Cell Assembly-based Task Analysis (CAbTA)

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Abstract. Based on an Artificial Neural Network model, Cell Assembly-based Task Analysis is a new method that outputs a task performance model composed of integrated mind-brain Cell Assemblies, which are currently believed to be the most plausible, general organisation of the brain and how it supports mental operations. A simplified model of Cell Assemblies and their cognitive architecture is described and then used in the method. A brief sub-task is analysed. The method's utility to research in Artificial Intelligence, neuroscience and cognitive psychology is discussed and the possibility of a General Theory suggested.

Keywords. Human-centred Computing, Artificial Intelligence, Neural Networks, Cell Assemblies, Task Analysis.

1 Introduction

A Cell Assembly (CA) is a collection of cooperating neurons and such neurons may be biological or artificial. CAs can represent both the content and the processes of thought in humans and in Artificial Intelligences (AIs). In contrast to the traditional separation of mind and brain, or hardware and software, CAs provide a single description of the physical and the informational.

There is a long history of ideas in computing influencing psychological theories [1] and as an example of this a new Task Analysis (TA) method has been developed. It describes human task performance in terms of a simplified model of the brain CAs involved. These CAs are based on an Artificial Neural Network (ANN) model. The new Cell Assembly-based Task Analysis (CAbTA) method exploits TA's practical, engineering approach to modelling human cognition. Overall, the approach is similar to that of GOMS – Goals, Operations, Methods and Selection rules [2, 3] – method's implementation of its output as symbolic AI production systems such as ACT-R [4, 5] and EPIC [6]. Similarly, CAbTA can describe CA-based ANN task performance in a sophisticated, consistent manner that can be directly related to an AI's CAs and their architecture at lower, operational levels, thus enhancing ANN design, implementation and testing.

1.1 Cell Assemblies and Brains

The human brain has around 10^{11} neurons [7] and there is considerable evidence, summarised by [8], that much of the brain is CA-based. There is a tight binding between the physical properties of a CA and its functional, information processing ones.

Although there are cortical areas that have specialised functions, defining exact functionality is often difficult because this depends on the tested task range. Such functionality problems remain at whatever physiological level of detail studied.

Predating Newell's [9] work on cognitive architecture, Hebb's 1949 theory [10] is that each concept is represented by a collection of firing neurons. Hebb's theory has been considerably extended [8], particularly with the development of CA-based ANNs. Hebb's concepts now represent Long Term Memory (LTM) and active mental content and processes, e.g. calculation [11], which CAs naturally represent as they must change over time. CAs can also modify processes by providing pre-ignition structure.

Powerful cognition in less neurally endowed species may involve as few as two hundred neurons [12]. In humans the size range of CAs is suggested as 10^3 to 10^7 neurons, although upper estimates may be "*super-CAs composed of many sub-CAs*" [8]. Most neurons, at different times, will have membership of different CAs, although type may be restricted, e.g. a neuron in the primary visual cortex might always be involved with visual processing.

Once ignited, CAs can persist for longer than it takes for a neuron to fatigue. Therefore, for CA persistence of several seconds or more there must be a pool of non-firing neurons that can replace fatiguing neurons (see PotN, section 2.1). With long term CA persistence, a neuron might fire repeatedly, fatigue, recover, and then fire repeatedly again.

The QPID Model. A simple model is that CAs can exist in four states: Quiescent, Priming, Ignited, and Decaying (Q, P, I and D, respectively, pronounced "Cupid"). While physiologically similar, functionally the four states differ significantly: Q-state CAs are structured for permanent storage; P-states prepare a CA for ignition and support cooperative and competitive attentional mechanisms; I-states are active CAs; and D-states prepare CAs for their LTM Q-state. The reality is complicated, e.g. P-state CA structure will change as priming approaches ignition; or D-state decay may return to some notional resting state, or remain primed for re-ignition, or suffer a refractory period where re-ignition is harder.

In QPID, a new Q-state is never quite the same as its precursor; the notionally same CA will differ in the set of neurons involved in each ignition, and neurons themselves change over time, e.g. synaptic growth. Thus, the CA's functional definition must be at a sufficiently high level of description that such differences can be ignored. Some concept of levels of detail is common in many areas. The super-CA/sub-CA proposal and QPID model fits well with TA's extensive use of levels.

Cell Assemblies and Artificial Neural Networks. CA-based ANNs use simplified neuron models that mimic brain operation. Most are self-organising, i.e. they can learn. Anderson [5] discusses learning in detail but ACT-R only models human learning like any other task. There is, however, a complete difference between modelling how people learn and the inherent, self-directed, internal learning that is typical in ANNs.

The Cell Assembly roBots (CABots) demonstrate both new object and environmental learning, and they can solve problems, all without human programmer intervention [13, 14]. They are the starting point for CAbTA's CA models.

CA-based ANNs suffer the same definition problems as biological CAs as once running, and learning, CA functionality is difficult to infer, even though the whole system can be inspected. Software functionality in symbolic AIs is well understood as these use traditional programming methods. Unfortunately, symbolic AIs lack any operational level mapping between brains and computers.

A variety of neuron models are available that run on CA-based simulators, e.g. the CABots used spiking neurons, some with adaptation [15]. While smaller than human brains, Furber, *et al*. [16] used neuromorphic hardware (SpiNNaker) to simulate, in real-time, billion neuron CA-based models.

Crucially, even simple CA-based systems have been proved to be Turing machines, given enough neurons, i.e. they can compute any legal mathematical or logical expression [17]. Therefore, anything written using traditional programming, including symbolic AI code, can be done using simulated neuron-based CAs. Currently, run-time efficiency remains a problem, but performance should continue to improve, although Huyck's CABots already run in real time on a PC.

The existing computational modelling work, e.g.[14], and computational theory [17] shows that CAs are a solution to all computable problems, and a reasonably simple implementation to many problems. Thus a CA-based TA could be implemented computationally reasonably easily.

1.2 Task Analysis and Symbolic Artificial Intelligence

GOMS output resembles program pseudo-code so is easy to implement as symbolic AI production systems like ACT-R and EPIC. Anderson and Lebiere [4] say such systems "*are the only modelling formalism capable of spanning a broad range of tasks, dealing with complex cognition ...*", and ACT-R has "*a profound sense of psychological reality*"; Anderson [5] sees EPIC as an ACT-R 6.0 precursor, contributing "Perceptual-Motor" modules. EPIC's developers' claims are more cautious [18, 6].

Anderson [5] defines cognitive architecture as a specification of how "*the brain … achieves the function of the mind.*" Problematically, symbolic AI systems' program code makes no attempt to mimic the brain, although Anderson [5] attempts, *post hoc*, some relationships to brain areas. The theoretical issue concerns simulation fidelity, how well one thing, a symbolic AI, can mimic another, the brain, when operationally they are completely different.

The Achilles' Heel of symbolic AIs is their reliance on human programmers. If a GOMS model changes, then its symbolic AI equivalent must be reprogrammed. While ACT-R, and other cognitive architectures like Soar [19], can learn, these typically work by parameter setting or generating new rules from old ones. Unlike CA-based ANNs, they are not capable of symbol grounding [20].

There are hundreds of TA methods and all have a cognitive, psychological component. As Kieras [3] notes, "*a task analysis for system design must be rather more informal and primarily heuristic in flavour compared to scientific research.*" Using Card, Moran and Newell's [2] cognitive psychology, GOMS is a psychologically sophisticated TA method, yet is easily criticised scientifically.

The basic engineering argument in GOMS, and generally in TA, is *that some cognitive representations and processes similar to those identified during an analysis must occur*. For example, a TA might identify using Short Term Memory (STM), but whether this is Miller [21], or Baddeley and Hitch [22, 23], or involves other temporary stores [24] is moot. Similarly, TAs will identify when decisions are made, but the decision making mechanisms are left unspecified. GOMS is good at predicting human performance, although Kieras [3, 25] is cautious, and there are exceptions [26].

1.3 Cell Assembly-based Task Analysis

The models of behavioural causality in the Square of Identity (Figure 1) possess two types of identity: (*i_1*) horizontally, where AI implementation is identical with biological specification; and (*i_2*) vertically, where cognitive, functional representations and their operational execution have traditional Identity Theory identity [27, 28]; or Feigl [29] in 1958: that mental events "*are identical with certain (presumably configurational) aspects of the neural processes*".

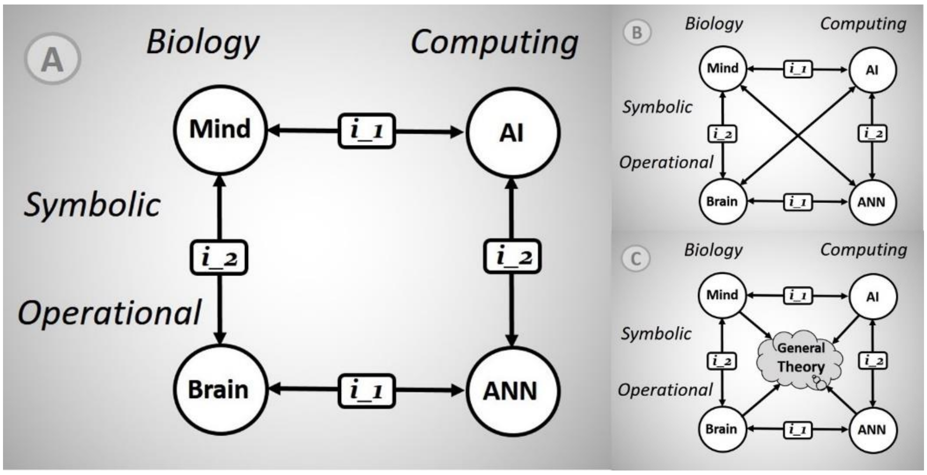


Fig. 1. The Square of Identity: (A) Main figure; (B) with interdisciplinary and cross-level identity functions; and (C) the General Theory possibility.

In the top half of Figure 1A, GOMS output pseudo-code is a mental model of task performance with *i_1* type identity with symbolic AIs (e.g. ACT-R, EPIC). Programmers must interpret and convert GOMS requirement specifications into symbolic AI ones, so *i_1* type identity will not be perfect. Even a compiler like automation would suffer the logical compilation deduction cheat: producing one legal program does not preclude other legal ones. Since, with enough neurons, a CA-based ANN is a proved Turing machine, then any GOMS-based symbolic AI could be re-implemented using CAs, with similar *i_1* caveats at the symbolic level.

The CAbTA approach covers all of Figure 1A. Starting with an operational level CA-based ANN model, this was used to design the mental, symbolic outputs of the task analysed. This could be used to build a CA-based symbolic AI with true identity (*i_2*) with its lower, operational level as there is only one CA, described at different levels. CAbTA's task models enjoy similar mind-brain *i_2* identity.

Accepting *i_1* identity limitations, Figure 1B illustrates the logical identities that allow interdisciplinary (biology versus computing) and inter-level (symbolic versus operational) reasoning. Of the figure's six identity functions, one example could use a simplified ANN-based mental model to reason about brain functions that for human psychology are unknown or too complicated to express. Similarly, as was done developing CAbTA, an operational level CA-based ANN model drove the symbolic level psychological model, which then allowed generation of the task's operational level brain model.

Figure 1C illustrates the General Theory possibility. This would provide description, explanation and models of the same type for human and artificial minds and their operations, because all would be CA-based.

The Square of Identity offers no protection from fault, in modelling or implementation. As engineering, TA makes no claims to meeting experimental cognitive psychology's scientific requirements. TA's practical approach, however, encapsulates scientifically known psychology, applying such to real task performance. CAbTA offers similar analytical power to GOMS, with similar symbolic level opportunities to GOMS' relationships to ACT-R and EPIC; but suffering the same problem, to be practical, i.e. good enough for engineering. GOMS, while expensive, is good at modelling task performance and has good predictive adequacy. The same can be expected of CAbTA.

2 The Cell Assembly-based Task Analysis Models

CAbTA has two models of task performance. The first models brain CAs and the second relationships between these CAs.

2.1 The Simplified Cell Assembly Model (SCAM)

The standard CA graphical representation plots number of neurons firing against time [30, 8]. Using this with the QPID model, a Simplified Cell Assembly Model (SCAM) is defined by eight parameters: four relating to time and four to number of neurons firing (Figure 2).

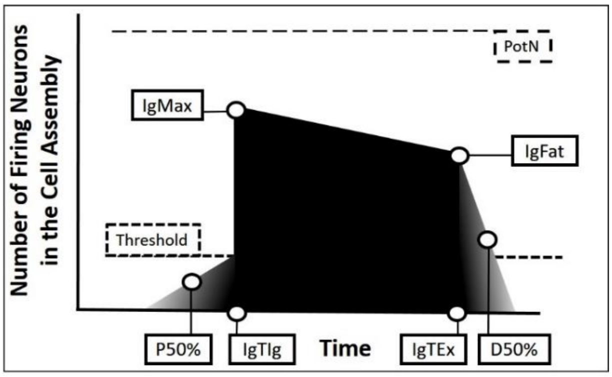


Fig. 2. The Simplified CA Model (SCAM) diagram.

The four SCAM parameters associated with number of neurons are:

PotN – **potential** number of **neurons** that could have CA membership;
Thresh – **threshold** where there are sufficient neurons firing for CA ignition;
IgMax – **maximum** number of firing neurons at CA **ignition**;
IgFat – **fatigue** as number of firing neurons at CA **ignition** extinction.

The four SCAM parameters associated with time are:

P50% - time when a CA is **primed** to **50%** of the required neurons firing to reach ignition threshold;

IgTIg – **ignited** CA's **time** of **ignition**;

IgTEx – **ignited** CA's **time** of **extinction**;

D50% – time when a CA **decays** to **50%** of the neurons firing at CA extinction (IgFat).

Each CA identified has an entry in the SCAM Table defined by these eight parameters.

2.2 The Cell Assembly Architecture Relationship (CAAR) Diagram

In the CAAR Diagram, each CA identified is represented by a box and the relationships between CAs by arrows. The latter are complex and analysts must consider: how CAs interact; what information is transferred; and CA priming and decay. Horizontally, the CAAR Diagram separates types of CA: Perceptual; Cognitive; and Motor. Within graphical constraints, sequence and time are represented vertically, increasing downwards.

The CAAR Diagram is "architectural"; it shows the changing structure between ignited CAs. This paper's CAbTA used a default cognitive architecture of Cognitive CA chains (Figure 3).

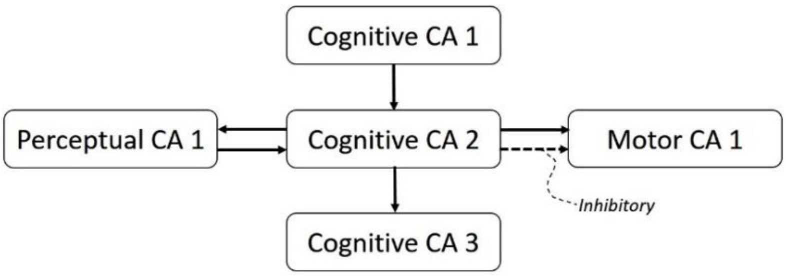


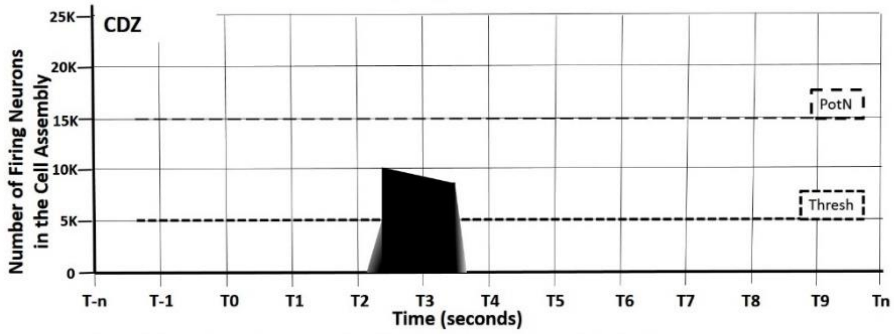
Fig. 3. The Default CAAR Diagram.

CAbTA is not architecturally prescriptive and this paper's analysis found alternatives, for example, when expert performance binds Perceptual and Motor CAs.

2.3 The Main Analysis Document (MAD)

Each CA has a standardised entry in the Main Analysis Document (MAD), Figure 4. The free text description is created during analysis and eventually the SCAM Table and Diagram are added. The CAAR Diagram is derived from the INPUTS/OUTPUTS list. Punctuation indicates time, from none meaning simultaneity and increasing separation using commas, semicolons, and colons; a full stop indicates no overlap in time.

00 **CA: COGNITIVE – Demo Zero (CDZ)**



ID	PotN	Thresh	IgMax	IgFat	P50%	IgTIg	IgTEx	D50%
CDZ	15	5	10	8	2.2	2.4	3.5	3.7

INPUTS:	CA: COGNITIVE – Demo Minus One (CDMO).
	CA: VISUAL – Demo Zero (VDZ).
OUTPUTS:	CA: VISUAL – Demo Zero (VDZ);
	CA: MOTOR – Demo Zero (MDZ),
	CA: COGNITIVE – Demo Plus One (CDPO).

Free text description of the CA's function in its task context and any relevant cognitive psychology and other considerations. How it is triggered (CDMO) and its visual loop with VDZ and its output to MDZ and, eventually to the next Cognitive CA (CDPO). …

Fig. 4. Each CA's MAD style.

3 Method

An overview is provided of the kettle filling task, data collection, and analysis.

3.1 The Task

The task analysed involves the task performer entering his home's kitchen, moving to the hot water preparation area and then lifting the kettle and moving it to the sink for emptying and refilling. This highly familiar task allows focus on the new TA method. The high level Activity List, see [31], in Figure 5 summarises the task.

This task's low level CAbTA demonstrates that the cognitive requirements are considerable. The right hand must weave a complex path to the kettle handle, avoiding objects, using overhead visual information (arrow <2> in Figure 5); when lifting the kettle <3>, its weight must be estimated kinesthetically for effective and efficient kettle location, velocity and acceleration over the drainer <4>. Except when the drainer is empty, each of the kettle's flights over it is different; the largest pan lid rises 30cm above drainer base height, 60% above kettle height.

To emphasise the task's cognitive complexity, programming a robot using traditional techniques, including symbolic AI, to do what non-psychologists would consider a simple task, would be difficult and expensive because of the variability in the task environment. Being more human-like, ANNs should provide a better robotic solution and CAbTA can provide a task specification that would allow robotic behavior to emulate human task performance.

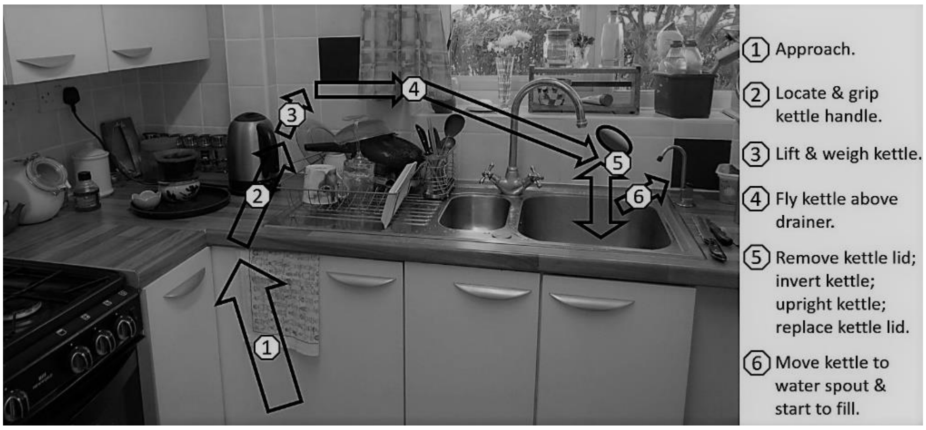


Fig. 5. 'The Task' as a high level Activity List.

3.2 Data Collection

Data was collected using a repeated trials, self-observation, heuristic approach, i.e. the first author, a TA expert (hence "heuristic"), observed himself more than thirty times over a month, making notes after each trial to create a far more detailed Activity List than the summary in Figure 5. Some trials recorded time at two task points (see section 4.1).

Even after more than two decades of domestic task performance, new things were learned during the CAbTA research. For example, the "approach" to the kettle's location was found to be invariant, starting with the right foot mid-doorway and taking three strides, and a right foot shuffle. Outside the kitchen was discovered a "shuffle zone" where, from any of four directions, footsteps were adjusted for mid-doorway launch.

As another example, the left hand was not adequately considered initially. Careful observation identified complex ballistic, and then visual negative feedback controlled, behaviours tracking the kettle's lid to interception near the black tile <4> in Figure 5.

Furthermore, the approach behaviour was observed and analysed for the other three house residents, i.e. with a more traditional separation between task actor and observer. Of the two long term residents, one, about the same height as the main subject, took the same three strides, launching on the right foot; the shorter one launched right-footed, but took five steps. In contrast, the third, an athletic man in his early thirties, who had only been in the house half a year, never repeated his approach and often was off target by a foot or more.

3.3 CAbTA Method

Expert task analysts will recognise the basic process of inferring mental states and processes from behavioural data, including inferences from the unobserved, such as estimating the kettle's weight. This is what makes TA different from mere performance observation, and what makes is so useful in engineering design and evaluation, although the cost is that the quality of a TA is dependent on the psychological expertise of task analysts. CAbTA's representation of such mental states and processes is no more complicated or difficult from the representations used in any sophisticated TA method.

The basic CAbTA analysis cycle starts by identifying a small set of related CAs associated with an Activity List line; some of these may have been suggested as outputs from already analysed CAs. Given a mnemonic name and an acronym, analysis begins with specifying CA type: Cognitive; Perceptual; or Motor. New entries for each CA are started in the MAD (section 2.3) and previously analysed CA inputs may be linked. Each CA has a new line in the SCAM Table, which, when completed, is copied under the MAD's standard table header.

The MAD's descriptive text is started by specifying each CA's function and the inputs that will ignite it. The text then records the issues considered and the reasons for the parameter values added to the SCAM table. For an expert, duration parameter estimation is relatively easy, although for priming (P50%) the preceding CAs need considering. In contrast, those relating to number of neurons must be based on a CA-based brain model. Analyst's decision consistency is more important than the assigned values as these can be later modified, e.g. by multiplying by appropriate constants. Once a SCAM table line is completed, then that CA's SCAM diagram can be drawn and inserted into the MAD.

New inputs between the CAs being analysed, and their outputs, between them and to putative subsequent CAs need determining. The information contained in the inputs and outputs needs specifying and for longer persisting CAs when transmissions occur. There may be cycles of CAs affecting each other, which may be excitatory or inhibitory, and transmitted information may change during cycles. Textual descriptions and the tabulated CA inputs and outputs are added to the MAD.

Next, the newly analysed CAs are added to the CAAR Diagram. Within graphic design limitations, this step should be automatic as all the information is already in the MAD. Experience suggests that adding to the CAAR Diagram will necessitate iteration of previous steps. Such cyclical changes are typical in TA and are exploited within CAbTA as part of its extensive cross checking procedures, essential for any manually performed TA, i.e. without specialised software support (section 5.1).

4 Results

The *main result* is the demonstration that a CAbTA is possible. The MAD describes each CA; the SCAM Table (Table 1) and CAAR Diagram (Figure 8) summarise the analysis, and the results are described in more detail in sections 4.2 and 4.3, respectively.

4.1 Time Results

From the kitchen entrance, timing data was collected from two steps in the task: (i) at kettle handle grip (CA 23 – MRHH); and (ii) at the end, filling the kettle (CA 64 – MPTSU): these were averaged at 4.1seconds and 9seconds, respectively.

Generally, time data is less important than sequence in most TAs. The time data was problematic in this study because, even though a highly practiced task, if the task was immediately repeated, then times tended to become shorter. Such repeated trials data was not included in the averages quoted above.

Table 1. The SCAM Table for the kettle filling task.

No.	ID	PotN	Thresh	IgMax	IgFat	P50%	IgTIg	IgTEx	D50%	ID Acronym
01	CKEC	10	2	7	6	-1.0	0.0	0.4	0.5	COG Kitchen Entrance Check
02	VKEG	20	10	15	14	-0.8	0.1	0.3	0.4	VIS Kitchen Entrance General
03	CMC	5	1	2	1.5	-1.0	0.4	2.5	4.0	COG Make Coffee
04	CAHWA	10	2	5	3	0.5	0.6	3.1	3.2	COG Approaching Hot Water Area
05	VAHWA	20	2	10	6	0.6	0.7	2.5	2.6	VIS Approaching Hot Water Area
06	MSHWA	10	2	7	6	0.6	0.7	3.0	3.1	MOT Stride to Hot Water Area
07	CKHWA	10	3	7	6	0.8	1.0	2.1	2.2	COG Kettle Hot Water Area
08	VKHWA	20	5	10	9	1.2	1.3	2.0	2.1	VIS Kettle Hot Water Area
09	CKH	5	1	3	2	1.5	1.6	3.5	3.6	COG Kettle Handle
10	VKH	10	3	7	6	1.6	1.8	3.3	3.4	VIS Kettle Handle
11	MRAB	5	1	2	2	1.9	2.0	2.1	2.2	MOT Right Arm Ballistic
12	VRH	15	2	5	4	2.0	2.1	3.2	3.3	VIS Right hand
13	CRH	12	3	7	6	2.1	2.2	3.4	3.5	COG Right hand
14	CHWA	15	5	10	8	2.2	2.4	3.5	3.7	COG Hot water Area
15	CRHA	25	5	15	12	2.3	2.5	3.6	3.7	COG Right Hand Approach
16	VRHA	25	10	15	14	2.3	2.6	3.3	3.4	VIS Right Hand Approach
17	MRHA	10	2	7	6	2.4	2.7	3.7	3.8	MOT Right Hand Approach
18	TRHKH	5	2	3	2	3.0	3.5	3.8	3.9	TOU Right Hand to Kettle Handle
19	CRHG	5	2	3	2	3.2	3.7	3.8	4.2	COG Right Hand Grip
20	MRHG	5	1	3	2	3.7	3.8	3.9	4.0	MOT Right Hand Grip
21	TRHG	5	1	3	2	3.7	3.8	3.9	4.3	TOU Right Hand Grip
22	CRHH	10	2	5	5	3.8	4.0	-	-	COG Right Hand Hold
23	MRHH	10	2	3	3	3.9	4.1	-	-	MOT Right Hand Hold
24	CLK	10	3	6	5	4.0	4.2	4.7	4.8	COG Lift Kettle
25	MLK	5	1	3	2	4.1	4.3	4.4	4.5	MOT Lift Kettle
26	KKW	5	1	3	3	4.2	4.4	4.5	4.6	KIN Kettle Weight
27	VLK	10	3	6	5	4.3	4.5	4.6	4.7	VIS Lift Kettle
28	CD	15	5	8	6	4.5	4.6	6.0	6.1	COG Drainer
29	VD	25	8	15	13	4.6	4.7	5.5	5.8	VIS Drainer
30	CMKS	25	5	15	12	4.7	4.8	6.6	6.7	COG Move Kettle Sink
31	VMKS	15	5	10	9	4.8	4.9	6.5	6.6	VIS Move Kettle Sink
32	MMKS	20	5	10	9	4.9	5.0	6.5	6.6	MOT Move Kettle Sink
33	MLHTKL	15	3	9	6	5.0	5.1	7.0	7.0	MOT Left Hand Track Kettle Lid
34	KLHTKL	10	2	6	5	5.1	5.2	7.8	7.8	KIN Left Hand Track Kettle Lid
35	MSBS	10	5	7	6	5.1	5.3	6.9	7.0	MOT Shuffle Body Sink
36	CS	5	2	4	3	6.5	6.7	-	-	COG Sink
37	VS	10	5	7	6	6.6	6.8	-	-	VIS Sink
38	CLHRKL	5	1	4	3	6.8	6.9	7.2	7.3	COG Left Hand Remove Kettle Lid
39	VKL	10	5	7	6	6.9	7.0	7.1	7.2	VIS Kettle Lid
40	VLH	10	5	7	6	6.9	7.0	7.1	7.2	VIS Left Hand
41	MLHRKL	7	2	6	5	7.0	7.1	7.7	7.7	MOT Left Hand Remove Kettle Lid
42	VKWL	10	5	7	6	7.1	7.2	7.3	7.4	VIS Kettle Without Lid
43	CEK	5	1	4	3	7.1	7.2	7.4	7.5	COG Empty Kettle
44	MRHIK	3	1	2	2	7.2	7.3	7.4	7.4	MOT Right Hand Invert Kettle
45	VKE	10	3	5	5	7.3	7.4	7.5	7.6	VIS Kettle Empty
46	CKE	3	1	2	2	7.4	7.5	7.6	7.6	COG Kettle Empty
47	CRHOK	5	1	4	3	7.5	7.6	7.8	7.9	COG Right Hand Orientate Kettle
48	VRHOK	10	5	7	6	7.5	7.6	7.9	8.0	VIS Right Hand Orientate Kettle
49	MRHOK	3	1	2	2	7.6	7.7	7.8	7.9	MOT Right Hand Orientate Kettle
50	CRKLLH	8	3	6	5	7.8	7.9	8.2	8.3	COG Replace Kettle Lid Left Hand
51	VRKLLH	10	5	7	6	7.8	7.9	8.2	8.3	VIS Replace Kettle Lid Left Hand
52	MRKLLH	10	3	7	6	7.9	8.0	8.1	8.2	MOT Remove Kettle Lid Left Hand
53	CMKT	15	5	10	9	8.1	8.2	-	-	COG Move Kettle Tap
54	VT	10	3	5	5	8.2	8.3	8.6	8.7	VIS Tap
55	VK	15	5	8	7	8.2	8.3	-	-	VIS Kettle
56	MMKT	15	5	10	8	8.3	8.4	8.6	8.6	MOT Move Kettle Tap
57	MHKT	6	1	3	3	8.4	8.5	-	-	MOT Hold Kettle Tap
58	CMLHTS	15	7	10	8	8.3	8.5	8.9	9.0	COG Move Left Hand Tap Switch
59	VLHTS	20	5	10	7	8.5	8.6	-	-	VIS Left Hand to Tap Switch
60	VTS	10	5	7	6	8.6	8.7	-	-	VIS Tap Switch
61	MMLHTS	15	5	8	7	8.7	8.7	8.9	9.0	MOT Move Left Hand Tap Switch
62	TLHTS	8	2	6	5	8.7	8.8	-	-	TOU Left Hand Tap Switch
63	CFK	10	3	7	6	8.8	8.9	-	-	COG Fill Kettle
64	MPTSU	5	1	3	3	8.9	9.0	-	-	MOT Pull Tap Switch Up
65	CMC …									COG Make Coffee

4.2 SCAM Results

Sixty four CAs were identified: 34.4% (22/64) cognitive; 39.1% (25/64) perceptual; and 26.6% (17/64) motor. Perceptual CAs were 80% (20/25) visual; the others were: 12% (3/25) touch and 8% (2/25) kinaesthetic and were not analysed further.

Ignoring those CAs still ignited at the end of the analysis, 48 CAs were analysed (Table 2).

Table 2. Average data for the 8 SCAM parameters.

CA Type	PotN	Thresh	IgMax	IgFat	P50%	IgTIg	IgTEx	D50%
All	11.1	3.3	6.8	5.7	*4.5*	*4.7*	*5.4*	*5.5*
Cognitive	10.4	2.8	6.6	5.2	*3.8*	*4.1*	*5.0*	*5.2*
Visual	14.4	5.0	8.6	7.5	*4.5*	*4.7*	*5.3*	*5.4*
Motor	9.5	2.6	5.9	4.9	*5.3*	*5.4*	*6.1*	*6.2*

Figure 6 shows the average SCAM Diagrams.

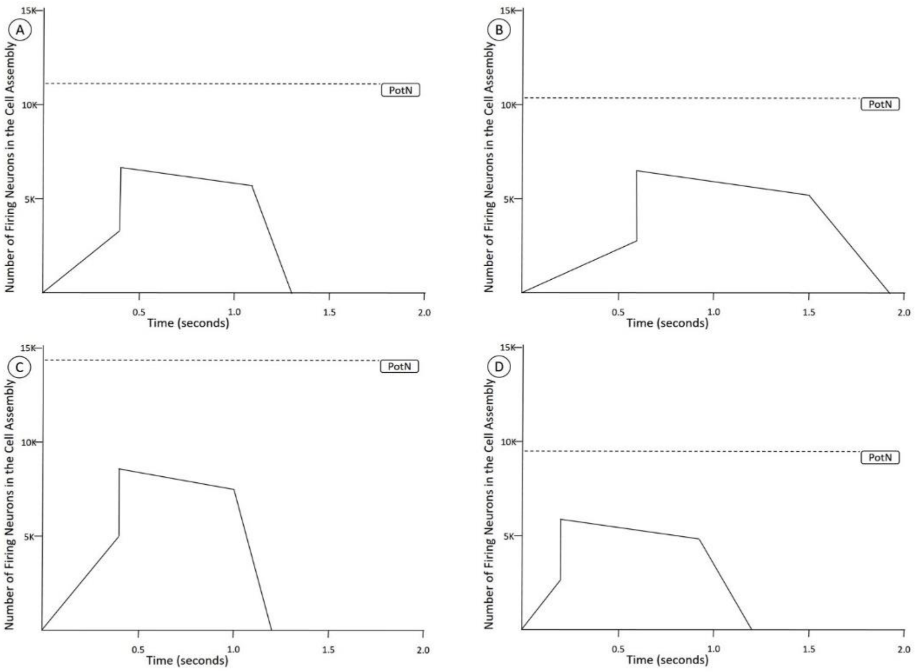


Fig. 6. Averaged SCAM diagrams: (A) All; (B) Cognitive; (C) Visual; and (D) Motor.

The differences in Figures 6b-d shows that the CA brain model and cognitive architecture appear to have been applied appropriately and consistently, e.g. neuron numbers (PotN) are highest for the large visual cortex (Table 3a).

Table 3a. Difference in PotN means.
(/ represents vertical parameter divided by horizontal one.)

	/All	/Cognitive	/Motor
Visual/	29.7%	38.5%	51.6%
Cognitive/	-6.4%	-	9.5%
Motor/	-14.4%	-	-

Similar, consistent results can be seen for Threshold and IgMax (Tables 3b and 3c).

Table 3b. Difference in Threshold means.

	/All	/Cognitive	/Motor
Visual/	51.6%	78.6%	92.3%
Cognitive/	-15.1%	-	7.7%
Motor/	-21.2%	-	-

Table 3c. Difference in IgMax means.

	/All	/Cognitive	/Motor
Visual/	26.5%	30.3%	45.8%
Cognitive/	-2.9%	-	1.1%
Motor/	-13.2%	-	-

Further, similar results were found for Fatigue (IgMax–IgFat), which overall was 16.2%: Cognitive 21.2%; Visual 12.8%; and Motor 17.0%.

Ignition Duration (IgTEx–IgTIg) analysis (Figure 7) suggests two CA types: short (<0.5seconds) or persisting (>1second). This result was not anticipated, but it is hardly surprising and is explicable in terms of brief CA chains versus complex CAs persisting.

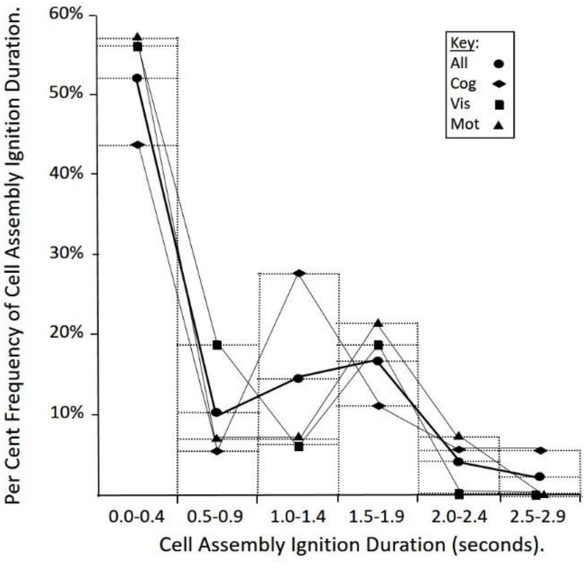


Fig. 7. CA Ignition Durations as line graphs and histograms.

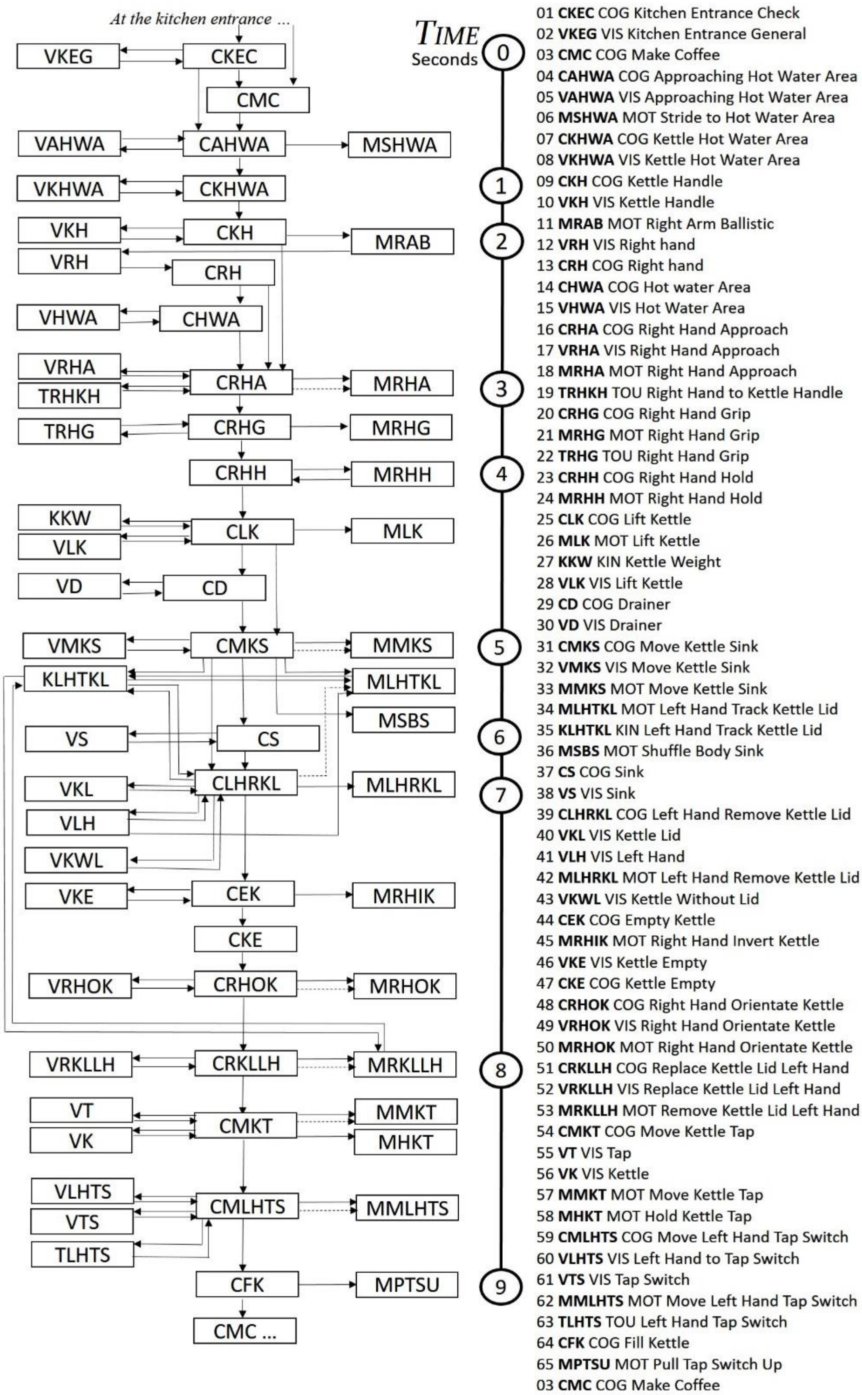


Fig. 8. The CAAR Diagram for the kettle filling task.

4.3 CAAR Results

The CAAR Diagram is shown in Figure 8. Ignoring touch and kinaesthetic CAs (5), inhibitory relationships (7), and external motor outputs, there remained 89 relationships in the CAAR Diagram, as summarised graphically in Figure 9.

The default CAAR model (section 2.2) was adhered to, although the "basic chain" had some branches (18 Cognitive CAs, 26 outputs). The intended, tight binding between cognitive/visual CAs (N=16) was observed (20 versus 21); only 5% (4/89) were visual/motor relationships. With one exception, all 14 motor CAs had cognitive inputs (N=17), although many motor CAs cause behavior that then provides sensory inputs back into the system.

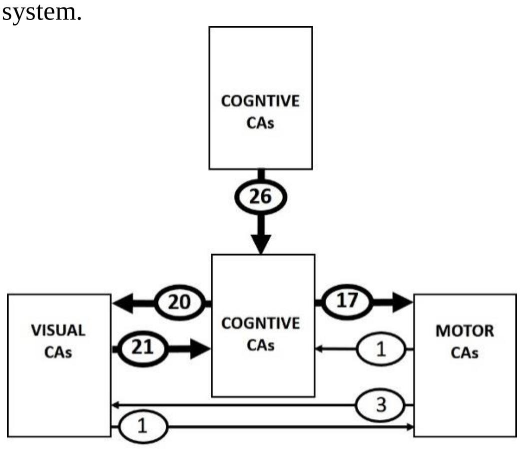


Fig. 9. CA relationships results.

5 Discussion

While GOMS facilitates implementation of symbolic level AIs, CAbTA completes the Square of Identity (section 1.3) at both symbolic and operational levels. This creates opportunities in AI, neuroscience and cognitive psychology for new intradisciplinary and interdisciplinary research.

5.1 Cell Assembly-based Task Analysis

Developing a TA method that produces putative cognitive/brain CAs is a major success. The initial analysis required repeated iterations as CAbTA was developed from scratch, e.g. a dozen different SCAM Diagram graphics were tried, and SCAM parameter redesign also changed these diagrams. The final two thirds of the analysis went smoothly and iteration involved changing CAs but not the method, i.e. in a manner similar to, and no more difficult than, any other sophisticated TA method.

The highly structured MAD was the core representation and contains the entire analysis; the SCAM Table and CAAR Diagram were generated from it, although were invaluable for reasoning about CAs.

Checking and Software Tools. Psychologically sophisticated TA methods are complicated to do and, when done manually, typographical and transcription errors are common. From the outset, CAbTA was designed with testing mechanisms and these proved necessary, even though copy-and-paste was used whenever possible.

There is a necessity for specialised software to support TA methods [32]. Such tools will make TAs easier, faster and less error prone and are likely to change the method. Tool programming can identify poor method specification, often where analysts use craft skills. Also, software can facilitate things impractical in manual analyses, e.g. a CAAR Diagram improvement might provide cycle information, e.g. using multiple arrowheads for the cycles observed between cognitive and perceptual CAs; or, automating SCAM Diagram drawing could easily incorporate desirable, non-linear P50% and D50% parameters.

The software engineering temptation is to automate CAbTA's manual method, i.e. tables and diagrams being produced from a MAD editor. More creative approaches could make a SCAM Diagram drawing package central, advantageously reducing analysts' inputs.

Levels. Sixty four CAs may seem a lot of analysis for nine seconds but other sophisticated TAs would probably produce similar amounts of detail. Possibly all CA-based TAs will be low level and therefore be unsuitable for long duration tasks, although many safety critical subtasks need detailed, if expensive, analysis, sometimes within other TA methods. A CA library might allow meta-level task description with only occasional descent to lower levels.

A CA meta-architecture needs developing and specifying. This might include distant brain areas, but mostly localised ones, e.g. sets of ignited CAs might initially just share neurons but over time become a super-CA with reliable lower level co-ignition, at least when there is not super-CA competition. Such a model hypothesises a tighter binding between CAs than that of just interacting with each other. In TA, the levels concept is ubiquitous so development would focus on brain and CA-based AI meta-architectures. Some cognitive psychology literature, e.g. on attention, may need redrafting to better fit CA level analyses.

5.2 Artificial Intelligence, Neuroscience and Psychology

The Square of Identity (Figure 1) summarises the integrated modelling of biological minds and brains and AI ones. CAs conflate descriptions of functional, symbolic levels and lower, operational ones as *i_2* type identity. Admittedly *i_1* biological and AI systems identity is weaker because of alternatives. As a General Theory, a CA-based perspective should profoundly influence AI, neuroscience and cognitive psychology models and theories. Existing experimental cognitive psychology and neuroscience could be re-expressed as similar CA-based systems and redirect future research towards better CA specifications and cognitive architectures for both human and machine intelligences.

Modelled on ignited CAs, which although ephemeral, can be studied in minds, brains and machines, the QPID model demonstrates how little is known about the Q, P and D states, e.g. how sub-ignition threshold CAs cooperate and compete.

If future AIs are CA-based, then CAbTA can facilitate systems development by suggesting: CA types needed, their properties and operations over time, how they interact, and their cognitive architecture. ANNs can test alternative CAs and architectures and the results fed back to cognitive and neuroscience research. Existing working CA-based systems give confidence in the ability to make CAbTA model simulations from spiking neurons, and would support further exploration of simulated CA behaviour [33].

6 Conclusions

CAbTA's theoretical core is the exploitation of TA as an engineering discipline, i.e. using the standard TA defence that, even if not quite right, similar mental operations to those identified must occur during task performance. The consequences are manifold.

A General Theory that integrates brain and mind in humans and machines is within the approach's scope.

AI, neuroscience and cognitive psychology can all benefit from adopting a CA perspective and CA-based theories and models. Exponential benefits should accrue to interdisciplinary collaborations where the CA view provides a common language, classes of models, and epistemology.

The CAbTA research reported here is novel but can only be seen as a first step to the development of Cell Assembly-based Task Analysis methods. The authors are looking to recruit resources, human and financial, to support further development.

References

1. Diaper, D. (1989) *Designing Expert Systems: From Dan to Beersheba*. in Diaper, D. (ed.) *Knowledge Elicitation: Principles, Techniques and Applications*. 15-46, Ellis Horwood.
2. Card, S., Moran, T. and Newell, A. (1983) *The Psychology of Human-Computer Interaction*. Lawrence Erlbaum: Hillsdale, N.J.
3. Kieras, D.E. (2004) *GOMS Models for Task Analysis*. in Diaper, D. and Stanton, N.A. (eds.) The Handbook of Task Analysis. 83-116. Lawrence Erlbaum Associates.
4. Anderson, J.R. and Lebiere, C. (1998) *The Atomic Components of Thought*. Lawrence Erlbaum; London.
5. Anderson, J.R. (2007) *How Can the Human Mind Occur in the Physical Universe?* Oxford University Press; Oxford.
6. Meyer, D.E. and Kieras, D.E. (1997) *A Computational Theory of Executive Cognitive Processes and Multiple-task Performance: Part I Basic Mechanisms*. Psychological Review, 104, 3-65.
7. Smith, K. (2010) *Settling the Great Glia Debate*. Nature 468,160–162.
8. Huyck, C. and Passmore, P. (2013) *A Review of Cell Assemblies*. Biologica Cybernetics, 263-288.
9. Newell, A. (1990) *Unified Theories of Cognition*. Harvard University Press.
10. Hebb, D. (1949) *The Organization of Behavior: a Neuropsychological Theory*. J. Wiley and Sons.
11. Tetzlaff, C., Dasgupta, S., Kluvicius, T. and Worgotter, F. (2015) *The Use of Hebbian Cell Assemblies for Nonlinear Computation*. Scientific Report, 12866.
12. Buzsáki, G. (2010). *Neural Syntax: Cell Assemblies, Synapsembles, and Readers*. Neuron, 68(3), 362-385.
13. Huyck, C., Belavkin, R., Jamshed, F., Nadh, K., Passmore, P., Byrne, E. and Diaper, D. (2011) *CABot3: a Simulated Neural Games Agent*. 7th International Workshop on Neural Symbolic Learning and Reasoning NeSYS'11.

14. Huyck, C. and Mitchell, I. (2018) *CABots and Other Neural Agents.* Frontiers in Neurorobotics, 12, 79.
15. Huyck, C. and Parvizi, A. (2012) *Parameter Values and Fatigue Mechanisms for FLIF Neurons*. Journal of Systems, Cybernetics and Informatics, 80-86.
16. Furber, S., Lester, D., Plana, L., Garside, J., Painkras, E., Temple, S. and Brown, A. (2013) *Overview of the SpiNNaker System Architecture*. IEEE Computer Society, 2454-2467.
17. Byrne, E. and Huyck, C. (2010) *Processing with Cell Assemblies*. Neurocomputing, 76-83.
18. Kieras, D.E. and Meyer, D.E. (1994) *An Overview of the EPIC Architecture for Cognition and Performance with Application to Human-Computer Interaction*. Human-Computer Interaction, 12, 391-438.
19. Laird. J., Newell, A. and Rosenbloom, P. (1987) *Soar: An Architecture for General Cognition.* Artificial Intelligence, 33.1, 1-64.
20. Harnad, S. (1990) *The Symbol Grounding Problem.* Physica D, 42, 335-346.
21. Miller, G. (1956) *The Magical Number Seven Plus or Minus Two: Some Limits on our Capacity for Processing Information.* Psychological Review, 63, 81-97.
22. Baddeley, A. and Hitch, G. (1974) *Working Memory*. Bower, G.H. (ed.) *Recent Advances in Learning and Motivation, Volume 8*. Academic Press, N.Y.
23. Oberauer, K. and 15 others (2018) *Benchmarks for Models of Short Term and Working Memory*. Psychological Bulletin, 144 (9), 885-958.
24. Morey, C. (2018) *The Case Against Specialized Visual-Spatial Short-Term Memory*. Psychological Bulletin, 144 (8), 849-883.
25. Kieras, D.E. and Butler, K.A. (2014) *Task Analysis and the Design of Functionality*. in *Computing Handbook: Information Systems and Information Technology*, (3rd ed.), Ch. 33. Taylor & Francis.
26. Jorritsma, W., Haga, P-J., Cnossen, F., Dierckx, R.A., Oudkerk, M and van Oojen, P.M.A. (2015) *Predicting human performance differences on multiple interface alternatives: KLM, GOMS and CogTool are unreliable*. Procedia Manufacturing, 3, 3725 – 3731.
27. Smart, J.J.C. (2007). *The Mind/Brain Identity Theory*. Stanford Encyclopedia of Philosophy.
28. Ullin, T.P. (1956) *Is Consciousness a Brain Process?,* British Journal of Psychology, 47, 44-50.
29. Feigl, H. (1958) *The 'Mental' and the 'Physical'*. in *Concepts, Theories, and the Mind-Body Problem*. University of Minnesota Press.
30. Kaplan, S., Sontag, M. and Chown, E. (1991) *Tracing Recurrent Activity in Cognitive Elements(trace): A Model of Temporal Dynamics in a Cell Assembly*. Connection Science 3: 179–206.
31. Diaper, D. and Stanton, N.A. (2004) (eds.) *The Handbook of Task Analysis for Human-Computer Interaction*. Lawrence Erlbaum Associates.
32. Diaper, D. (2001) *Task Analysis for Knowledge Descriptions (TAKD): A Requiem for a Method*. Behaviour and Information Technology. 20.3, 199-212.
33. Carillo-Reid, L., & Yuste, R. (2020). *What Is a Neuronal Ensemble?* in The Oxford Research Encyclopedia of Neuroscience. Oxford University Press.