cambridge Mindware Lab combine mindware tutorials with core EF training for particular *g* functions such as problem solving or decision-making to help with rapid instructed learning and help bridge contexts for far transfer.

2. Brain Cross-Training ('Multi-Modal' Training)

This type of training (sometimes called 'multi-modal training') augments traditional computer-based cognitive training with other strategies such as exercise, brain nutrition/nootropics, sleep adequacy, intermittent fasting, and meditation.

For example, new neurons are generated in the adult hippocampus each day. The quantity cells produced can be increased by physical exercise (57). Many of these go through a process of programmed cell death, but their survival is enhanced through effortful learning (58). Based on these findings, psychologists have developed combined executive function and physical training programs that have proved effective, such as Shors' MAP training (59).



A cross-training brain training study published in the journal *Intelligence* in 2018 (60) found that multi-modal training – but not fitness training alone - could augment fluid intelligence (G*f*).

Multi-modal fitness and cognitive training to enhance fluid intelligence

Ana M. Daugherty [a, g], Christopher Zwilling [a, g], Erick J. Paul [a, g], Nikolai Sherepa [a, g], Courtney Allen [a, g], Arthur F. Kramer [b, c, d], Charles H. Hillman [c], Neal J. Cohen [a, e], Aron K. Barbey [a, f, g, h, i]

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Highlights

- Fitness-cognitive-mindfulness interventions were designed to bolster intelligence.
- Fitness-cognitive training showed control-adjusted gains in visuospatial reasoning.
- Fitness only training did not bolster fluid intelligence performance.
- Individuals varied in benefits to fluid intelligence from mindfulness training.

The research team behind this study concluded:

> *"Because fluid intelligence test scores predict real-world outcomes across the lifespan, boosting intelligence ability via multi-modal intervention that is effective even in young, healthy adults is a promising avenue to improve reasoning and decision making in daily life."*

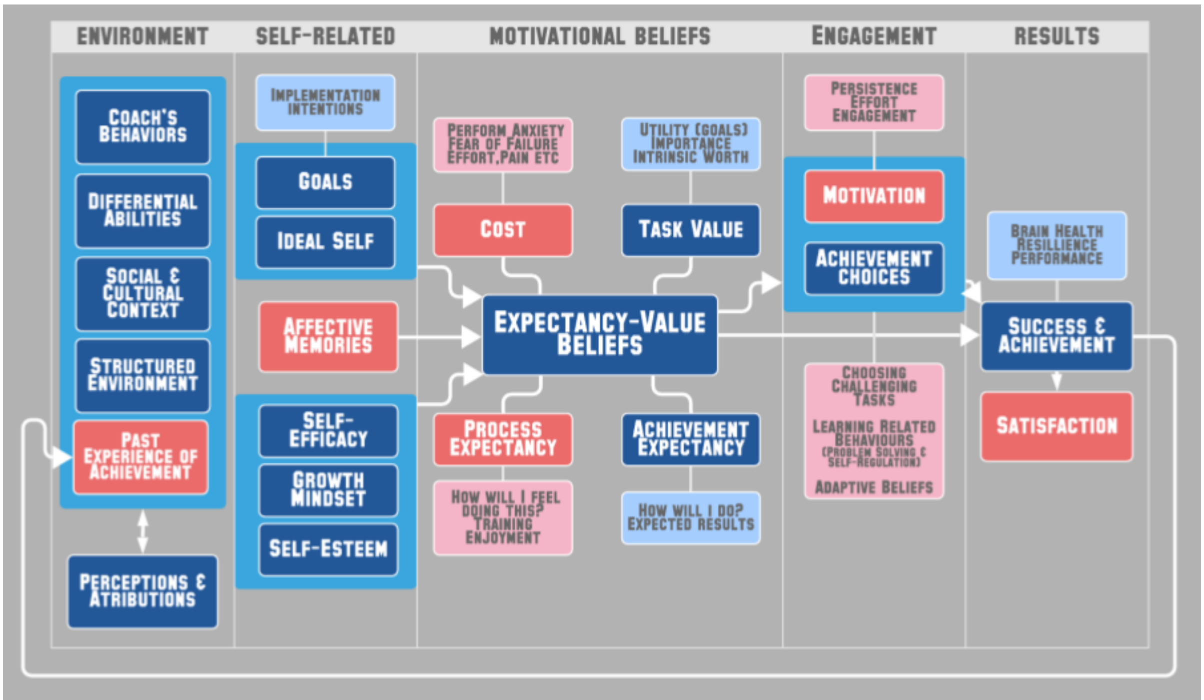
For another example of brain cross-training, a study found n-back accuracy (a measure of working memory) after **post-training sleep** was significantly improved compared training earlier in the day (61).

At Cambridge Mindware Lab we adopt a number of cross-training strategies to augment cognitive training gains.

3. Self-Regulated Learning & Cognitive Tracking

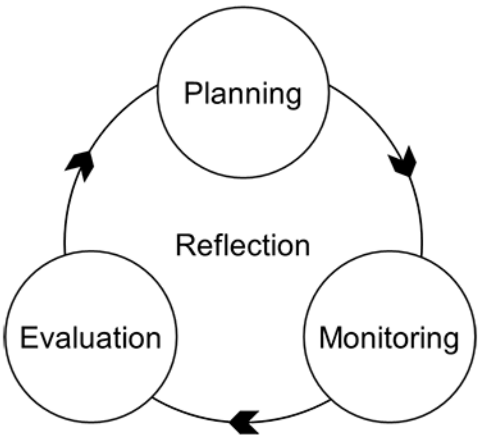
To help with training motivation and program completion, at Cambridge Mindware Lab we make use of evidence-based adaptations of the Expectancy-Value Theory (EVT) for motivation (62, 63, 64), Self-Regulated Learning (SRL) theory (65, 66, 67), and various known principles of gamification.

According to the EVT, achievement-related task choices are motivated by 1) expectation for success (how will I do?), and 2) the subjective task value which depends on the importance of doing well, the utility value, the intrinsic value (enjoyment) and cost (effort/time, performance anxiety, competition with other goals). My own Expectancy Value Motivation Model – incorporating other relevant factors in addition to the expectancy-values ones - is shown here:

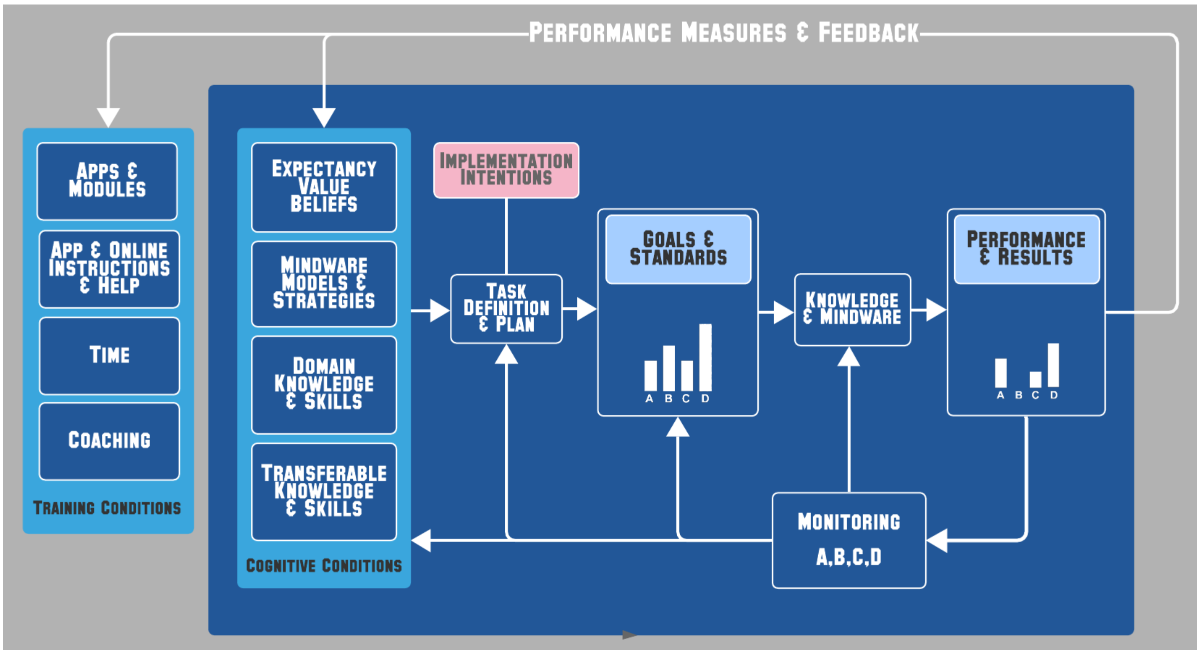


Adapted from Eccles et al.,1983; Pintrich & Schunk, 2002; Doménech-Betoret et al., 2017.

According to most models in Self Regulated Learning (SRL) research there are three phases - 1. Planning (task analysis, planning, goal setting); 2. Performance monitoring (e.g. through metacognition and the use of strategies); 3. Evaluation (reflection and judgement of overall process, learning and adapting for future performance).



Continuous feedback for performance to check against expectations is critical in this process, as well as valid measures of the cognitive functions that are the targets for far transfer. My own SRL model, incorporating what is relevant for our own training programs, is shown here:



Adapted from Winne (1996); Winne and Hadwin (1998)

4. Environmental Multipliers

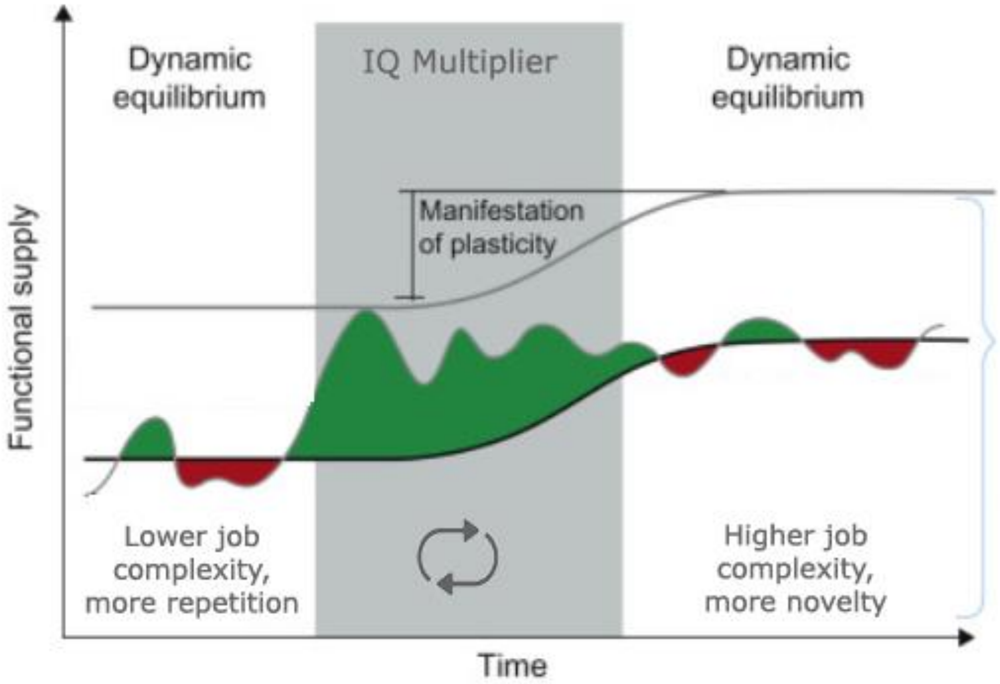
Multiplier effects (68) are analogous to the so-called 'law of attraction'. Small initial IQ differences (e.g. 5 IQ points) can magnify over time through ongoing IQ-environment feedback loops into large IQ differences.

> *"...through the interplay between ability and environment, the advantage can evolve into something far more potent.*

So we have found something that acts as a multiplier."
Dickens & Flynn

For instance, after cognitive training, an individual may pass an aptitude test that gives access to a more highly cognitive demanding educational or work environment. This environment over time then augments cognitive ability through an adaptive, neuroplasticity process.

This two-way ability-environment multiplier process can increase the influence of any initial difference in ability— whether its source is genetic or through cognitive training. The process is a positive feedback loop and the multiplier trajectory of this loop can evolve over a matter of a years. This graph illustrates the process. Green represents periods where demands may exceed cognitive ability, driving plasticity changes and increased IQ.



Environmental multipliers can also be defined within a 'situated cognition' framework (69) – where intelligent organization of our environment and use of apps and technologies can augment our cognition and executive functioning.

5. Cognitive Coaching

A number of studies have demonstrated that expert coaching can benefit app-based brain training programs. Here is one example looking at the benefits of coaching working memory (WM) training for spatial WM and mathematical ability (70).

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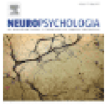

Coaching positively influences the effects of working memory training on visual working memory as well as mathematical ability

Michel Nelwan [a, b], Constance Vissers [b, c], Evelyn H. Kroesbergen [b]

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Highlights

- Coaching might lead to improved effects of working memory training.
- Visual working memory seemed to profit most from coaching.
- Mathematical abilities improved during working memory training when highly coached.
- Coaching is likely to be important for near and far transfer of training.

At Cambridge Mindware Lab we develop customized coaching programs to for *g*CODE and *g*CODE+ training – as reviewed in this paper.

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