A Neurocomputational Instructional Indicator of Working Memory Load in Cognitive Load Theory

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Abstract
This work expands the scope of an earlier neurocomputational study of learning-performance aspects of human behaviour in automated learning environments by applying metrics of instructional efficiency within the conceptual framework of cognitive load theory. The test bed is a simulated learning environment, in which the organization of the learning content is represented as a dependency graph of topics. The human learning behaviour is neurocomputationally recorded per completed topic in terms of externally-assessed performance and introspective mental effort. The statistically representative behavioural instances monitored are mapped within the patterns of two Kohonen self-organizing maps (SOM); PSOM is a compressed version of the human performance space and ESOM is a compressed version of the human introspective mental-effort space. PSOM and ESOM are, in essence, models of learning behaviour for the specified learning environment, and can be used to a) pinpoint instructional design weaknesses associated with the dependency graph of the learning content and b) indicate working memory load levels and cognitive load characteristics associated with instructional design. The latter is achieved by combining mental effort and performance behavioural patterns, an established dual-data metric referred to as instructional efficiency, within the interpretational framework of cognitive load theory.

Keywords: Cognitive Load; Self-Organizing Maps; Working Memory; Instructional Design.

Introduction
Understanding how people learn and acquire knowledge has been a focal point in education for at least the last three decades, as there is an acute demand for the efficient dissemination and assimilation of knowledge (Sweller, 1999). Although information technology has long been applied to education, there is still a technological gap between learning behaviour and instructional design. In recent years attempts have been made to construct intelligent adaptive systems to monitor student learning (e.g. Ben-Naim, Marcus, & Bain, 2007), part of a spectrum of studies based on Artificial Intelligence methodologies and Web engineering (Wenger, 1987; Brusilovsky, 1999; Shang, Shi, & Chen, 2001), but there are standing issues in measuring instructional efficiency.

The present work has been partially based on a relevant earlier study on modelling human learners (Revithis, 2001), and strengthens the applicability prospects of autonomous Internet-based learning environments (Shi, Revithis, & Chen, 2002). It introduces a novel approach to assessing instructional design, based on collective (as opposed to individual) working memory load, which is linked to cognitive load theory (Sweller, 1994; Sweller, van Merriënboer, & Paas, 1998).

In the first part of this paper the characteristics of learning environments are discussed in relation to the human cognitive system, and the importance of working memory load is analysed. In the second part a learner behavioural model based on a dual SOM neural network is introduced and described in terms of its usage as a collective cognitive load indicator. The last part is devoted to a short discussion on some of the model’s implementation details and on pointers for future work.

Situated Learning
There is a link between human cognitive architecture and learning behaviour from the standpoint of instructional design. Learning environments largely determine the functional specifications for the acquisition of knowledge as is discussed next.

Learning Environments and Human Cognitive Architecture
A generic learning environment is comprised of a varying number of learners and an instructor. The learning goal, within this type of environment, is the acquisition of the predetermined learning content (ultimately, knowledge) by the learners; this is principally facilitated via a system of interactions between the learners and the instructor.

As a convention, such an environment is considered equivalent to a unit of study (e.g. introductory algebra) and its learning content can be introduced in a series of sessions, in each of which a thematically-distinct topic is presented to
the learners (e.g. mathematical equation preliminaries, mathematical operations and their properties, solving a quadratic equation, etc.) The structure of the learning content can be depicted in a dependency graph of topics. Each topic contains part of the learning content, and has a number (greater or equal to zero) of prerequisite topics. The network of prerequisites is dictated by the knowledge required prior to engaging in a certain topic; it would be a violation of the dependency graph to engage in a topic without having successfully completed all prerequisite topics, which would suggest lack of prerequisite knowledge during acquisition of new knowledge (Figure 1). A topic is successfully completed by a learner if the learner has performed adequately in the topic assessment.

![Figure 1: Example of a dependency graph of a five-topic learning content of a learning environment.](image)

Each topic has a high level of content self-sufficiency, so that a learner can focus his or her efforts on it without being forced to attend to multiple topics simultaneously. While topics are self-sufficient they are often not independent as certain topics require knowledge either found in another topic or distributed across multiple topics. This situation, resulting in the formation of a network of content-dependencies depicted in the dependency graph, dictates a specific ordering within the learning environment and suggests its structure for instructional design.

Every human who enters a learning environment, has certain prior knowledge (i.e. background knowledge). According to schema theory (Bartlett, 1932; Minsky, 1975; Bobrow & Winograd, 1977; Larkin, McDermott, Simon, & Simon, 1980; Chi, Glaser, & Rees, 1982; Mayer, 1992) knowledge is organized into lossy-compressed, retrieval-oriented, categorical, long-term, memory units, called schemas, and plays a particularly critical role in the acquisition and application of new knowledge (Sweller, van Merriënboer, & Paas, 1998). In general, schema knowledge is instrumental in interpreting new knowledge when referenced by working memory.

Whether background knowledge is sufficient or not for the environment is usually determined via some type of screening (evaluation test) at enrolment. However, a number of learners with an insufficient knowledge base might eventually enter the environment without being alerted, due to imperfections of the screening mechanism. Such a knowledge mismatch leads to incompatibility of the learners’ existing schemas with the knowledge content of the environment or lack of necessary schemas.

Typically, the learners go through systematic evaluation so that the instructor can obtain qualitative information on their acquired knowledge. The overall learner’s feedback provides uniquely valuable information on the effectiveness and efficiency of the instructional design of the learning environment.

**Working memory load considerations**

The set of all possible sequences for successfully completing all the topics, based on the constraints of the dependency graph, forms the environment space. As the number of topics increases the cardinality of the environment space becomes explosively large. The learner needs to explore that space in the most beneficial way, having to select the best completion path (i.e. traversing the environment, from topic to topic, in such an ordering so that a high degree of knowledge acquisition is achieved).

Knowledge acquisition can be impaired in any educational setting. This study assumes an empirically supported explanation of why this could happen, which is based on working memory load (Miyake & Shah, 1999; Kalyuga, 2006). Learners receive information primarily via their audio-visual sensory system into their sensory memory and then process it while it is temporarily retained in working memory; such processing employs schema-encoded knowledge residing permanently in long-term memory (Sweller, van Merriënboer, & Paas, 1998). These fundamental elements of human cognitive architecture point to working memory as a focus of conscious mental functioning. In such an architecture, the impact of cognitive load on knowledge acquisition is substantial.

The capacity of working memory is affected by both the natural constraint of no more than a few chunks of information being present at any time (Miller, 1956; Cowan, 2001), and the contents of the knowledge base residing in long-term memory in the form of schemas. Straining working memory can be due to a combination of working memory capacity overload, and lack of compatible or automated schemas in long-term memory (Sweller, van

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1 Theoretically, if $S(x)$ is the cardinality of an environment space of $x$ topics, then $\lim_{n \to \infty} S(xn) = n!$. In Algorithmic theory (Cormen, Leiserson, Rivest, & Stein, 2009) the dependency graph is a directed acyclic graph (DAG), which is potentially sparse. Each topic in the dependency graph corresponds to a node in the DAG, and each dependency is represented by an edge; then, each way to complete all the topics is a topological ordering of the DAG. If the DAG is very sparse the complexity of the cardinality of the topological ordering set is generally $O(n!)$, where $n$ is the number of topics in the learning environment. Practically, the number of dependencies is sufficiently large, therefore the complexity bound can drop, in the worst case, to $o(n!)$.  

2 A chunk of information is a piece of information, which is being handled by working memory as a unit (i.e. a single element), instead of a group, or a set, of disparate pieces.
Merrienboer, & Paas, 1998). Such a capacity overload imposed on working memory, which can severely impair knowledge acquisition and learning, has been specified as high cognitive load, and plays an instrumental role in cognitive load theory (Sweller, 1994). Schema-deficient incoming information can cause, in effect, a communication breakdown between working memory and long-term memory since there are no schemas in long-term memory to explicate the new knowledge (schema referencing failure); similarly, incoming information with a very high degree of complexity\(^3\) can cause working memory to overload. In both cases, the consequence can be viewed as a form of working memory capacity virtual shrinkage (Figure 2).

Figure 2: Knowledge acquisition as a function of working memory load and schema-based knowledge. Although the physical capacity of working memory remains unchanged, it is practically reduced when retaining schema-deficient or highly complex information.

### The Behavioural Learner Model

Human behaviour has unlimited variability and scope, but it is naturally bounded, albeit moderately, when associated to a specific environment, as in the case of a learning environment, since only certain behaviour is meaningful in any particular environment. As will be discussed in the next section, a form of mild behavioural-space reduction, which takes place naturally in situated learning, is an initial working assumption in modelling learning behaviour in this study.

In a learning environment, the instructor decides whether the learning content is cognitively accessible to, and instructionally appropriate for the learners. The instructor has to examine the totality of the learners’ feedback and use a decision mechanism to determine the degree of knowledge acquisition currently offered within the environment.

Situated behaviour within a learning environment can provide information to construct a model of the learners’ performance. Furthermore, it can provide sufficient information to build a behavioural learner model, allowing for the assessment of instructional design and working memory load as a function of cognitive strain and performance during knowledge acquisition.

The model introduced in this study is based on performance and introspective metrics in order to quantitatively characterize the learners’ behaviour and estimate their cognitive load. The behavioural learner model, which fits the characterization of a behavioural outcome model (Sun & Ling, 1997), is implemented as a computational dual self-organizing neural network, the characteristics and architecture of which will be presented next.

### Architecture and Function of the Model

Computational modelling offers a powerful way of interpreting and understanding cognitive phenomena and human behaviour (Sun, Coward, & Zenzen, 2005; Scarborough & Sternberg, 1998; Polk & Seifert, 2002). Neurocomputational cognitive models are based on neurologically inspired computational systems, known as artificial neural networks (or connectionist networks), which allow reliable interpretations of human behaviour within the realm of cognitive psychology (Parks, Levine, & Long, 1998; McLeod, Plunkett, & Rolls, 1998; Thomas & Karmiloff-Smith, 2003; Elman, 2005). One type of such modelling network is the class of self-organizing feature maps (Willshaw & von der Malsburg, 1976; Kohonen, 1982; Kohonen, 2001).

In particular, the Kohonen self-organizing neural network (SOM) possesses a range of powerful statistical characteristics, including approximation of the input space, topological ordering, density matching, and feature selection (Haykin, 2009). It employs a Hebbian-type (Hebb, 1949) neural learning mechanism, the result of which resembles topographic maps in the brain that produce comparable output if given the same input (Blasdel & Salama, 1986; Livingstone & Hubel, 1988; Merzenich & Kaas, 1980). In general, Hebbian neural mechanisms exhibit “ecological validity” (Munakata & Pfaffly, 2004) since they situate themselves in the environment without the need for error-driven or goal-oriented interaction. The importance of the self-organization approach to cognitive modelling is indicated by the claim that neural self-organization is the causal and sustainability factor of classifiable behaviour, present from simple biological neural mechanisms through to higher-order cognitive mechanisms (Kelso, 1995).

The behavioural learner model is based on two Kohonen neural networks that map the learners’ behaviour within the learning environment. The first neural network, called PSOM, represents the learners’ cognitive performance per

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\(^3\) Information complexity is defined here in terms of element interactivity; that is, the degree of semantic dependence amongst the constituents of information (Sweller, 1994). A relational complexity metric proposes a compatible and rigorous neurocomputational approach on information complexity and working memory processing capacity (Halford, Wilson, & Phillips, 1998).

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topic, whereas the second one, ESOM, represents the learners’ cognitive effort per topic, during their learning process. Both behavioural maps are formed after PSOM and ESOM have undergone training that exposes each neural network to a sizeable data set of representative past cases of learners who have successfully completed all topics. In the case of PSOM, the training set consists of numerical data on learners’ performance on topic evaluation tests, whereas, in the case of ESOM, it consists of learners’ self-evaluation, numerically-scaled, introspective data on the mental effort which was required for each topic to be successfully completed (Figure 3).

During the training session each neural network is sequentially presented with performance (or mental effort) vectors of numerical data (representing scores) in order for the network to converge to a stable state according to the machine learning and termination characteristics of the Kohonen neural network algorithm (Haykin, 2009). The significance and efficiency of the learners’ behavioural mapping depends on how statistically representative of the learner population the training set is. Following the assumption that a mild form of behavioural-space reduction takes place naturally in situated learning, both the performance and mental effort behavioural spaces for any learning environment are generally much smaller than the vast theoretical space of human behaviour, but still prohibitively large. However, the explosively large space of situated learning behaviour can be compressed into a manageable set of behavioural patterns in the form of two topological behavioural maps; the latter maps, PSOM and ESOM, represent statistically dominant cognitive behavioural patterns for performance and mental effort, respectively. Due to the SOM properties (Haykin, 2009) it is expected that each map would be a close approximation of the situated behavioural space it compresses provided that it has been trained using a statistically representative subset of that behavioural space (Figure 4).

At the completion of the training, PSOM constitutes a topological cognitive behavioural map of the learners’ performance in each topic of the learning environment. The structure of PSOM is a two-dimensional lattice where each node (neuron) retains a vector pattern of performance. Similarly, the trained ESOM network maps the learners’ mental effort in each topic of the environment, where each node (neuron) of its two dimensional lattice retains a vector pattern of mental effort. The size of each lattice is primarily a function of how many patterns of performance (or mental effort) the model designer determines as appropriate to be represented by the SOM network, and in the simulations it was in the order of 100 nodes.

It is important to clarify that each node on either map contains not the performance (or mental effort) of a single learner in the environment, but a performance (or mental effort) pattern; that is, it represents the centre of a cluster of similar performances (or mental effort) for a statistically dominant group of learners. Therefore, each node represents a distinct family of characteristic learning behaviours drawn from the learners’ situated behavioural space. Due to the SOM topological property, neighbouring nodes represent similar behaviours.

**Cognitive load metrics and instructional efficiency**

The formation of learner behaviour maps allows for determinations to be made in relation to the learners’ cognitive response to the instructional design of the learning environment. It has been shown (Revithis, 2001) that a performance-based neural self-organizing learner model can decisively assist in revealing behavioural patterns associated with topic dependencies that are not depicted in the dependency graph. For instance, learners might tend to perform poorly if they take topics in a certain order despite the fact that the specific ordering does not violate the graph of known dependencies. Specifically, in the example in Figure 5, the graph depicts a hidden dependency, according to which Topic S is also a prerequisite of Topic J; this was revealed by the trained PSOM behavioural patterns, in which learners tend to perform poorly on Topic J if Topic J is completed before Topic Z and Topic S. Lack of inclusion of such hidden dependencies in the dependency graph can be attributed to inefficient instructional design, provided that all learners have sufficient background knowledge.
before entering the learning environment. PSOM can be
decisive in determining which ordering of topics is optimal
in terms of knowledge acquisition, and which topics present
a challenge to the learners.

![Diagram of dependency graph of a five-topic learning content](image)

Figure 5: Example of a hidden dependency in a
dependency graph of a five-topic learning content.

Mental workload can be measured by various methods
including subjective/introspective, physiological and
performance-based methods (Wierwille & Eggegmeier,
1993). Among all these methods it has been shown that the
subjective measurement of cognitive load is less intrusive,
easier to implement than the physiological measurement
approach, and just as valid (Paas, van Merriënboer, &
Adam, 1994; Marcus, Cooper, & Sweller, 1996).

Furthermore, it has been suggested that humans can easily
introspect on their mental load using a numerical scale
(Gopher & Braune, 1984), and that the scaling convention
does not affect the result of the introspection (Borg, 1978;
Hendy, Hamilton, & Landry, 1993). This evidence supports
the decision to include a subjective metric of mental effort
(ESOM) in the model.

By combining performance and introspective data in the
behavioural model the learning environment can be
evaluated in terms of cognitive load and instructional
design. The pairing of performance and mental effort scores
is aligned with suggestions from the literature that highly
recommend such a combined metric for instructional design
measurement of efficiency (Sweller, Merriënboer, &
Paas, 1998; Marcus, Cooper, & Sweller, 1996).

The data (scores) recorded in the trained PSOM and
ESOM are critical in determining the learners’ cognitive
inclinations; based on such data the instructor can deduce,
among others, where the learners usually excel in terms of
knowledge acquisition, where they struggle but still achieve
well, where they fail to perform, and where they perform
adequately. Combining performance and mental effort
norms the learners’ scores can be interpreted based on
cognitive load theory and meaningful conclusions can be
reached indicating cognitive load levels.

In Figure 6 an example is presented for the case of a five-
topic learning environment. It is assumed here that the
instructor accesses the trained PSOM and ESOM
components of the model and detects a universally
consistent pattern cluster (i.e. grouping of patterns contained
in the lattice nodes) allowing a profile for each topic in the
environment to be constructed.

![Graph of cognitive load profile](image)

Figure 6: Topic profiling in terms of cognitive load in the
context of learners’ dual scores (P, E) for a five-topic
learning environment.

Specifically, it is observed that the majority of learners
tend to achieve very well in Topics Q and J although
success in the latter topic comes after great effort. On the
other hand, they perform poorly in Topic S without much
effort but in Topic Z performance is poor in spite of a high
effort, whereas they achieve above average in Topic B
without putting in maximum effort. Assuming that these
patterns were retrieved from both cognitive maps the
instructor can proceed in the determination of a cognitive
load pattern for the environment. For example, it can be
determined for Topic J that, since both mental effort and
performance are high, the germane cognitive load is most
likely high. For Topic Q, on the other hand, it can be
determined that low mental effort combined with high
performance indicates either low extraneous cognitive load,
or high extraneous cognitive load combined with low
intrinsic cognitive load. Depending on the cognitive load
indications the instructor can make reliable assumptions
about the learners’ level of acquired knowledge and
working memory load, and pinpoint with high confidence
weaknesses in the environment in terms of instructional
design.

The interpretational diagram in Figure 7 illustrates the
organic relationship between the neurocomputational
components of the learner model and the implications for
cognitive load. Germane, extraneous and intrinsic cognitive
load levels are indicated in relation to performance and
teaching effort scores in accordance with cognitive load
theory. In particular, the germaine ($G$) and extraneous ($E^*$)
cognitive load axes are placed in the diagram in relation to
the performance ($P$) and mental effort ($E$) axes. An intrinsic
cognitive load axis could not be depicted due to the


![Inclusion of a subjective metric of mental effort](image)

**Table: Cognitive Load Indications**

<table>
<thead>
<tr>
<th>Topic</th>
<th>Mental Effort</th>
<th>Performance</th>
<th>Cognitive Load Indications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q</td>
<td>Low</td>
<td>High</td>
<td>Low Extraneous/(High Extraneous + Low Intrinsic)</td>
</tr>
<tr>
<td>J</td>
<td>High</td>
<td>High</td>
<td>High Germane</td>
</tr>
<tr>
<td>S</td>
<td>Low</td>
<td>Low</td>
<td>Low Germane</td>
</tr>
<tr>
<td>Z</td>
<td>High</td>
<td>Low</td>
<td>High Extraneous, Low Germane, High Intrinsic</td>
</tr>
<tr>
<td>B</td>
<td>Medium-High</td>
<td>Medium-High</td>
<td>Medium-High Germane</td>
</tr>
</tbody>
</table>

**Memo**

- $P$: Performance
- $E$: Effort (mental effort)
- $Tx$: Topic
complexity of its relationship to the other components of the diagram. Selected example points in this nested diagram are placed on $G$ and $E^*$ axes depicting cognitive load levels for different combinations of performance and mental effort scores.

For instance, low mental effort coupled with low performance indicates low germane cognitive load (“cube” example point). Similarly, high mental effort coupled with low performance indicates high extraneous, low germane and high intrinsic cognitive load (“doughnut” example point). In some cases, the graphical depiction is ambiguous due to the absence of the intrinsic cognitive load axis from the diagram; this signifies that the cognitive load indication is conditional on either the graphically-absent intrinsic cognitive load level or the complexity of the relationship between types of cognitive load. For example, low mental effort coupled with high performance indicates either low extraneous cognitive load (“rhomb” example point), or high extraneous cognitive load combined with low intrinsic cognitive load (not depicted in the diagram). Also, high mental effort coupled with high performance indicates high germane cognitive load (“hexagon” example point) and either low extraneous cognitive load combined with high intrinsic cognitive load (not depicted in the diagram) or high extraneous cognitive load combined with low intrinsic cognitive load (not depicted in the diagram).

It is important to note that the relationship between performance & mental effort scores and levels of cognitive load is independent of the validity of the learner model; this is due to the fact that the latter is a stand-alone model of situated learning behaviour with no reference to specific interpretational assumptions from cognitive load theory. Therefore, if the interpretational diagram (or framework) is substantially revised the model can be equally employed to provide revised indicators of cognitive load for the specified learning environment.

**Implementation Remarks and Future Work**

The model consists of two artificial neural networks, PSOM and ESOM, of different semantic content (i.e. performance and mental effort, respectively) but identical structure. Specifically, each neuron weight vector of either neural network has a) encoded performance (and mental effort, respectively) in the same range of discretized real numbers $[0, 1]$, and b) has the same number of elements, which corresponds to the number of topics in the learning environment (Figure 8).

The implementation of ESOM presents no challenges in terms of representing mental effort using the specific neuron structure and lattice size as has also been clearly demonstrated in previous studies of modeling behaviour using compatible SOM structures (Revithis, 2001; Revithis, Wilson, & Marcus, 2006). PSOM semantic encoding, on the other hand, poses the question of the feasibility of the neural network to detect and represent behavioural inclinations linked to hidden topic dependencies. However, elaborate tests in controlled simulations were conducted using training data sets with predetermined embedded behavioural norms (Revithis, 2001), which demonstrated the ability of the PSOM neural network to successfully form such representations for the case of a five-topic learning environment.

Future work includes the design and implementation of empirical studies using real data in order to evaluate the model’s performance on actual learning environments as well as its scalability.

**References**


Citation details for this article: