The Task Analysis Cell Assembly Perspective.

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Abstract

An entirely novel synthesis combines the applied cognitive psychology of a task analytic approach with a neural cell assembly perspective that models both brain and mind function during task performance; similar cell assemblies could be implemented as an artificially intelligent neural network. A simplified cell assembly model is introduced and this leads to several new representational formats that, in combination, are demonstrated as suitable for analysing tasks. The advantages of using neural models are exposed and compared with previous research that has used symbolic artificial intelligence production systems, which make no attempt to model neurophysiology. For cognitive scientists, the approach provides an easy and practical introduction to thinking about brains, minds and artificial intelligence in terms of cell assemblies. In the future, subsequent developments have the potential to lead to a new, general theory of psychology and neurophysiology, supported by cell assembly based artificial intelligences.

Keywords: Ergonomics, Cognitive Psychology, Artificial Intelligence, Neuroscience, Task Analysis, Artificial Neural Networks, Cell Assemblies.

.1 Introduction

There already exists a strong relationship between a cognitive ergonomics Task Analysis (TA) method and Artificial Intelligence (AI) of the symbolic sort. These are, respectively, Goals, Operations, Methods and Selection rules (GOMS, e.g. Card, Moran and Newell, 1983; Kieras, 2004) and production systems such as ACT-R (e.g. Anderson and Lebiere, 1998, Anderson 2007) and EPIC (Meyer and Kieras, 1997). Anderson and Lebiere claim that such systems "*are the only modelling formalism capable of spanning a broad range of tasks, dealing with complex cognition ...*" (p3), and in their enthusiasm go so far as to claim for ATC-R "*a profound sense of psychological reality*" (p13); Anderson (2007) sees EPIC as a precursor to ACT-R 6.0, contributing "Perceptual-Motor" modules. EPIC's developers are rather more cautious in their claims (e.g. Kieras and Meyer, 1994; Meyer and Kieras, 1997).

A fundamental problem with these production system symbolic AI approaches involves "cognitive architecture" which Anderson (2007, p7) defines as "*a specification of the structure of the brain at a level of abstraction that explains how it achieves the function of the mind.*" There is a problem concerning his "level of abstraction" notion. At the level of program code, these symbolic AI systems make no attempt to mimic the human brain, other than as functional, i.e. psychological, modules, although Anderson (2007) attempts, *post hoc*, to relate some of these to brain areas. The theoretical issue concerns simulation fidelity, here how well one thing, a symbolic AI, can mimic another, the brain, when at the level of operation they are completely different types of thing. This paper proposes a solution by using a different sort of AI, one which does attempt simulation of how both the brain and the mind operates and which uses a single, common modelling representation for both.

There are hundreds of different TA methods and virtually all of them have a cognitive, psychological component, although the psychology generally is not that good. As Kieras (2004) rightly notes, "*a task analysis for system design must be rather more informal and primarily heuristic in flavour compared to scientific research.*" Based on the cognitive psychology of Card, Moran and Newell (1980), GOMS is one of the more psychologically sophisticated of TA methods yet is easy to criticise as scientifically inadequate. For example, when a task performer needs to access Long Term Memory (LTM), a GOMS analysis can identify this but is pretty well independent of alternative theories of human LTM architectures and processes, i.e. a GOMS analysis would hardly change whether one modelled human LTM like computer backing store, or as memory traces with different strengths, or as multiple traces.

The basic theoretical 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, at some point in a task it might be necessary to store information temporarily, which the TA might call using Short Term Memory (STM), but whether this is the STM of Miller (1956) is moot, never mind the Baddeley and Hitch (1974, Baddeley, 1976) alternative architecture of their Working Memory, which has been considerably developed subsequently, e.g. Oberauer *et al*. (2018), and there are a number of other temporary and buffer like stores that are hypothesised to be common in all human minds, although the precise theoretical specification of these remain controversial, e.g. Morey, *et al*. (2018). Similarly, most TAs will identify when decisions are made in tasks, but the cognitive decision making mechanisms are left unspecified.

Given the difficulty of predicting human performance, e.g. for its traditional application of training design, GOMS is really very good, although Kieras (2004, Kieras and Butler, 2014) are carefully cautious about this, and there are exceptions (e.g. Jorritsma *et al*., 2015). While no one has ever successfully developed a general task taxonomy, i.e. a specification of sub-tasks or other task components that, together, could be used to specify any task performed by people (e.g. Balbo *et al*., 2004), GOMS does produce a modular, reusable output that resembles program pseudo-code. Indeed, it is a short, obvious step to implement such generic GOMS modules as software tool support to facilitate predicting task performance and, on such coat-tails, to implement the GOMS model as a symbolic AI. Given the tight binding between GOMS and systems like ACT-R and EPIC, it is unsurprising that they share similar theoretical limitations.

This paper's proposal involves a modern take (Huyck & Passmore, 2013) on Hebbian Cell Assemblies (CAs). Hebb's (1949) theory is that concepts are represented in the brain by a collection of neurons firing, e.g. there is not a Grandmother Cell that represents one of one's grandmothers, but rather there is a Grandmother CA, a collection of neurons that can fire persistently, with or without external stimulus from the environment. Though Hebb's 1949 work predates work on cognitive architecture (Newell, 1990), Hebb's cognitive architecture is elegant and straightforward: each mental representation of a concept is represented in the brain as a unique CA., i.e. this is the identity thesis of Smart (2007 for a summary) and of his colleague Ullin (1956); also of the similar, independent work of Feigl (1958) who says of mental events, that they "*are identical with certain (presumably configurational) aspects of the neural processes*".

CAs are normally implemented as a simplified model of neurons to mimic how the human brain might operate. The main proposal in this paper is that it is possible to model the behavioural and cognitive psychology of task performance using a putative CA based brain model and, in theory, the same model could be implemented as a CA based AI. One problem for GOMS and ACT-R that a CA approach automatically deals with are memory representation issues; Hebb's theory is one of LTM, i.e. CAs represent the conceptual contents of LTM.

Attractive if not completely compelling evidence for the CA approach is that like nearly all Artificial Neural Networks (ANNs), CA based ones are self-organising, i.e. they can learn. This is the Achilles' Heel of nearly all symbolic AIs, they need human programmers first. Thus, if a GOMS model changes then its symbolic AI equivalent would have to be reprogrammed. Anderson (2007) discusses learning in some detail (e.g. Chapter 5), but it is hardly surprising that ACT-R can model human learning since, at least in theory, following a TA is should be able to model any task performed by people, including ones involving learning. There is, however, a critical difference between being able to model human learning and the basic, inherent, inevitable and unstoppable learning that is fundamental to ANNs, including CA-based ones.

The 'Cell Assembly roBots' (CABots) demonstrate in a virtual environment the learning of both aspects of the environment and new objects within it, and it has a problem solving capability, all without the intervention of human programmers (Huyck & Mitchell, 2018). While ACT-R, and other cognitive architectures like Soar (Laird *et al.*, 1987) can learn, these typically work by parameter setting or generating new rules using old rules. They are not capable of, for instance, symbol grounding (Harnad, 1990). CAs provide an ability, for instance, to ground symbols, suggested as early as Hebb (1949).

There is considerable evidence, summarised by (Huyck & Passmore, 2013) that much of the human brain does use a CA architecture. The Strong CA Hypothesis, that all brain function is by CAs, is almost certainly untrue, although specialised brain areas may develop during neonatal tuning from a general CA architecture, e.g. Blakemore and Cooper (1970); and that cortical plasticity allows some recovery of function after localised brain insult, also might be plausibly explained by general purpose CAs becoming tuned in adulthood. The Weak CA Hypothesis, that the brain's default architecture is CA based, remains plausible.

On a more cautious note, much of our current understanding of CAs comes from work on ANNs. There is a serious issue of the biological plausibility of such ANNs. For example, while it is now possible to simulate a billion neurons in real time in a system (Furber, *et al*., 2013), these artificial neurons are really represented as a rather simple algebraic equation and, as such, are an extremely simplified model of the brain's physiology. While, for example, Huyck's Fatiguing Leaky Integrate and Fire (FLIF) neurons (Huyck and Parvizi, 2012) are a better simulation of brain neurons than early ANNs, e.g. perceptrons (Rumelhard and McClelland, 1986), or, earlier, compartmental models (Hodkin and Huxley, 1952), they fail to model fundamental neural physiological properties such as spike trains. Even FLIF neurons fail to model basic physiology such as different neurotransmitters, other temporal neuron properties, and much else.

An absolutely crucial, and it seems sometimes overlooked, property of even quite simple CAs is that Byrne & Huyck (2010) have proved that they can be Turing machines, i.e. that, given enough neurons, they can compute the result of any legal mathematical or logical expression. The critical consequence of this is that anything that can be written using traditional programming approaches, including symbolic AI code, can be done using simulated neuron based CAs. At the moment, run-time efficiency remains a major problem, but it is believable that performance will continue to improve in the relatively short term future. On the other hand, Huyck's CABot already runs in real time on a PC.

Hebb's original theory has been considerably developed, particularly in recent years. A simple but critical improvement is that Hebb's concepts have been extended to most mental content and, indeed, to representing processes. On the latter, CAs naturally represent processes as CAs change over time, e.g. a grandmother CA is updated during a visit to her, and this is akin to a run time process description of computer program code (Osterweil, 1987; Diaper and Kadoda, 1999). CAs can also represent processes by providing structure to CAs pre-ignition, for example, for doing mental arithmetic, Natural Language (NL) parsing, and for other sorts of common problem solving and planning.

As concepts, Hebb's CAs can fire persistently over time and this remains a fundamental property of newer CA models, although, more accurately, they have the capability of persistence because in some tasks this may not be required, e.g. in a self-terminating, visual, serial search task the target CA would not persist for long if the target is the first item, but may have to persist for minutes in other circumstances. Critically for the brain, CAs can be ignited for longer than it takes a neuron to fatigue. Therefore, for CA persistence on the order of several seconds and above, there must be a pool of non-firing neurons that can be swapped in to replace fatiguing neurons so as to maintain an ignited CA (see PotN, section 2). Furthermore, with very long term CA persistence a member neuron might fire, fatigue, recover and then re-fire. Indeed, it is essential that the particular neurons that are firing in an ignited CA change over time so that the CA can perform processes, for example, doing a calculation (Tetzlaff *et al*., 2015). Even when a CA functions as an LTM item, this will change over ignitions, even when general learning is slight (see the QPID model below).

The brain has around 10^{11} neurons (Smith, 2010) and the size range of ignited CAs has been suggested as 10^3 to 10^7 neurons (Huyck and Passmore, 2013), although the upper estimates probably refer to "*super-CAs composed of many sub-CAs*". Even with all these brain neurons, most neurons will, at different times, have membership of different CAs, although CA type may be restricted, e.g. a neuron in the visual cortex might always be involved with visual processing, but be in millions of different CAs during its existence.

In the absence of alternative theories and appropriate physiological evidence, a simple model is that CAs can exist in four states: Quiescent, Priming, Ignited, and Decaying. For simplicity, it is assumed that all four states are physiologically similar, i.e. that the Q, P and D states are but weaker versions of a CA in the I-state, with fewer neurons but these may still be shared, at different times, across numerous CAs. Functionally, however, the four states may differ significantly: Q-state CAs are structured for permanent storage. The role of CAs in their P-state is to prepare a CA for ignition and support processes such as attentional mechanisms involving competition between CAs. The reality in brains in undoubtedly very complicated and a P-state CA probably has a very different structure at the start of priming to just before ignition as it evolves into a form ready for ignition; it is also possible that CAs may exist in the P-state without on some occasions ever igniting. The D-state is involved with preparing a CA for its LTM storage and may be equally as complex in its structures and functions. The physiology and functionality of these transition states is not so much under researched as virtually unresearched.

In a typical QPID cycle the new Q-state is not quite the same as its precursor. When the notionally same CA is ignited on different occasions, not only will these differ as to the set of neurons involved in each ignition, but the CA itself will not be quite the same. Thus, the functional definition of a CA must be at a sufficiently high level of description that such differences usually can be ignored. From Scott-Phillips *et al*. (2011) in the context of their distinction between proximate and ultimate explanations in evolutionary theory, it may be that functional and physical descriptions are of different types: the physical, brain TACAP models being proximate and addressing “How?” questions and the mental, functional ones may be ultimate models and addressing a highly specialised epistemological type of “Why?” questions.

Some concept of levels of description, of detail, is common in many areas of human endeavour. The super- and sub-CA proposal and the QPID model fits neatly with the extensive use of the levels concept in TA, and with this paper’s CA based approach. Emphasising that a TA model is an analysts’ model and different from that of task participants and other involved parties, e.g. managers, (Diaper, 2004 and *ibid*.), one difficult “judgement call” (Kieras, 2004) is the level at which a particular TA is pitched. Most TA methods involve some form of task decomposition into subtasks, and sub-subtasks, down to the level analysts select (N.B. different levels may be chosen for different parts of the same task). Many methods do simply decompose tasks, but not all. For example, the old but still popular Hierarchical Task Analysis (HTA) method (Annett and Duncan, 1967; Annett, 2004) decomposes task goals rather than recorded task components. As such, HTA is an analysis technique that can be used after task data is collected and represented.

This last point about HTA is crucial to this paper, which similarly only discusses an analysis technique and not a full TA method. Traditionally, a TA method early on will involve multiple information sources and data collection techniques; observation of performance, interviews and questionnaires are common, but many other data sources and techniques have been used over the decades. In nearly all TA methods, whatever data is collected, it is combined to produce some sort of Activity List (AL), otherwise known as a ‘task protocol’ (N.B. this is different from a ‘task transcript’).

While varying greatly in style, generally an AL is a prose description of how a task is performed and the strong recommendation of Diaper (1989a, 2004, and *ibid*.) is that an AL should consist of a list of short sentences that each describe a task step, at the level chosen, and each line should identify a main agent and the action(s) performed towards one or more things (agents or objects), perhaps using other things (tools). It is some such AL representation that HTA and this paper’s work uses as input to their analysis techniques. One word of caution, however, data collected with one TA method in mind may not be suitable if other analysis techniques are then used; missing data being the most obvious problem, but there are more subtle ones.

This paper is not proposing yet another TA method or, even, analysis technique, at least, not at the moment. This is one of the reasons why “Perspective” appears in its title. A perspective is “a point of view” and in the scheme of things as used here, is a very general theoretical formulation, perhaps a high level framework. Within a Popperian (e.g. Popper, 1979) scientific epistemology, the claim is that only well specified hypotheses can be experimentally tested and that disproof of one does not necessarily disprove the more general framework from which that false hypothesis was derived; metaphorically, pruning twigs from a knowledge tree may not damage its main branches.

Perspective, as used in this paper, is a "General Theory of Psychology" (section 5.3.3), perhaps akin to cognitive psychology's one that has the axiom, "The mind is an information processing device." The claim is that all psychological phenomena can be described and, ultimately, explained within the perspective defined by its primary axioms (Diaper and Stanton, 2004). As an extension, the CA equivalent would be something like, "The mind and brain are information processing devices that both use common, although differently described, cell assemblies."

Cognitive psychology's axiom is implementation independent, i.e. it has no constraints on how the brain works, its architecture, processes and so forth, because it is only concerned with mental models, of information processing. In contrast, the CA perspective provides for a firm cognitive architecture that relates and explains concomitant brain and cognitive function. This and similar issues are more properly and completely covered in the Discussion (section 5.2).

The version of TACAP that is used in this paper is described in section 2. There remains, however, one further major issue concerning the "Perspective" in the TACAP title.

TACAP, as used in this paper, deliberately exploits the limitations of TA to provide a *demonstration* of what may be possible and an example of potential utility. The emphasis is that it is only a demonstration and this leads to what at first might seem an odd claim: we do not care if everything in the demonstration is wrong.

It is very likely that none of the brain CAs identified in this paper will ever be found to exist, but using the TA defence (see above), something similar must occur, and it remains possible that in a training programme based on a TACAP approach, some CAs from the TA will cause similar CAs in trainees. Similarly, the mental, functional TA descriptions provided may also all be wrong, but this may also be a matter of poor TA, which is not at all a concern in a demonstration. As for AI, the proposals concerning similarities with brains cannot be worse than that for the GOMS to ACT-R/EPIC relationship, howsoever the CAs proposed are wrong in detail, since the symbolic systems have no claim to any hardware realism. What is provided in this paper is a demonstration of the potential of a CA based perspective within the practical, engineering limitations of TA.

Before returning to the topics introduced above in the Discussion section (section 5), the TACAP version developed (section 2) and its application and the results (sections 3 plus Appendix I, and 4, respectively) are reported.

.2 The Task Analysis Cell Assembly Model

An advantage of this first demonstration using TA and the CA notion is that it can exploit TA's heuristic approach (see Kieras, 2004, quoted above) and, as argued immediately above, as applied psychology the description of task performance needs only to be plausible.

The following subsections outline the models and representations finally used. In their development a considerable variety of things were tried and rejected, sometimes simply because they were just too awkward to use. Leaving such to historians of science, this paper tends to concentrate on what was found successful and relatively easy to use. One of the biggest determinates of the development programme was consistency. Most TAs are performed iteratively and our development work was an extreme example as we would not only return to initially analysed task steps and re-analyse them, but sometimes we would even change the graphics and notational style to what was found later to be a better approach. Indeed, particularly during the early analysis stages, decisions were made about the nature of the CAs and their relationships that quite fundamentally changed the earlier analyses, which had to be redone, some of them several times.

.2.1 The Simplified Cell Assembly Model (SCAM)

The standard, simple graphical representation of a CA plots number of neurons firing against time (Kaplan *et al*., 1991, Huyck and Passmore, 2013). Unsurprisingly, this graph resembles that of an individual neuron's firing and, indeed, most negative feedback systems.

The lifecycle of a simple CA is: (a) there is a background level of neuron firing (quite a lot in the brain, but it is not organised, section 4.2.3); (b) a CA starts to develop, usually due to "priming" from already ignited CAs, and the number of neurons firing in the CA starts to increase, probably in an exponential manner (N.B. competition between a number of alternative CAs at this stage may be a critical part of autonomous cognitive decision making and attentional mechanisms); (c) sufficient neurons fire such that the CA's "threshold" is reached; (d) at which point a large number of neurons rapidly join the CA which then "ignites"; (e) as with most negative feedback systems, there is an overshoot as firing neuron CA membership climbs to its ignition state; (f) after the overshoot the function stabilises at a level which may be several times higher than threshold; (g) the CA then persists and there is a slow decay in the number of neurons firing to support the ignited CA, due to neuron fatigue, if nothing else; (h) at some point the CA will extinguish, either because there are insufficient neurons firing to maintain ignition, or because the CA becomes inhibited by the firing of other CAs; (i) the CA's neuron activity drops below threshold and the CA decays, although what it decays to may depend on the type and context of a CA, i.e. it may decay to background levels, or have a refractory period like neurons and be harder to re-ignite, or it may remain above background so that it is primed for re-ignition (sections 4.2.3 and 5.3.1).

Many CAs will be more complicated than this simple model, particularly ones that persist for long periods, minutes if not hours, as fatigued neurons are replaced. All sorts of things might change during a CAs persistence phase (g) due to CA competition, cooperation and, even, combination or division. Thus, this part of the model might present a saw tooth profile rather than a relatively smooth decline in the number of neurons firing in an ignited CA; for example, see Appendix I: CA 06 MSHWA – Motor Stride to Hot Water Area.

The Simplified Cell Assembly Model (SCAM) is shown in Figure 1 and each CA is represented as a single dimension array consisting of a unique identifier (ID) and eight parameters, four relating to number of neurons and four to elapsed time. We have not modelled the overshoot (f) because we have no idea as to its function, if it has one. Also, because so little is known or even theorised about background levels, priming and decay, this part of the SCAM is simplified to two parameters (P50% and D50%).

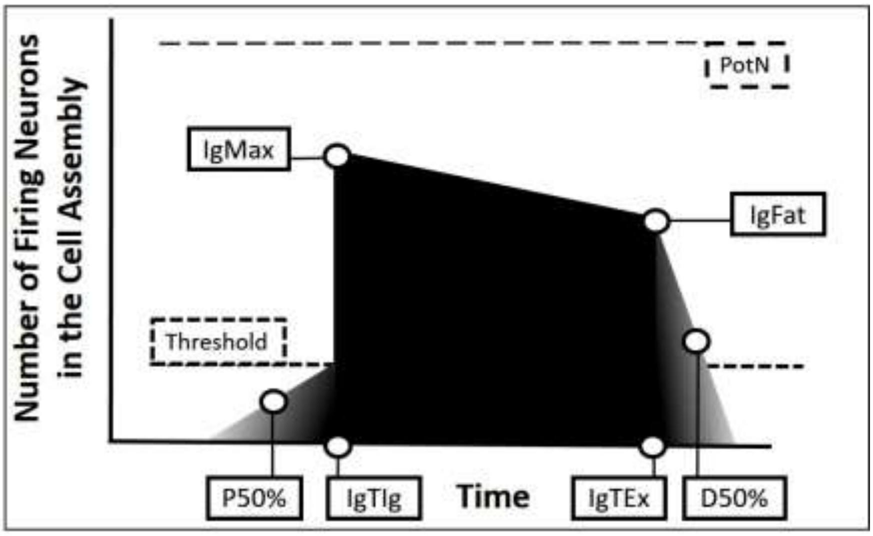

Figure 1 The SCAM diagram. The four lower parameters are measures of time and the four floating ones are measures of neuron numbers.

The four SCAM parameters associated with number of neurons are:

> **PotN** – the **potential** number of **neurons** that could have membership of the CA;
>
> **Thresh** – the **threshold** at which there are sufficient neurons firing to cause CA ignition;
>
> **IgMax** – the **maximum** number of neurons that fire at CA **ignition**;
>
> **IgFat** – the number of firing neurons after neuron **fatigue** at the end of CA **ignition**, i.e. at CA extinction.

N.B. In some cases IgFat may equal Thresh, in which case the CA will then decay, but in other cases the CA may be supressed so that at CA extinction IgFat > Thresh, as shown in the SCAM diagram.

The four SCAM parameters associated with time are:

> **P50% -** the time at which a CA is **primed** to **50%** of the neurons firing that are required to reach its ignition threshold;
>
> **IgTIg** – an **ignited** CA's **time** of **ignition**;
>
> **IgTEx** – an **ignited** CA's **time** of **extinction**;
>
> **D50%** – the time at which a CA **decays** to **50%** of the neurons that were firing at CA extinction (IgFat).

Even within the limited demonstration analysis, across CAs there is a considerable range of shapes to the SCAM diagrams and each of the eight parameters have some variation. This is desirable and if it were not so then a parameter could be treated as a constant.

For each CA identified, values for each parameter have to be estimated and while this is relatively straightforward from observational data for the four time parameters, those associated with the number of neurons may be wild guestimates. Far too little is known about brain CAs and the guestimates may be in error by an order of magnitude or two. On the other hand, generally the expectation is that errors will be consistent, so subsequent corrections based on new research might fix such errors by multiplying by a simple equation, or even just a constant. Explanations for choosing parameters for individual CAs are included in the main analysis (Appendix I).

While a crucial analysis component, with practice the SCAM diagrams became quite easy to visualise and their main representation during analysis was in the SCAM table.

.2.2 The SCAM Table

Each identified CA is represented as a line in the SCAM table using the CA's unique identifier and the eight SCAM parameters. Table 1 shows the first few lines of the main analysis.

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

Table 1 Example lines from the main analysis' SCAM table (Table 2).

While perhaps not ergonomically optimised, once one can visualise SCAM diagrams then the SCAM table becomes one of the three critical analysis tools. For example, the task timeline as represented by the ignition and extinction of each CA (IgTIg and IgTEx, respectively) can be seen by simply running down the table's two columns for these parameters.

The SCAM table had many uses during analysis and was crucial for iteration during analysis and for maintaining consistency and for error checking. Such roles are particularly important because of the complexity of another main analysis representation, the Cell Assembly Architecture Relationship (CAAR) diagram.

.2.3 The Cell Assembly Architecture Relationship (CAAR) Diagram

The tidiness of the CAAR diagram shown in the results of the main analysis (Figure 9) belies its origins, which were pages of handwritten scrappy notes and diagrams. The basic procedure was to identify the next potential, small set of CAs that together would represent a cognitive task step. The possible inputs would have been identified during analysis of CAs earlier in the task and then the relationship between the CAs being analysed would be worked out; finally, the possible outputs would be identified.

In the CAAR diagram each CA identified is represented by a box and the relationships between CAs, i.e. how one CA ignites, maintains or supresses another, and what information is passed between CAs during their ignition, are represented by arrows. CA priming and decay also need to be considered.

The CAAR diagram has elapsed task time, approximately within graphical constraints, increasing vertically downward. Horizontally, CAs are arranged by type, from left to right: Perceptual; Cognitive; and Motor. The perceptual CAs are further subdivided as being Visual, Touch and Kinaesthetic ones These CA types always represent the first character of each CA's ID, i.e. V/T/K, C, or M.

Figure 2 shows a generic CAAR diagram. It is the template for the pattern that was the most commonly found in the main analysis (section 4.3).

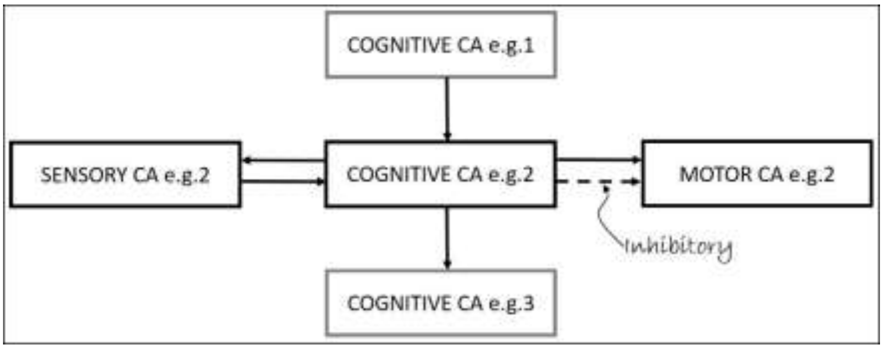

Figure 2 Generic CAAR Diagram.

In its present form the CAAR diagram shows only a limited amount of the information that it could contain. Iteration between CAs, e.g. where each of a pair is helping to maintain the other, is a critical property that is shown in neither diagrammatic or tabular representation; in the rough, hand drawn diagrams multiple arrow heads were used to show such iteration. Further possible refinements are left to the Discussion (section 5.3.1), although the reason why the CAAR acronym includes "Architecture" is that it is all the considered but currently unrepresented aspects of each CA, and how it relates to others that is architectural and potentially puts it beyond just a set of 1960s cognitive psychology style boxes and arrows. Description and explanation of many of these factors is included in the text associated with each CA in the full main analysis (Appendix I). Further description of the TACAP analysis techniques' method is in section 3.2.

.3 The 'First Steps to Making Coffee' Example

It all started as a very quick investigation after the inspiration to join the TA and CA concepts. After a few days it became clear that the whole TACAP analysis enterprise would require considerable, long term, effort. There were weeks of trial and error as everything from the basic concepts, the notations, and the graphics had to be worked out. For example, at least half a dozen diagram styles were tried before developing the SCAM diagrams used in this paper; there were similar graphical problems with the CAAR diagram; and the SCAM table had to be reformatted a number of times as the eight SCAM parameters were themselves developed. In the end, just nine seconds of expert task behaviour was analysed, and it takes over sixty CAs to do so.

.3.1 Task Selection and Data Collection Method

We appreciate the view of those who think that never again should there be a TA paper that uses the making_a_hot_beverage example. In our defence, the CA perspective is novel, so, on practical grounds, it is reasonable to choose an extremely familiar task, indeed, probably the one most commonly chosen to introduce students to TA. Furthermore, the demonstration analysis, in time, is rather short, so there is not much coffee making to worry the cognoscenti.

Data was collected using a repeated trials, self-observation, post sub-task recording, heuristic approach, i.e. the first author, who is a TA expert (hence "heuristic"), watched himself, many times (more than thirty) doing the first part of his making coffee routine and then making written notes after each trial. During some of the trials timing data (to the nearest 0.1 seconds) was recorded at two points during the task using a small mobile phone's digital stopwatch held in the left hand (section 4.1). The initial observations took place over several days and additional trials were done over the following month during the first stages of the main analysis.

Against any objections to this heuristic method, there are a number of advantages for what, we keep stressing, is only a demonstration of a possible analysis technique and not a new TA method. First, the task is a very highly practiced one, with a history of over 20 years in the current house and unchanged after about half a dozen years since the kitchen was remodelled. Second, its nigh invariant repeatability allowed access to renewed observations when they were needed, and they were. For example, the subject was unaware and failed to initially record what happened to the left hand while the kettle, grasped in the right, was moved to the sink for filling. Third, the subject was already expert at such self-observation because, using his TA expertise, he continuously works at prosaic task optimisation, ideally with an end result that he can continue to think of other things while performing the common and mundane. Thus, the data collection approach adopted provided high quality data, indeed, much higher quality than from most TAs that involve analysts recording the performance of other people.

As a further defence, the subject-analyst discovered new details of how he performed the task of which he was previously unaware, for example, the pattern of steps taken outside and across the kitchen (section 3.3.2), as well as the example of the empty left hand's actions mentioned above. At the least, this demonstrates that a TA was done and that the demonstration is not based merely on a desktop, thought-experiment exercise.

The three other residents in the house were also observed doing the same kettle filling task (see Appendix I: CA 06 MSHWA – Motor Stride to Hot Water Area) which, at least, demonstrated that a more traditional TA with subject and analyst separate was feasible.

.3.2 Analysis Method

The AL resulting from the data collected was very simple and along the lines: enter kitchen; go to hot drinks preparation area; grip kettle in right hand; move kettle over sink; remove kettle lid with left hand; invert kettle to empty it; replace lid with left hand; move kettle under water spout; fill kettle. As soon as the analysis started, each such AL line was rapidly elaborated, often supported by further task observations, and soon the ordered list of identified CAs effectively became the AL used for further analysis.

At this early stage of research it is not feasible to provide a detailed method for the TACAP analysis technique, and it is undesirable to do so. Method specification in TA is extremely difficult, to the extent that Diaper (2001) suggests that it is necessary to develop analyst support software to support method specification. While such tools' superficial, primary function is to make analysis easier and less error prone, to teach and guide a neophyte analyst requires supporting software to have an explicit and detailed model of the method. The discipline required of programming means ready identification of missing and, much more frequently, underspecified parts of a method, which expert analysts bridge using their craft skills, often without being aware they are doing so. Indeed, HTA is often described as a "methodology" and its massive under-specification is seen as an advantage, for the experts who have served their apprenticeship.

Once the TACAP analysis technique settled down during the latter two thirds of the analysis, it was all done online, indeed, as if there was software tool support and with the analyst having the role for the desirable but missing program code. Of course there was a lot of printing for off-line checking and editing, but during analysis the only paper was a couple of very scrappy sheets with a hand drawn version of the CAAR diagram, and a lot of annotations, crossings out, etc. On-screen, centred was the main analysis document (Word); to the left was the SCAM table (Word) and to the right the CAAR diagram (PowerPoint). The acronym glossary (Appendix II) was also always available. Usually, a small set of CAs would be analysed as a group, the most common pattern being that shown in Figure 2 (Section 2.3).

The first step was to create an entry for each CA in the main document and to copy and paste (to minimise typographic errors) the ID and spelled out acronym into the glossary, and the ID into the SCAM table. As an example of cognitive architecture, the default is that at least one, already analysed, input will go to the new cognitive CA. There may be more than one known, analysed input, and during analysis, occasionally, there is a floating output, where an earlier CA must have this, but the analyst was not sure of its still unanalysed destination CA. Note, it is only a default, but with the advantage that exceptions, and there are some, are bought to the analyst's attention for especial consideration. It is an example of architecture in that other defaults could have been chosen, for example, making perceptual CAs the default and have some sort of Perception – Cognition – Motor cycle or left–then–right scan, i.e. P_C_M_P_C… or P_C_M_C_P_C…, respectively. The TACAP default model is more of a tree with C usually mediating between P and M, i.e. C_P_C_P… & C_M_C_M… . There are positive and negative arguments for any of these architectures, but they are all only defaults and the analysis allows alternatives, for example when perceptual and motor systems become tightly bound in some expert behaviours (section 4.3).

Once the new CA set's inputs have been cut and pasted to the tabular entries in the main document, then each CA is described as text (Appendix I) and the relationships between the CAs are added during writing the text, i.e. when a CA has an output to another member in the set being analysed, then the output is copy and pasted as input to the appropriate CA. This is just the sort of thing an analyst's support tool would do automatically. Also, while writing the text, the SCAM table is gradually filled in. In most cases the values assigned to entries in the

SCAM table are explained in the Appendix I text, while attempting to avoid too much repetition. The order in which data was entered to the SCAM table was driven by the linear sequencing of the natural language text. After the first few CAs were analysed the SCAM diagrams were not drawn simply because the analyst could visualise them from the SCAM table and each diagram took quite some time to produce, which would have interfered with the main analysis processes; a trivial software tool is needed to draw the SCAM diagrams automatically from the table.

At the end of a CA's writing process, the outputs to yet unanalysed CAs will be entered. This text will be what is copy and pasted when it is the turn of these CAs to be analysed. This led to inserting some new IDs in the SCAM table ahead of their analysis.

A further feature of the Input/Output tabular specifications in the main analysis (Appendix I) is their punctuation. No punctuation between lines means that the two inputs or outputs occur in parallel and increasing punctuation strength, i.e. comma, and though rarely used in the main analysis (Appendix I), semicolon and colon, show increasing separation in time; a full stop indicates the termination of one input or output before the start of another, although both are within the main analysis' description of a particular CA. Checking the punctuation at the end of analysing a set of CAs was an important part of the error checking routines.

Unlike the SCAM diagrams, it was found important to regularly update the CAAR diagram during analysis. This was no simple transposition from its very rough paper representation to its accurate computer version. The CAAR diagram is a triumph of graphic design in that it shows over sixty CAs and their relationships in way that can be printed on a single sheet of A4 paper, without sacrificing readability. Many designs were tried and some of the earliest would have needed a dozen or so pages rather than just one. Furthermore, because it was prepared in PowerPoint, the analyst's default graphical editor for decades, it is actually quite easy to animate the diagram (Appendix III). This is returned to in the Discussion (sections 5.1 and 5.3.1).

On the other hand, using PowerPoint was a bit of a pig, even for a real expert, as the small scale pushed PowerPoint's resolution when drawing the arrows. It was essential to keep the CAAR diagram up to date, no matter that it was time consuming to do. When there was iteration in the analysis, returning and modifying CAs already analysed, then the CAAR diagram, the SCAM table and the main text's tabular specifications were always changed together. Usually, changing one analysed CA resulted in changing other ones as well.

The method adopted was designed to minimise error and facilitate error checking, e.g. every output must have its input, in the architecture, to another CA, which shows one of the chosen simplifications, not modelling the internal processes of a CA (section 2.1). It is necessary to check that every CA is correctly represented in each of the four main representations: the main analysis document, the CAAR diagram, the SCAM table and the SCAM diagrams. Especial care needs taking where previously analysed CAs have been changed by dividing or combining them as this will likely to have changed their IDs, which is the key identifier in all the main representations. The acronym glossary (Appendix II) was only updated occasionally once the analyst had learned his own acronymic CA IDs, and he used them all the time when reasoning about relationships between CAs.

.3.3 Analysis Introduction

Subsections 3.3.1 and 3.3.2 are intended to provide an introduction to the task and a flavour of the style used in the full main analysis in Appendix I. Subsection 3.3.3 contains a strong recommendation to readers that, before they read the results in section 4, that they familiarise themselves with some of main analysis in Appendix I and with the main representations used.

.3.3.1 The Coffee Making Decision

Prior to the start of the analysis in the kitchen, the subject has made the decision to make a small mug of coffee. This decision could be based on many things, from habit or time since last coffee, or thirst or other dehydration indicators, or just the need for a break, and so forth. Numerous CAs will have been involved in making this decision, but a critical issue is what one or more cognitive CAs are primed or already ignited at the kitchen's entrance. There may be intervening activities so that the time from making the decision to arriving at the kitchen entrance might be five or more minutes.

One possible model would involve the decision making CAs igniting a coffee making one that would persist until task completion. One could even suggest that this CA would contain a plan of what is involved in making a small mug of coffee. There is some evidence that this model is not that plausible. First, with intervening tasks then such a CA would have to persist, ignited, while many other CAs are deployed. Furthermore, the make coffee CA might just be part of a list of tasks to complete and such a dynamic task list CA would have complex behaviours as tasks are completed and, sometimes, the list order might be shuffled, some tasks deleted or postponed, and so forth. Note, arguments involving consciousness are weak to irrelevant, e.g. that people do not perform loads of intervening tasks while thinking "must make a coffee, must make a coffee, must …".

At a minimum, when the coffee making decision is made then a 'Make Coffee' CA must be ignited as a record of the decision. This CA can be of modest size as the decision record and, if one chooses, one could call it a "goal". There is evidence that this CA does not remain ignited in the widely reported phenomenon of one going to a room and then realising one cannot remember why one went there, i.e. the CA fails to reignite in its now appropriate context.

In the analysis that follows, the assumption is that the CA 'Make Coffee' has been previously ignited and remains sufficiently primed that it will reignite with suitable environmental input, e.g. from vision. The analysis starts at the kitchen entrance and the evidence suggests that the host of go-to-the-kitchen CAs that brought the subject to this spot all close down. This is suggested by the final kitchen entrance approach behaviour described in the next subsection.

.3.3.2 Before the Kitchen's Entrance

Before the kitchen entrance there is a shuffle zone. The following observations are a direct consequence of the research reported in this paper. The kitchen entrance has no door and there are four routes to arrive at the entrance, from North West to South East withershins respectively: corridor, stairs, lean-to, and lounge (Figure 3). Whichever route the subject takes to the kitchen entrance, he always arrives with his right foot planted in the centre of the kitchen entrance, that foot may be over the entrance's low, wooden floor bar, or the whole foot, up to a couple of centimetres clear, in front of or behind the bar (Figure 4B), but the right foot is always aligned at a right angle to the entrance's bar and at the centre of the entrance. Indeed, experiments requiring the left foot to be the kitchen entering step result in noticeably clumsy initial steps within the kitchen and the body, moving at a reasonable domestic speed, is unbalanced (e.g. balancing arm movements, hip and upper body twists and similar ergonomic inefficiencies). The right foot entrance is achieved by a shuffle in the area outside the kitchen, particularly easy to observe as, when necessary, a half step will be taken when coming down the corridor, and also, after descending the stairs, where although either foot may have started at the top, steps are adjusted in the shuffle zone. The shuffle zone is less clear from the lean-to because usually its door is closed before taking steps towards the kitchen entrance, but rationally a shuffle must exist because the right foot is inevitably correctly placed, as it is from the lounge, which requires a complex, short curved route of about 130 degrees so shuffling is again less easily observed.

Figure 3– The "Shuffle Zone" outside the kitchen entrance.

3.3.3 Further Context

Rarely is "a picture worth a thousand words", which is, say, well into three typed sheets of A4. To cater for a divers readership, however, what is offered a quick, photographic story, hopefully, to help both task visualisation and comprehension. Just a bit from the first few seconds …

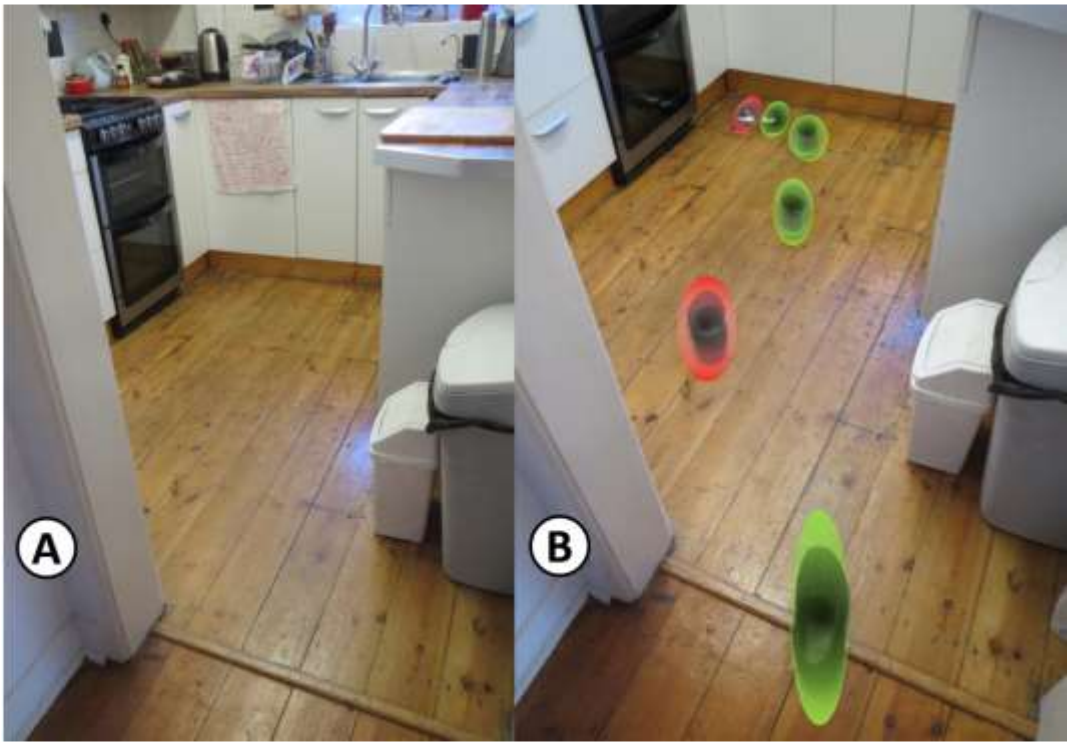

Figure 4 (A) The kitchen entrance; (B) The "strides" across the kitchen: right foot in green; left in red.

These photographs were taken opportunistically and the kitchen is "as found", without any prior preparation, or any tidying. Figure 4A shows the kitchen's ground geography, for illustration, but note the top of the photograph and the important context and focus of visual attention, already getting ready for kettle identification.

Figure 4B shows the "invariant" strides from the entrance to the hot water preparation area (Appendix I, CA 04 CAHWA to CA 06 MSHWA). The left foot, in red, takes the first and third strides and on the photograph the precision of foot placement is roughly represented by the shading. The right foot (shown in green) launches the strides and, from the shuffle zone (section 3.3.2), the foot may be before or over the bar on the entrance's floor. The next right foot stride is fairly precisely placed but with the left foot very accurately and correctly located, the right foot then makes a forward and then curving motion to locate the feet closely adjacent and, concomitantly, the whole body, well balanced in a tight corner space, where it is expertly placed. The visual and cognitive systems, however, are primarily concerned with the hot drinks preparation area, and how to pick up the kettle.

Figure 5 General view of the kitchen. *Figure 6 View of the hot water preparation area.*

Figure 5 shows the general view of the kitchen, say about midstride on the right foot (see above). The target is the kettle, but there are potential obstacles to its left and right. The coffee filter cone to the left is where it usually is, but the draining board to the right often presents novel problems when not empty.

Figure 6 shows the view once at the hot water preparation area. Binocular vision is an asset here, for detecting that the steel sieve handle to the right of the kettle is in front of it; and there is a lot of leftward lean on the translucent plate.

Figure 7 The views from the hands' locations approaching the hot water preparation area: (A) right hand; (B) left hand.

Fifty centimetres or so below the eyes, the view from the hands is rather different, and Figure 7 presents the start of the "flight path" views: 7A shows about where the right hand starts its final approach to the kettle and what it has to navigate (obviously some climb is essential); 7B shows the left hand's "view" and its target will later be somewhere around the black tile, catching up with the top of the kettle after it has been lifted (Appendix I: CA 33 MLHTKL).

Figure 8 View of the target kettle in the hot water preparation area.

Moving the right hand to the, exactly identified, kettle handle without error, i.e. with no contact with any other objects, and, also, smoothly, curvaceously, etcetera, is a behavioural triumph. At this range the angle between the point of view in Figure 8 and the right hand's flight path (Figure 7A) is, in computational terms, impressive, massive, etc. On the other hand, it is just what CAs are so neat at describing, explaining and, even, is expected of them because they are flexible and capable, by themselves, of learning. The right hand is under visual negative feedback control, but it is typical of expert performance that only little control compensation is required from the planned motor output (N.B. this "planned" output in CA terms is just the initially ignited CA that, while ignited, evolves with sensory feedback, and other relevant inputs, and, perhaps its own temporal structure, i.e. as a process – see Introduction).

3.3.4 The Main Analysis

It is only for reasons of space that the main analysis is Appendix I and none of it is here in the main body of the paper. Section 4's "Results" are a high level description of the analysis, but in one sense the real results reported in the paper is the main analysis itself.

A completely new analysis technique has been developed and to understand the paper it is necessary for readers to have some understanding of the technique in application and the issues that were considered when assigning parameters to the SCAM table and relationships in the CAAR diagram. The issues considered include various psychological aspects and some basic neuroscience because the SCAM table, and the whole analysis, like other TAs, is performer centred and so the estimates of CA properties, size and so forth, relate to the human brain and not to possible ANN CA implementations (section 5.3.2). Although, as stated in the Introduction, if the estimates are in error by even a couple of orders of magnitude, then at this stage we are not at all concerned; it could be easily corrected by further research.

The main results in Appendix I contains graphical, tabular and textual descriptions of over sixty CAs. First time readers are strongly recommended to examine the first few CA descriptions (the fourth 'Cognitive Approach Hot Water Area (CAHWA)', is where the analysis starts to settle down after the first few analysed task steps). The initial descriptions tend to be longer and more descriptive and later ones rather briefer; and somethings are not repeatedly mentioned.

It is essential to consider the main analysis in Appendix I in conjunction with the SCAM table and the CAAR diagram, which are produced below in Table 2 and Figure 9.

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

Table 2 – The SCAM table.

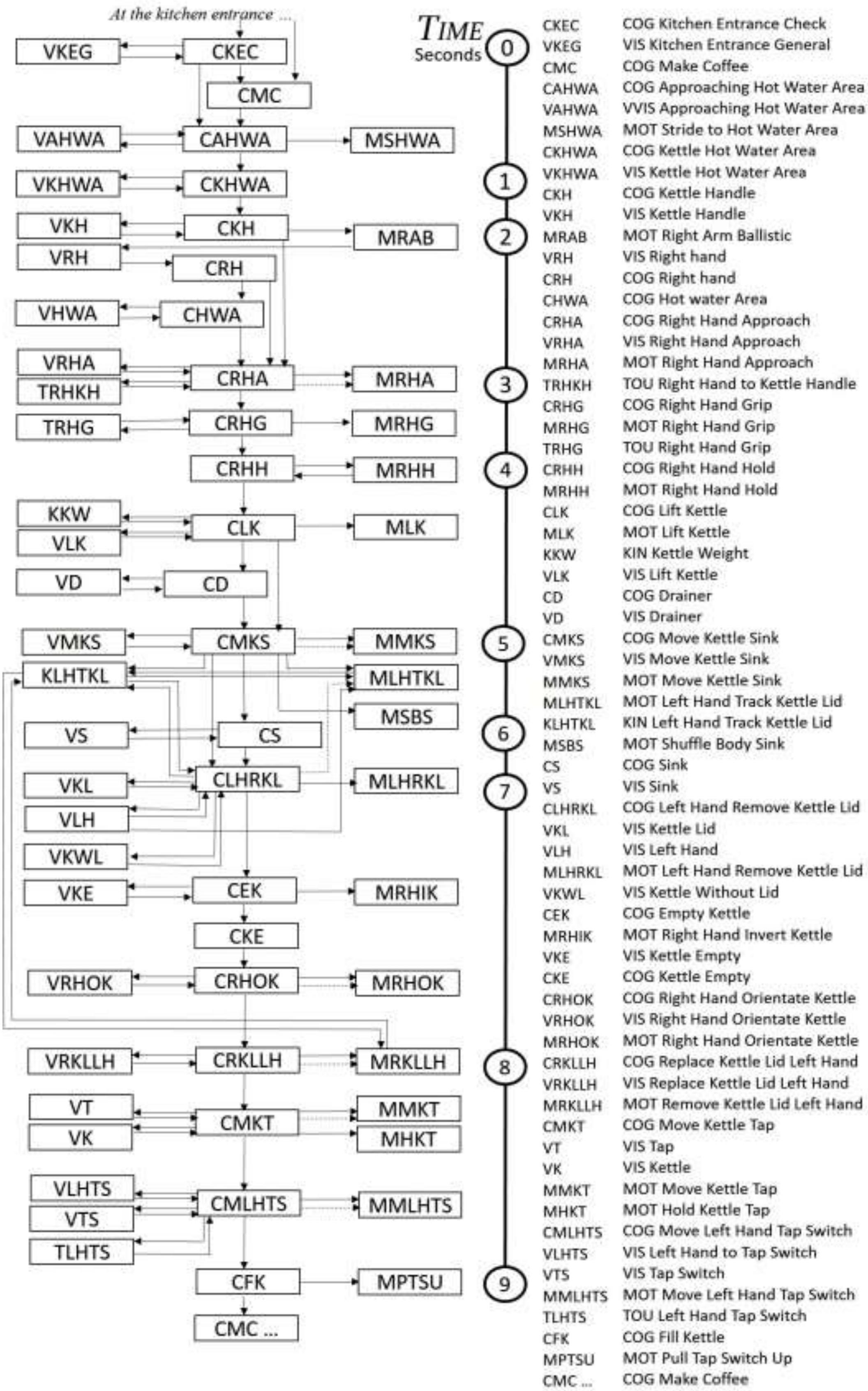

Figure 9– The CAAR Diagram.

.4 Results

Everything in this results section is potentially nothing more than analyst artefacts. What these results present are the consequences of the decisions made by the analyst at a lower level of analysis, i.e. these results are the collective description of applying the TACAP analysis technique. Furthermore, and particularly because the analysis was iterative and decision consistency was a primary concern, then patterns in the data presented here have sometimes been deliberately imposed during analysis. For example, thresholds will tend to be larger with the larger CAs (PotN) so any correlation between the two is deliberate and therefore rather uninteresting.

On the other hand, at the very least these results demonstrate that the analysis has been applied in a tidy and consistent manner. They also give an insight into the detail and complexity of analysing at the low levels chosen, and hint at what more complete and relevant task examples would require.

.4.1 Time Results

Timing data to the nearest 0.1 seconds was collected over several days using the stopwatch function on a mobile 'phone. From the kitchen entrance, data was collected from two easily identified steps in the task: (i) when the kettle handle is gripped and ready for the kettle's lift from its base (CA 23 – MRHH); and (ii) at the end of the analysed task portion when the kettle starts to fill (CA 64 – MPTSU). According to the main analysis, these times were 4.1 seconds and 9 seconds, respectively.

Time data is nearly always a problem in TAs, as it was in this study. As illustration of TAs typical problems with time data, the first measure at MRHH had a recorded range of 3.3 – 4.2 seconds. The first problem is that a first opportunity sample would tend to be around 4 seconds but if repeated half a dozen times then the times would decrease to around the 3.5 second mark, i.e. even highly practiced performance improves with several goes at the same task. Secondly, if only first times are considered then there is still half a second of variability, much of which depends on the state of the drainer and the concomitant complexity of the right hand's flight path to the kettle handle (section 3.3.3).

Generally, time data is far less important than sequence data in most TAs and it is one more craft skill of analysts to give a single time estimate to each task step. The estimates in the main analysis are, in this tradition, mostly interpolated, approximately correct and on the higher side of the range of times recorded.

.4.2 SCAM Results

There were 64 CAs identified in the main analysis: 34.4% (22/64) were cognitive; 39.1% (25/64) were perceptual; and 26.6% (17/64) motor. Of the perceptual CAs, 31.3% (20/64) were visual and there were 5 other perceptual CAs: 4.7% (3/64) touch and 3.1% (2/64) kinaesthetic.

The general, as an average (arithmetic mean), CA from the main analysis can be drawn, as can the SCAM models for the three main types of CA: cognitive, visual and motor. To do so, the five non-visual sensory CAs (3 x touch, 2 x kinaesthetic) and those CAs that are still ignited at the end of the analysis, were removed from the data, leaving 48 CAs on which the following analysis is based. Table 3 gives such average data.

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*

Table 3 Average data for the 8 SCAM parameters.

The four time metrics (in italics in Table 3) require a little manipulation before they can be used to draw versions of the SCAM diagrams. The details of this are included below because they provide an example of suboptimal analysis technique design, which is addressed in the Discussion (section 5.3.1).

The time parameters (t0 – t3) in Table 4 are calculated to correspond to the start of a CA, i.e. t0 = 0.0 seconds, and the priming time to ignition (t1), the duration of the ignition until extinction (t2), and the decay to zero (t3).

Since P50% is the time at which there is 50% of the neurons firing to reach threshold, then, for graphical purposes, the simplified linear priming in the SCAM requires P50% to be doubled for the average time to ignition, after subtracting from the data's time of ignition (IgTIg), i.e.

t1 = (IgTIg – P50%) x 2

The time a CA is ignited (t2) is simply the difference between its extinction minus its ignition time, with the elapsed priming time added for graphical purposes, i.e.

t2 = (IgTEx – IgTIg) + t1

As with t1, the full elapsed decay time requires D50% to be doubled, after subtraction from the extinction time (IgTEx), and then the elapsed time to extinction (t2) needs adding, i.e.

t3 = ((D50% – IgTEx) x 2) + t2

Table 4 shows the data as used to represent the average SCAM diagrams.

CA Type	PotN	Thresh	IgMax	IgFat	t0	t1	t2	t3
All	11.1	3.3	6.8	5.7	0.0	0.4	1.1	1.3
Cognitive	10.4	2.8	6.6	5.2	0.0	0.6	1.5	1.9
Visual	14.4	5.0	8.6	7.5	0.0	0.4	1.0	1.2
Motor	9.5	2.6	5.9	4.9	0.0	0.2	0.9	1.1

Table 4 Average data for the 8 SCAM parameters as used to draw the average SCAM diagrams in Figure 10.

From Table 4 are derived the following four SCAM diagrams in Figure 10.

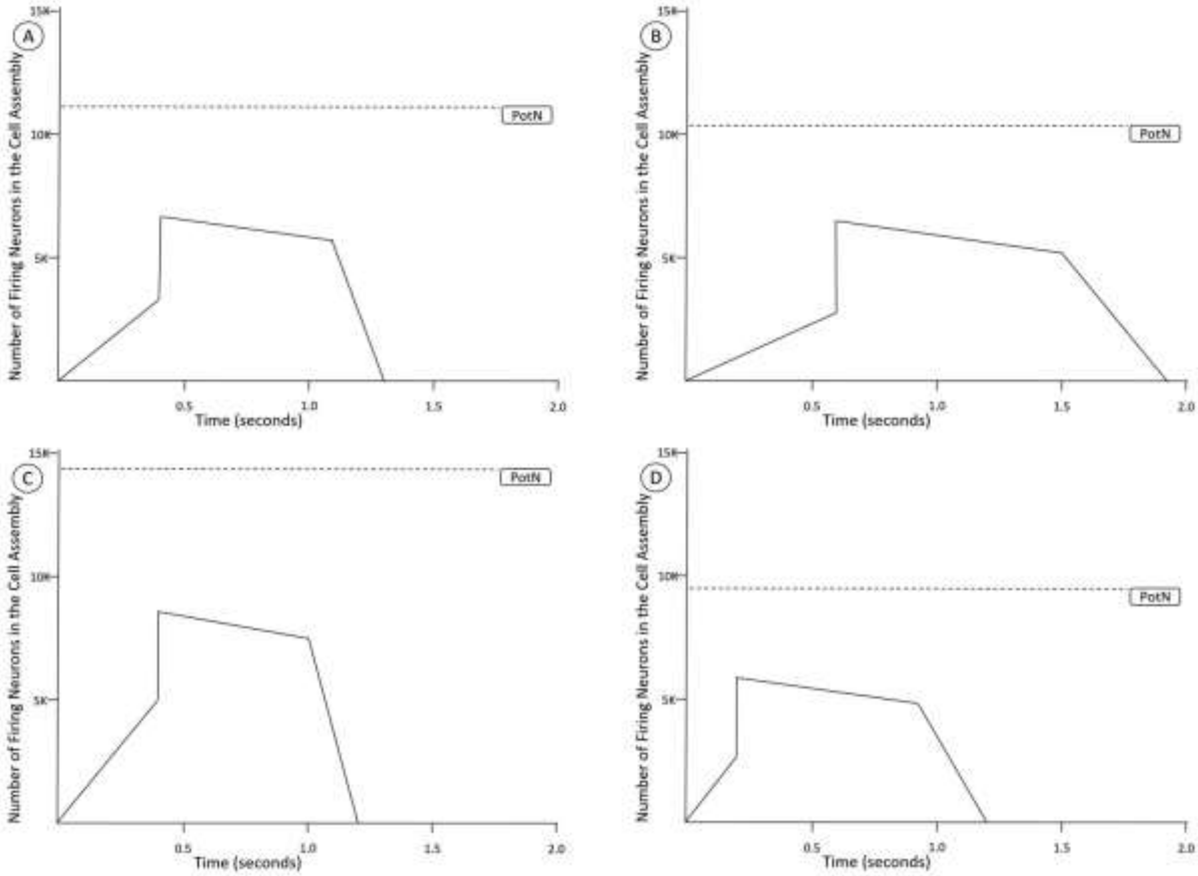

Figure 10 Average SCAM diagrams: (A) all; (B) cognitive; (C) visual; and (D) motor.

For the task analysed, Figure 10A shows the shape of the general CA, but this may involve inappropriate averaging whereas the differences between the three classes of CAs (B, C, and D) is of interest because, at the very least, the results show that the analyst's theoretical model has been successfully applied. This is a *post hoc* result in that it was possible that after the analysis the SCAM diagrams would not be as anticipated; the results, however, are as expected.

The number of neurons potentially in a CA (PotN) is highest for the visual CAs, and as can be seen in Table 5a, they are nearly 30% higher than the overall mean and nearly 40% higher than the cognitive CAs' mean and 50% higher than the motor CAs' mean.

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

Table 5a Difference in means for PotN. The backslash represents how parameters are divided, i.e. vertical parameter divided by horizontal one.

The results in Table 5a reflects the theoretical assumptions that the visual cortex is large and visual processes complicated, so visual CAs will be concomitantly large, particularly when compared to those of the motor cortex and, although a great deal of the human cortex appears unspecialised, it has a great deal to do at any moment, i.e. there will be many cognitive CAs ignited in parallel and not just those identified in a specific analysis.

The same pattern of results can be seen for differences in the means for both estimates of Threshold and IgMax, as can be seen in Tables 5b and 5c, respectively.

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

Table 5b Difference in means for Threshold. The backslash represents how parameters are divided, i.e. vertical parameter divided by horizontal one.

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

Table 5c Difference in means for IgMax. The backslash represents how parameters are divided, i.e. vertical parameter divided by horizontal one.

Again, these results confirm that the theories have been successfully applied, in this case, that CAs, which may involve many neurons, i.e. a large PotN, will also tend to be large (IgMax) and with a relatively high Threshold to match.

The raw data summarised in Tables 5a-c could be subjected to statistical analysis, but it is not done so in this paper because: (a) most differences would not be significant, given the sample sizes and even using non-parametric tests; (b) such analyses would be *post hoc* and therefore statistically weak; and (c) we would be guilty of data hunting and significance chasing. On the other hand, clearly the potential is there for later, better planned research, to use decent analytical statistics.

.4.2.1 Fatigue Results

CAs are not simple negative feedback circuits in that the model of brain CA ignition is that they will fatigue, even with recruiting additional neurons from their potential pool (PotN), unless post ignition activity from other CAs adds to a CA's activity. N.B. the possibilities are for: (a) functionally just replacement neurons to maintain the current CA; or (b) similar, functionally related neurons, which might, for example, be involved in learning, even just up-dating one of one's Grandmother CAs when one visits her (see Introduction). Otherwise, a CA will fatigue and extinguish, “naturally”, i.e. they have a “life-expectancy”, without CA external neural support.

Fatigue, in terms of the number of K neurons, is simply: IgMax – IgFat. To compensate for different numbers of CAs in the three types analysed (N = All 48; Cognitive 18; Visual 16; Motor 14) Fatigue% is Fatigue divided by the size of the CA at ignition, i.e. ((IgMax – IgFat) / IgMax) x 100.

The fatigue data has been analysed in some detail. The overall view is given in Table 6.

	Fatigue	**IgMax**	**Fatigue%**
All	1.1	6.8	16.2%
Cognitive	1.4	6.6	21.2%
Visual	1.1	8.6	12.8%
Motor	1.0	5.9	17.0%

Table 6 Fatigue and percentage Fatigue, i.e. the latter corrected for differing numbers of CA types.

Stressing that there can be no hope of statistically significant results, it was hypothesised that the 8.4% difference in Fatigue% between cognitive and visual CAs could be interpreted as: (a) a difference between types of CA; or (b) due to time, that cognitive CAs last longer (Figure 10). Data for the duration of ignition (IgTEx – IgTIg) and Fatigue (IgMax – IgFat) were examined in detail but all attempts at even the most speculative hypothesis testing was thwarted by Fatigue’s range (0-3 K neurons for Cognitive and Motor CAs and 0-4 for Visual ones) and that the large majority of CAs had a Fatigue value of one.

*.4.2.2 Ignition Duration Result*s

Following the above, failed, analysis, the CA ignition duration data (IgTEx – IgTIg) was examined further The investigation was driven by a desire to understand the distribution of data that underlies, and thus causes, the arithmetical average values used in the SCAM diagrams (Figure 10). The duration of a CA is one of its two primary features, and it can be argued its most important, not merely theoretically, but, critically, ignition duration is a measure in time (seconds), and time is linear. The estimates of the size of CAs may be wildly incorrect (Introduction), but whatever the caveats about timing tasks expressed in section 4.1, one can have more confidence about sequence; the time estimates in the analysis can only be in error by a couple of tenths of a second, because the times must fit the sequence. Furthermore, and consequentially, examination of the ignition duration data is less open to analyst bias, and thus of great potential value.

Using bins of half a second, Figure 11 summarises the ignition duration of the types of CA. This figure represents the same data in two ways, as a histogram and a line graph.

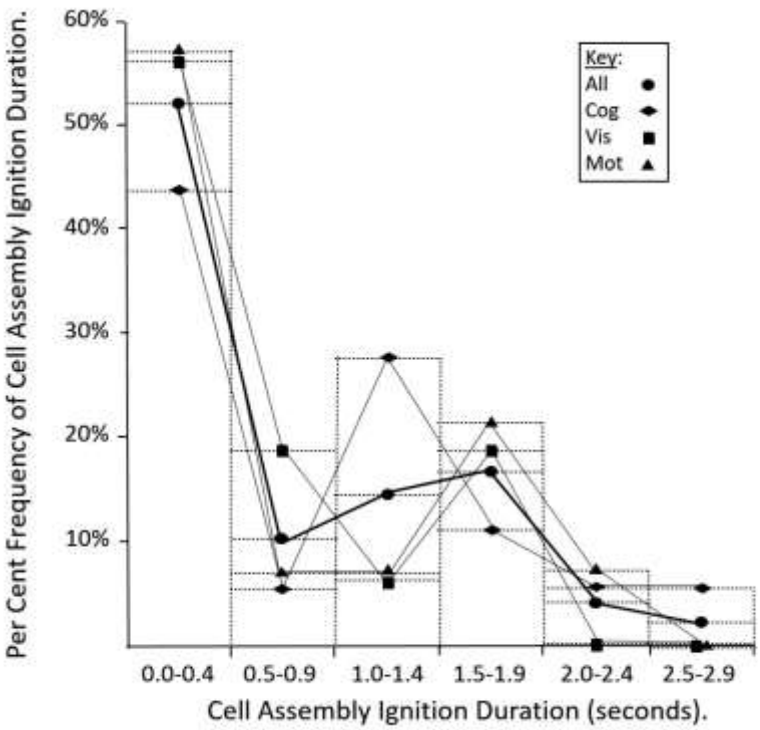

Figure 11 Ignition durations of CA types presented as both line graphs and histograms.

One would need a lot more data, but there is a hint that these CA ignition duration results are bi-modal, i.e. half the CAs last for less than half a second and most of the remainder last for over a second, with a few lasting over two seconds. It would not be implausible that, in the task, that there are two types of CA: short lasting ones and persisting ones.

*.4.2.3 Priming and Decay Result*s

There is background activity in brains caused by neurons firing that appears random (section 2.1). The amount of such background activity may vary. For example, in the visual system there is, overall, more activity in the optic nerve in darkness than under normal viewing conditions, because retinal processes use lateral inhibition, but this background lacks the highly organised transmission of spike trains down the optic nerve bundles that signal retinal receptive field stimulation of varying spatial frequencies, and their location. What happens when disorganised activity reaches the visual cortex? The various forms of pattern recognition CAs are not ignited, although people do report fleeting and vague visual experiences in darkness (phosphines). We hypothesise that in such circumstances the overall background activity in the visual cortex may be quite high, but insufficient to ignite any of the vast number of potential visual CAs.

Little is really known about the relationship between background neural activity and potential CA ignition and the same is so for both priming and decay: see the QPID model (Introduction). For example, with higher levels of background activity, would a CA need more, the same, or less priming to reach ignition? Theoretically all are possible. Similarly, are CA thresholds changed by an elevated background?

When a CA extinguishes, the evidence is that there is an initial rapid decay of member neurons, but what is less clear is whether the later stages of decay return to whatever is the background level, or remain above this level for an appreciable time, or suffer a refractory period where the CA is harder to re-ignite. Furthermore, different CAs, and in different circumstances, may behave differently.

Perhaps the most unsatisfactory aspect of the SCAM used concerns priming and decay. Just looking at the SCAM diagrams (Figure 10), the priming and decay functions look exaggerated. This is undoubtedly caused by the single linear parameter used for each (P50% and D50%). Figure 12 shows a redrawn general SCAM diagram with more plausible priming and decay functions. These issues are returned to in the Discussion (section 5.3.1).

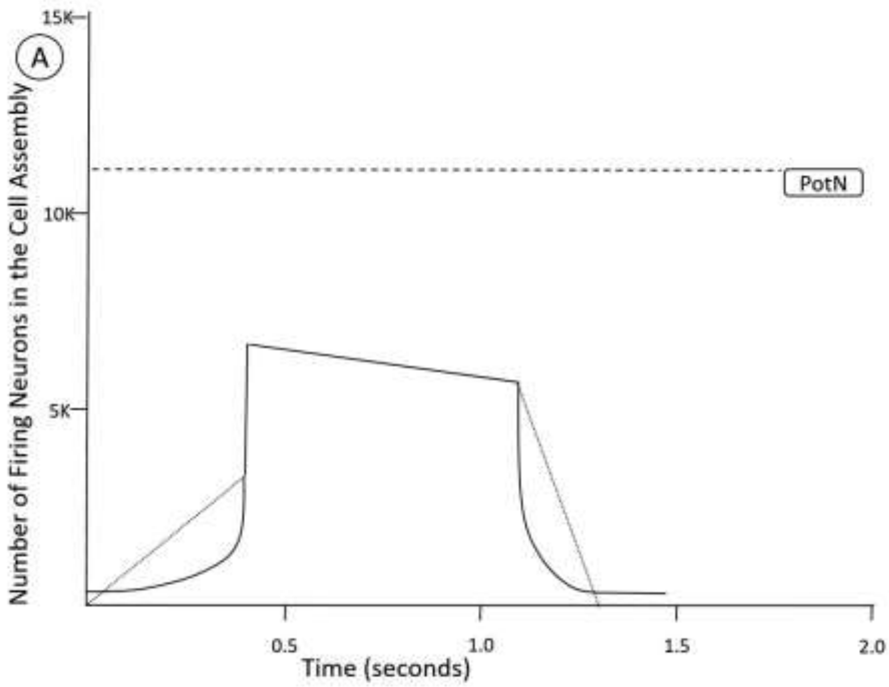

Figure12 Redrawn general SCAM diagram with original Figure 1 shown with dotted lines where these two figures differ.

.4.3 CAAR Results

In the SCAM, which does not model internal CA processes, for every output from a CA there is its equivalent input to another CA or to a motor output that goes outside the system studied. Therefore, one can either model CAAR inputs or outputs as the results of one simply mirroring the other. The following analysis models outputs from CAs. Due to lack of data, the following results are ignored: (a) the five non-visual perceptual CAs (touch and kinaesthetic); (b) the seven inhibitory relationships (all between cognitive and motor CAs); and (c) system external motor outputs.

There were 89 relationships identified from the main analysis' CAAR diagram (Figure 9) and their outputs, and to where these outputs go, is summarised in Table 7.

	Visual →	Cognitive →	Motor →
→ Visual	0	20	3
→ Cognitive	21	26	1
→ Motor	1	17	0

Table 7 Input-Output numbers between CAs of different types from the CAAR Diagram (Figure 9); horizontal output to vertical input.

The same results can be represented graphically (Figure 13), where it is easier to see the cognitive architecture that was used during the main analysis (Appendix I).

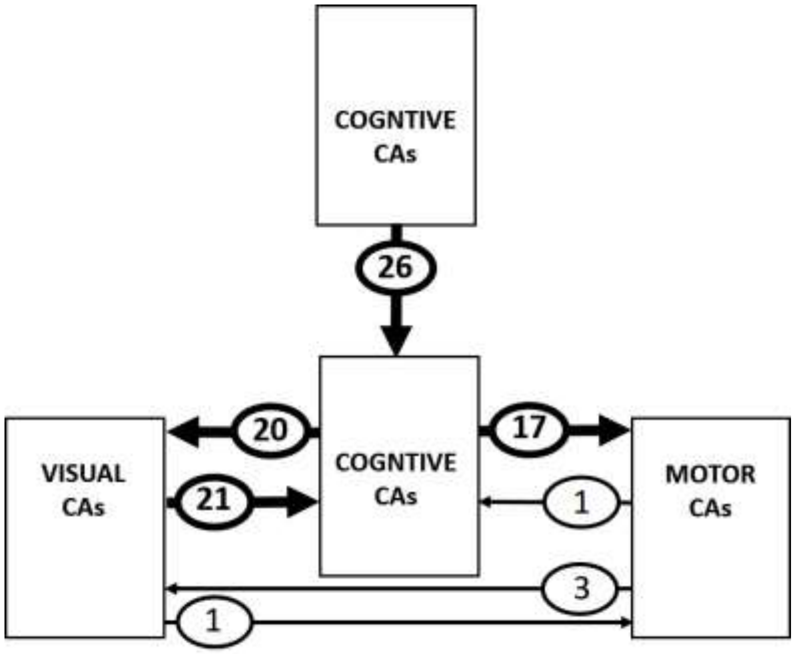

Figure 13 Graphical representation of Table 7's Input-Output numbers between CAs of different types from the CAAR Diagram (Figure 9); main relationships in bold.

Figure 13 confirms that in the vast majority of cases the Generic CAAR model (see section 2.3 and its Figure 2) was adhered to successfully during analysis. The centre portion of Figure 13 represents the basic chain of cognitive CAs, although noting that while there were 18 cognitive CAs, there were 26 outputs from one cognitive CA to another because some cognitive CAs may output to more than one CA of this type, i.e. the "basic chain" does have some branches or overtakes.

The intended, tight binding between cognitive CAs and visual ones (N=16) is well illustrated in Figure 13. That the outputs between cognitive and visual CAs is not equal (20 versus 21 relationships) is caused mostly by the occasional tight binding of motor and visual CAs. For example, the ballistic movement of the right arm (CA 11 MRAB) directly primes the visual system to expect the appearance of the right hand (CA 12 VRH) without going through an intermediate cognitive CA. Less than 5% (4/89) of the relationships analysed show such direct binding of motor and visual processes.

With one exception, inputs to the 14 motor CAs are from cognitive ones (N=17). There are only four outputs from the motor CAs as most of their outputs will be to the mid or hind brain and body movement systems. Many of these system external motor outputs will have inputs back into the system via sensory inputs. For example, when a hand is under negative feedback control then there is a cycle of: motor CA output → motor behaviour → optical input → visual CAs → cognitive CAs → motor CAs → motor CA output … .

.5 Discussion

The authors consider the research reported to be fantastically successful, *for a first demonstration!* This section therefore starts with the positives, first at the level of TA (5.1), and then at a more rarefied, philosophical level concerning the integration in a single model of both brain and mental function (5.2). The final sub-section (5.3) suggests possible future developments of the work, including: development of a CA based TA technique; AI implementation of CAs; more general theoretical considerations; and some practical near term potential developments by the authors, and, they hope, others.

.5.1 Task Analysis with a Cell Assembly Perspective

That it is possible to carry out a TA using a CA perspective is itself a success. The authors have worked for some years, together and independently, developing CA-based models and by exploiting TA's applied psychological approach, it is perhaps not surprising that they could identify putative CAs to associate with the task analysed. In terms of difficulty this is perhaps akin to attempting a *tabula rasa* GOMS analysis where every module decomposed must be invented from scratch, i.e. without reference to any previous GOMS analyses.

A more impressive success is the development of the first TACAP technique. The authors claim that their main analysis in Appendix I is their main result and the technique's success can be judged by the difference between the first third of the analysis, when they were in an iterative development mode, and the latter two thirds, which went quite smoothly and, relative to other TA approaches, quite quickly. While they are very cautious with the results (section 4), these generally indicate that they applied the various theories about mind, brain and CAs in a consistent manner.

In the end, the three representations developed, the SCAM diagrams, table and the CAAR diagram, were not only effective alone but were well integrated in that changes to one were usually relatively easy to propagate to the others, even though done manually (section 3.2). Naturally, we take Diaper's (2001) point that complex method development, and particularly method specification, must be done with analysts' software tool support. This topic is continued in section 5.3.1.

Acknowledging that the initial, main analysis covered but 9 seconds of elapsed task time, it is possible that any CA-based TA will always be at a low level of analysis and would therefore be unsuitable for analysing task of more than a few minutes. On the other hand, even if this were so, there are many tasks or subtasks which are super safety critical, and therefore worthy of detailed, if expensive, analysis, e.g. the time between V0, when an aircraft is committed to take-off, and rotation, when the aircraft has sufficient airspeed and height above ground that it can safely start to climb; or during an aircraft's handover from one sector to another by air traffic controllers; and numerous similar situations. Furthermore, first a CA-based technique might be used only on especially important subtasks and other TA methods used for the bigger task and, second, a library of CAs might allow overall task description at some meta-level that would then require only occasional descent to more detailed levels when appropriate.

Beyond the scope of this paper, a meta-cognitive architecture at the CA level needs developing and specifying. While such an architecture might include relatively distant brain areas, the expected focus would be within a localised brain area where, for example, two spatially adjacent, ignited CAs might already, or start, to share neurons and such sharing increases so as to create a super-CA; on subsequent ignitions, ignition of either will ignite the other. Such a model hypothesises a tighter binding between CAs than that of two interacting with each other, but which don't share any, or not very many, neurons. It might be possible to distinguish super-CAs from separate, interacting ones behaviourally in that ignition of one component CA (nearly) always causes ignition of the other(s) in the super-CA, whereas with separate CAs, then in some circumstances one CA igniting does not cause its sometimes related one(s) to ignite. There aren't great problems on the TA side about this since the levels concept is ubiquitous in TA, but a great deal remains to be done on CA meta-architectures, in the brain and in CA-based AIs. Much of the cognitive psychology literature, e.g. on selected and divided attention, may also need some redrafting to fit better at a CA level of analysis.

.5.2 Psychology, Neuroscience and Artificial Intelligence

The relationship between brain and mind remains one of the great scientific puzzles. Neuroscience involves describing the physiology and biochemistry of the brain whereas scientific cognitive psychology describes the mind as an information processing device (see Introduction). At best for such models of brain and mind, they represent two different descriptions of the same thing, a physical one and a functional one, respectively. Such different descriptions of a thing are often conflated, for example, describing the heart as a "muscular fluid pump" combines its physical physiology with its function as a pump; for further discussion see Scott- Phillips *et al*. (2011) in the context of their distinction between proximate and ultimate explanations: the former correspond to physical, brain, descriptions and the later to mental, functional ones.

There are a number of problems with careless conflation of different descriptions. An obvious one concerns establishing functionality. For example, one might describe an electric hand drill as a device for making holes, but if it is considered as a spike rotator, then its functionality can be extended to sanding and polishing and, using a crank, such a drill can perform tasks involving linear reciprocating motion, e.g. sawing. Furthermore, multiple functionality is common in biology, e.g. that bones provide structural support and the production of red blood cells. The brain is particularly complicated because a great deal of the cortex is unspecialised, as far as currently known, and can be involved in many and apparently very different tasks. Such a property is central to the SCAM and its PotN conception.

There are areas of the cortex that do have a specialised functionality, but just what this might be is difficult to establish with complete certainty. Whatever physiological methods are used, the basic problem is the range of tasks tested. As a hypothetical illustration, one might find a brain area that is always active during language tasks, and careful experimentation might show this area is only active during parsing, but whether it is a specialised language parser, or part of one, would remain moot. Apart from the problems of specifying functionality, it is always possible that the same area may be active in tasks that are untested, say when riding a bicycle or listening to music, and the range of untested tasks is effectively infinite.

The logical problems remain at whatever physiological level of detailed studied, from single cell recording to what are quite large brain areas, i.e. relative to the size and number of neurons involved, and this is also the case with CA-based models. Indeed, it might seem that the problems are hardest at the CA level, but they do have a subtle advantage in that ignited CAs exist only temporarily and so searching for fixed brain neuron or area functionality will often be bootless. A further, more important advantage to using CAs to model both brain and mind is that there is a tight binding between the two such that the physical properties of a CA closely match their functional, information processing ones. No such tight binding exists for the physiology of larger brain units and traditional cognitive psychology, and while there is a similar tight binding at the level of single cells, we hypothesised in the Introduction that a Grandmother neuron might be better understood as being a frequent member of a Grandmother CA, which also solves the problem of what happens if such a cell dies.

CA-based ANNs also suffer the same logical problems in that once they have been running, and learning, for some time, then the function of a particular CA is difficult to infer, even though the state of the whole system is open to inspection. In contrast, with symbolic AIs such as ACT-R, the function of each of its software modules is well understood as these are programmed using traditional software methods, i.e. the functionality is as well understood as for that of any piece of correctly running software code. Although the authors are confident they could do so, with sufficient resources, they have not attempted to implement anything from their first TACAP analysis as a CA-based ANN. Their plans on this are discussed further in section 5.3.4.

The authors' view is that a major benefit of this first TACAP analysis is that of a precursor to a General Theory of both brain and mind. This is discussed further in section 5.3.3. TACAP is intended to encourage cognitive scientists of all sorts to consider both the neural and cognitive at the CA level and, by exploiting the applied cognitive approach of TA, facilitate creative, sensible proposals about CAs and their architecture. When TA is done well, then it places quite severe constraints on what is "sensible" and, as illustrated throughout Appendix I, a considerable amount of psychology is involved; and with TACAP, some neuroscience as well.

.5.3 Future Developments

This TACAP paper is the start of a story. While research on both TA and CAs has been going on for decades, it is their combination that makes TACAP unique. The following subsections outline work that needs doing to further develop TACAP (sections 5.3.1 and 5.3.2), how it might have substantial theoretical consequences (5.3.3), and the authors' near term plans for TACAP development (5.3.4).

.5.3.1 *Method and Software*

Continuing from section 5.1 and the essential requirement to develop analyst support tools, Figure 14 shows one high level, user perspective of the suite of tools that need developing for this paper's TACAP technique.

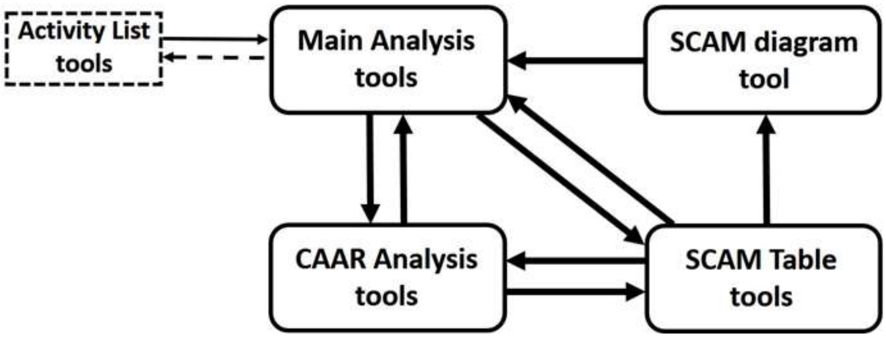

Figure 14 Software tools suite required to automate the TACAP technique.

It is assumed that existing or new tools would support analysts working with various types of task performance data and that AL lines would be imported into the Main Analysis tools. It is envisaged that the latter is the analyst user's main interface that, apart from free text entries, would automate the decisions made and, of course, test and flag inconsistencies, a.k.a. current errors, in an ongoing analysis. From the early stages of a TACAP analysis, as CAs are identified they would create SCAM Table entries and, as the parameters are filled in, then there may be feedback to the Main Analysis tools. Once each CA's SCAM table's row of data are all filled in, then a SCAM diagram is created for that CA and made available in the Main Analysis tools. The SCAM Table tools also seed the CAAR Analysis tools with both identified CAs and their location on the task timeline. The analyst user must still specify relationships between CAs, but producing the CAAR diagram should be at least semi-automated. Furthermore, much more sophisticated relationships between CAs could be relatively easy to specify than was realistic with the first, manual analysis, e.g. cycles of feedback between CAs could be indicated, say by multiple arrow heads, and types of input/output could also be coded beyond the simple excitatory or inhibitory relationships used in this first analysis.

Noting the priming and decay parts of the SCAM, P50% and D50%, were clumsy for producing the SCAM diagrams manually (section 4.2.3 and Figure 12), a simple power function would could easily be applied in a SCAM diagram production tool.

Similarly, the sub-optimal entries to the SCAM table with respect to generating SCAM diagrams in a manual analysis (section 4.2, Tables 3 and 4 and Figure 10) involve trivial software calculation, allowing future tools to optimise the user analyst's ease of input as the simple backend software would take care of the rest. These are examples that emphasise the importance of software tools to support the development and specification of complex methods.

While a design feature of the first TACAP analysis was to include various capabilities to cross-check within and across the main representations, the suspicion is that the analysis is not entirely error free, notwithstanding many hours of testing. As an example, only after the first draft of this paper was completed was it discovered that CA VHWA (Visual Hot water Area) was correctly present in the CAAR diagram but entirely absent from the SCAM table and

Appendix I; most of the testing had been done between the latter two. The belief is that a reasonable analysts software suite would not only make analyses better, and nigh error free, but would reduce analysis time to a third or a quarter of what it might take to do manually.

Experience with developing such tools, e.g. Diaper's (e.g. 2001) LUTAKD toolkit, suggests that in addition to being essential for method specification, such tools are also likely to change the method itself, not least because what was implausible effort in a manual analysis becomes easy with appropriate software. Nigh impossible to predict in advance, as an example, one candidate would be the animation of the CAAR diagram. For the initial TACAP analysis, the CAAR diagram was done in PowerPoint (section 3.2) and for the expert user it is relatively easy to animate the timeline and the CA boxes and the arrows. Like envisaging the SCAM diagrams without drawing most of them (section 3.2), the CAAR diagram was only animated in the analyst's mind during analysis. The animation (Appendix III) was only done after the main analyses were completed. On the other hand, for less visually adept analysts, they might well find an automatically animated CAAR diagram of considerable help. It should certainly help when presenting such work to conference or seminar audiences.

.5.3.2 Artificial Intelligence

The evidence is that CAs do exist in the brain (Harris, 2005; Huyck and Passmore, 2013; and Introduction), although a great deal of our understanding of CAs has arisen from AI work with ANNs. No doubt there are interesting scientific research opportunities involving the mimicry of brains and minds (section 5.3.3), but future, practical applications of CA-based AIs depends on identifying roles and functions. One CABot, for example (Huyck *et al.,* 2011*)*, was implemented as a robot in a virtual, simple games-like environment with a general role of operating as a user's assistant. TA is rarely done frivolously because it is expensive in time, money, and human resources, of expert analysts and task performers. Monitoring and assisting users in complex, safety critical tasks, particularly when tasks and their environments are variable and require rapid decision making, for example in aviation as mentioned in section 5.1, would seem to provide appropriate and useful application areas for development of versions of the TACAP approach and their useful implementation as CA-based AI assistants.

Building the CABot systems provides confidence that such CA-based AIs, with only minimal initial programming, are able to learn to carry out tasks. They will develop their own CAs by unsupervised learning, by trial and error. As discussed in section 5.2, it is difficult to infer such CAs' functionality even though there is the potential to inspect every state in every program cycle. Unless particular CAs are forced on a system, then it is unlikely that AI CAs will coincide with brain and mind CAs, i.e. both AIs and people can learn to perform the notional "same" task but the fine details at the CA-level will differ. The same is true between any two people and, anyway, even frequently repeated tasks by the same person will not use quite the same CAs each time. We cope with these within and between differences in people and it will be necessary to extend the same coping strategies to genuinely intelligent, flexible, self-learning AIs.

We believe that CA based AIs will become increasingly popular. They are capable of learning new domains and while all AI systems are currently domain specific, CA-based systems will be more flexible than Expert/Knowledge Based Systems or symbolic ones. A virtual agent with a simulated neural brain will function in an environment, and learn significant aspects of that environment. Upfront programming effort required in symbolic AI development, and maintenance, will be replaced by the self-programming capabilities of CA-based systems, although there may be a cost if it is necessary to provide learning nurseries for new CA-based AIs. Perhaps within only a few decades, but after the emancipation of the early CA-based AIs, people will have another highly intelligent species with which to share planet Earth; and one that can talk to us in our own languages.

.5.3.3 General Theories of Psychology and Neuroscience

A General Theory is, within its scope, a theory of everything. General Theories are quite common in psychology, even if below cognitive psychology's axiom concerning the mind as an information device, and they are often quite simple. What makes a CA-based General Theory attractive is the "tight binding" (section 5.2) between psychology and physiology. A possible future development might be the deliberate conflation of description of brain and mind, producing descriptions where a CA has physical properties, presumably an improvement of the SCAM table, and functional ones, what the CA does and its relationships to other CAs.

Traditionally, psychology has borrowed from other technologies, from Victorian hydraulics, e.g. people feel pressure, to computing, and even changing psychological models as technologies improve, e.g. Diaper's (1989b) PDP8 versus PDP11 models of cognition (the PDP8 models do operations in registers whereas the PDP11 ones dispense with registers altogether). With CAs, for once the direction might be opposite, in that there is a chance for such a psychology to focus physiological studies, i.e. having posited the existence of one or more CAs, then the physiologists might try and find them.

Such possibilities may be some considerable time away as at the moment too little is known about CAs, in brains, minds and in AIs. Indeed, the TACAP development was explicitly intended to encourage cognitive scientists to think and work at the CA-level and, over time, thus might an international community become established.

.5.3.4 Practical Near Term Developments

While the authors wish to enthuse others with a practical approach to CA-orientated thinking, they have some near term plans following this paper's publication. They will offer seminars and conference presentations focusing on special aspects of the TACAP research suitable for different audiences. The full animation of the CAAR diagram (Appendix III) might be particularly useful for these (section 5.2). At least one on-line presentation will also be developed.

We are also in the process of developing a proto-neural cognitive architecture. We can currently implement simple associative memories, and generic rule based systems in simulated spiking neurons. Combining these will make a proto-neural cognitive architecture, which could be used for executing tasks to simulate, at a neural level, task execution. An obvious extension would be to extend our existing binary CAs to more complex ones that behaved as those described in the analysis (Appendix I). This would enable us to develop the TA mechanism in step with a neural cognitive architecture.

.6 Conclusions

The authors believe that this is a 'John the Baptist' paper that starts a new chapter in the combination of psychology, neuroscience and AI. In the end, it is probably not what they have done that is important, but how they did it. The TACAP provides an easy entrance for others to learn to think at the CA level. Appendix I, the main analysis, is crucial for such a purpose as it contains 65 examples of CAs which others can study and use as a basis for identifying CAs in more appropriate tasks.

Although the trend in ergonomics is to study general systems above the level of tasks, as Sociotechnical Systems (e.g. Stanton and Harvey, 2017), and sometimes called Systems-of-Systems (Harvey and Stanton, 2014), the essential need for the detailed study of some tasks will remain. Recently the terms "Artificial Intelligence" and "AI" have entered popular awareness, although, like "psychology" for much longer, the general public may know little beyond the terms themselves. Just how intelligent, if at all, some of the systems that these days claim to be AI is open to question, but the AI cat is now out of the bag and genuinely intelligent systems may result from AI's commercialisation.

TACAP is at least paddling hard to catch the crest of the coming AI wave. As a new approach it lacks much of the baggage of older TA approaches, which might further commend it for development.

Acknowledgement

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References

Anderson, J.R. and Lebiere, C. (1998) *The Atomic Components of Thought*. Lawrence Erlbaum; London.

Anderson, J.R. (2007) *How Can the Human mind Occur in the Physical Universe?* Oxford University Press; Oxford.

Annett, J. and Duncan, K.D. (1967) *Task Analysis and Training Design*. Occupational Psychology, 41, 211-221.

Annett, J. (2004) *Hierarchical Task Analysis*. in Diaper, D. and Stanton, N.A. (Eds.) *The Handbook of Task Analysis for Human-Computer Interaction*. 67-82. Lawrence Erlbaum Associates.

Baddeley, A. (1976) *The Psychology of Memory*. Harper and Row: N.Y.

Baddeley, A. and Hitch, G. (1974) *Working Memory*. Bower, G.H. (ed.) *Recent Advances in Learning and Motivation, Volume 8*. Academic Press, N.Y.

Balbo, S., Ozkan, N. and Paris, C. (2004) *Choosing the Right Task-Modelling Notation: A Taxonomy*. in Diaper, D. and Stanton, N.A. (eds.) *The Handbook of Task Analysis for Human-Computer Interaction*. Ch. 22, 445-465. Lawrence Erlbaum Associates.

Blakemore, C. and Cooper, G.F. (1970) *Development of the Brain Depends on the Visual Environment*. Nature, 228, 477-8.

Byrne, E. and Huyck, C. (2010) *Processing with Cell Assemblies*. Neurocomputing, 76-83.

Card, S., Moran, T. and Newell, A. (1983) *The Psychology of Human-Computer Interaction*. Lawrence Erlbaum: Hillsdale, N.J.

Diaper, D. (1989a) *Task Analysis for Knowledge Descriptions (TAKD): The Method and an Example*. In Diaper, D (ed.) *Task Analysis for Human-Computer Interaction*. 108-159. Ellis Horwood.

Diaper, D. (1989b) *Designing Expert Systems: From Dan to Beersheba*. in Diaper, D. (ed.) *Knowledge Elicitation: Principles, Techniques and Applications*. 15-46. Ellis Horwood.

Diaper, D. and Kadoda, G. (1999) *The Process Perspective*. in Brooks, L. and Kimble, C. (Eds.) UK Academy for Information Systems 1999 Conference Proceedings. 31-40. McGraw-Hill.

Diaper, D. (2001) *Task Analysis for Knowledge Descriptions (TAKD): A Requiem for a Method*. Behaviour and Information Technology. 20, 3, 199-212.

Diaper, D. (2004) *Understanding Task Analysis for Human-Computer Interaction*. in Diaper, D. and Stanton, N.A. (Eds.*)* *The Handbook of Task Analysis for Human-Computer Interaction*. 5-47. Lawrence Erlbaum Associates.

Diaper, D. and Stanton, N.A. (2004) *Wishing on a sTAr: The Future of Task Analysis for Human-Computer Interaction*. in Diaper, D. and Stanton, N.A. (eds.) *The Handbook of Task Analysis for Human-Computer Interaction*. 603-619. Lawrence Erlbaum Associates.

Feigl, H. (1958) *The 'Mental' and the 'Physical'*, in *Concepts, Theories, and the Mind-Body Problem*, University of Minnesota Press. (quote from p.150).

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.

Gibson, J.J. (1950) *The Perception of the Visual World*. Houghton Mifflin: Boston.

Harnad, S. (1990) *The Symbol Grounding Problem.* Physica D 42, 335-346.

Harris, K. (2005) *Neural signatures of cell assembly organization*. Nature Reviews Neuroscience, 6, 399-407.

Harvey, C. and Stanton, N.A. (2014) *Safety in System-of-Systems: Ten Key Challenges*. Safety Science, 70, 358-366.

Hebb, D. (1949) *The Organization of Behavior: a Neuropsychological Theory*. J. Wiley and Sons.

Hodgkin, D. and Huxley, A. (1952) *A quantitative description of membrane current and its application to conduction and excitation in nerve*. Journal of Physiology, 117, 500-544

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.

Huyck, C. and Mitchell, I. (2018) *CABots and Other Neural Agents*. Frontiers in Neurorobotics 12:79.

Huyck, C. and Parvizi, A. (2012) *Parameter Values and Fatigue Mechanisms for FLIF Neurons*. Journal of Systems, Cybernetics and Informatics, 80-86.

Huyck, C. and Passmore, P. (2013) *A Review of Cell Assemblies*. Biological Cybernetics, 263-288.

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.

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.

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.

Kieras, D.E. and Meyer, D.E. (1997) *An Overview of the EPIC Architecture for Cognition and Performance with Application to Human-Computer Interaction*. Human-Computer Interaction, 12, 391-438.

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.

Laird. J, Newell, A. and Rosenbloom, P. (1987) *Soar: An Architecture for General Cognition.* Artificial Intelligence, 33.1, 1-64.

Marr, D. (1982) *Vision: A Computational Investigation into the Human Representation and Processing of Visual Information*. W.H. Freeman: San Francisco, CA.

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.

Miller, G. (1956) *The Magical Number Seven Plus or Minus Two: Some Limits on our Capacity for Processing Information.* Psychological Review, 63, 81-97.

Morey, C. (2018) *The Case Against Specialized Visual-Spatial Short-Term Memory*. Psychological Bulletin, 144 (8), 849-883.

Newell, A. (1990) *Unified Theories of Cognition*. Harvard University Press.

Oberauer, K. and 15 others (2018) *Benchmarks for Models of Short Term and Working Memory*. Psychological Bulletin, 144 (9), 885-958.

Osterweil, L.J. (1987) *Software Processes are Software Too*. 9th. International Software Engineering Conference, IEEE Computer Society Press.

Popper, K.R. (1979) *Objective Knowledge: An Evolutionary Approach*. revised edition. Oxford University Press: England.

Rumelhard, D. and McClelland, J. (1986) *Parallel Distributed Processing*. MIT Press.

Scott-Phillips, T.C., Dickens, T.E. and West, S.A. (2011) *Evolutionary Theory and the Ultimate–Proximate Distinction in the Human Behavioral Sciences*. Perspectives on Psychological Science, 6(1), 38–47.

Smart, J.J.C. (2007). *The Mind/Brain Identity Theory*. Stanford Encyclopedia of Philosophy.

Smith, K. (2010) *Settling the Great Glia Debate*. Nature 468,160–162.

Stanton, N.A. and Harvey, C. (2017) *Beyond Human Error Taxonomies in Assessment of Risk in Sociotechnical Systems: a New Paradigm with the EAST 'broken-links' Approach*. Ergonomics, 60, 2, 221-233.

Tetzlaff, C., Dasgupta, S., Kluvicius, T. and Worgotter, F. (2015) *The Use of Hebbian Cell Assemblies for Nonlinear Computation*. Scientific Report, 12866.

Ullin, T.P. (1956) *Is Consciousness a Brain Process?*, British Journal of Psychology, 47, 44-50.

APPENDIX

I Cell Assembly Descriptions – The First Steps to Making Coffee

II Acronym Glossary

III Animated CAAR Diagram