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Luca Longo
*Technological University Dublin*, luca.longo@tudublin.ie



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# Cognitive Effort for Multi-agent Systems

Luca Longo and Stephen Barrett

Department of Computer Science and Statistics - Trinity College Dublin
{llongo,stephen.barrett}@cs.tcd.ie

**Abstract.** Cognitive Effort is a multi-faceted phenomenon that has suffered from an imperfect understanding, an informal use in everyday life and numerous definitions. This paper attempts to clarify the concept, along with some of the main influencing factors, by presenting a possible heuristic formalism intended to be implemented as a computational concept, and therefore be embedded in an artificial agent capable of cognitive effort-based decision support. Its applicability in the domain of Artificial Intelligence and Multi-Agent Systems is discussed. The technical challenge of this contribution is to start an active discussion towards the formalisation of Cognitive Effort and its application in AI.

## 1 Introduction

Theoretical constructs of attention and cognitive effort have a long history in psychology [11]. Cognitive effort is often understood as a multi-faceted phenomenon and a subjective concept, influenced by attention, that changes within individuals in response to individual and environmental factors [18]. Such a view, sustained by motivation theories, contrasts with empirical studies that have tended to treat attention as a static concept [6]. Theories of information processing consider cognitive effort as a hypothetical construct, regarded as a limited capacity resources that affects the speed of information processing [11]. Studies suggest that, even though cognitive effort may be a hypothetical construct, it is manifest as a subjective state that people have introspective access to [10]. Attention can be related to physiological states of stress and effort, to subjective experiences of stress, mental effort, and time pressure, and to objective measures of performance levels to breakdown in performance. These various aspects of attention have led to distinct means for assessing cognitive effort including physiological criteria such as heart rate, performance criteria such as quantity and quality of performance and subjective criteria such as rating of level of effort. Despite the interest in the topic for the past 40 years, there is no universally accepted and clear definition of cognitive effort often referred to as mental workload [9]. There appears to be little work to link the measurement of workload by any one paradigm to others and the lack of a formal theory of cognitive effort has lead to a proliferation of several methods with little chance of reconciliation [7]. Formalising cognitive effort as a computational concept would appear to be an interesting step towards a common definition and an opportunity to provide a usable structure for investigating behaviours. The goal of this paper is to facilitate such a development through the presentation of a formalisation of cognitive

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effort in a organised fashion using formal tools. The principal reason for measuring cognitive effort is to quantify the mental cost of performing tasks to predict operator and system performances. It is studied from the point of view of artificial agents: our formalism does not aim to be the de-facto standard but it provides the tools necessary for its own revision. We are concerned with two key issues: *How can we formalise cognitive effort as a usable computational concept? How can we provide cognitive effort-based decision supporting capabilities to an artificial agent?*

The methodology adopted to model cognitive effort is presented in section 2. The subjective nature of the concept is underlined in section 3 where a literature review identifies some of the main factors, amenable to computational treatment, that influence cognitive effort along with related works. We present our heuristic formalism in section 4. In 5 an optimisation problem in multi-agent systems is presented that aims to clarify a possible application of our heuristic formalism. We address open issues and future challenges in section 6.

## 2 Attacking the Phenomenon: Our Approach

Cognitive effort is a subjective, elusive concept and its precise definition is far from trivial. Indeed, the contextual aspect of the phenomenon may render attempts at both precise and generally applicable definition impossible in practice. Our approach tries to study the essential behaviour of cognitive effort and seeks to capture some of its aspects in a formalism structured as an open and extensible framework. Our method is based on a generalist assessment of the available literature, seeking to merge together different observations, intuitions and definitions towards a tool for the assessment of Cognitive effort in practical scenarios. The multi-agent paradigm is a powerful tool for investigating the problem. Although an agent's cognitive model of its human peer is not necessarily precise, having at least a realistic model can be beneficial in offering unintrusive help, bias reduction, as well as trustable and self-adjustable autonomy. It is feasible to develop agents as cognitive aids to alleviate human bias, as long as an agent can be trained to obtain a model of a human's cognitive inclination. Furthermore, with a realistic human cognitive model, an agent can also better adjust its automation level [19].

## 3 Cognitive Effort and Related Work

The assessment of the cognitive effort expended in the completion of a task is dependent on several factors such as individual skill, background and status that means the individual's *subjective experience* and *cognitive ability*. Self-regulation theories [4] suggest that individuals with different levels of cognitive ability may react to changes in task difficulty in different ways because their *perception* of the task may be different. High ability individuals have a larger pool of cognitive resources than their counterparts who need to make larger resource adjustments to achieve the same outcome. People of low ability who perceive a high degree of difficulty in a task, will expend greater cognitive effort [20]. Similarly, *intentions* play a role on attention, and individuals with strong intentions allocate more cognitive effort to a task: highly conscientious individuals choose to work harder and persevere longer than their counterparts [1]. In the literature, curiosity, motivation, psychological stress, anxiety are often referred as *arousals* [11] and have a strong impact on attention and therefore on cognitive effort. Similarly, time plays a central role on attention as well: *time-pressure* may increase the amount of attention an individual needs to allocate on a task. Furthermore, performing a task requires an interval of *time* in which an individual has to elicit an amount of cognitive effort. Finally, *contextual biases* may influence attention over time: these may be unpredictable external distractions, contextual or task-related constraints. All these factors represent a sub-portion of all the possible factors used by several existing models of workload and mental effort. The popular NASA-Task load index, for instance, consists of six clusters of variables such as mental, physical and temporal demands, frustration, effort and performance [8]. The Subjective Workload Assessment Technique is a subjective rating technique that considers time load, mental effort and psychological stress load to assess workload [14].

Multi-agents systems are often used to model social structure where artificial agents collaborate with each other towards a common goal [17] seeking to find the best solution for their problems autonomously without human intervention. Most of the work in agent-based systems has assumed highly simplified agent models and artificial agents developed so far incorporate a wide range of cognitive functionalities such as memory, representation, learning and sensory motor capabilities. However, at present, there is a weak consideration of cognitive effort in multi-agent systems [16]. Integrating cognitive effort in an artificial agent may increase its robustness in terms of interdependence with other agents and the ability in the decision-making process, without loosing any of the freedom of choice such agents will be expected to possess.

## 4 A Presumption-Based Heuristic Formalism

As discussed briefly in section 3, models of cognitive effort involve a highly contextual and individual-dependent set of factors. Our approach begins by focusing on a set of context-dependent influencing factors, each representing a *presumption or interpretation of facts in literature* useful for inferring cognitive effort. Each presumption needs to be formally conceptualised in order to be computable, and in the following paragraphs we present six factors with different difficulty of formalisation. The set of factors considered here can be expanded, refined, criticised and reducted: we provide these as illustrative of our approach. The aim of our framework is to be open, extensible and applicable in different contexts where only some influencing factor can be monitored, captured and conceptualised formally.

**Cognitive Ability.** Some people obviously and consistently understand new concepts quicker, solve new problem faster, see relationship and are more knowledgeable about a wider range of topics than others. Modern psychological theory views cognitive ability as a multidimensional concept and several studies, today known as IQ tests, tried to measure this trait [5]. Carroll suggested in his work [3] that there is a tendency for people who perform well in a specific range of activities, to perform well in all others as well. Prof. T. Salthouse suggested in his recent work [15] that some aspects of people's cognitive ability peak around the age of 22 and begin a slow decline starting around 27. However, he pointed out that there is a great deal of variance among people and most cognitive functions are at a highly effective level into their final years, even when living a long life. Some type of mental flexibility decreases relatively early in adulthood, but how much knowledge one has, and the effectiveness of integrating it with one's abilities may increase throughout all of adulthood if there are no pathological diseases. This research provides suitable evidence to model cognitive ability with a long-term growing function as the flexible sigmoid function proposed by Yin [22]:

$$CA : [1..G_{th}] \in \aleph^3 \rightarrow [0..1] \in \Re$$
$$CA(G_{th}, G_r, t) = CA_{max} \left(1+\frac{G_{th}-t}{G_{th}-G_r}\right)\left(\frac{t}{G_{th}}\right)^{\frac{G_{th}}{G_{th}-G_r}}$$

where CA is cognitive ability whose maximum level is defined by $CA_{max}$ (in this case equal to 1) and t is the age in years of an individual. $G_{th}$ is the growing threshold, set to an average of mortality of 85 years and $G_r$ is the growing rate, set to 22 years that identifies where the curve reaches the maximum growing weight and from that, increases moderately. The properties $G_{th}$ and $G_r$ are flexible because they may be set by considering environmental factors.

**Arousal.** The concept of arousal plays an important role in assessing cognitive effort. It is sometimes treated in literature as a unitary dimension, as if a subject's arousal state could be completely specified by a single measurement such as the size of his pupil. However, this is an oversimplification since arousal is a multidimensional concept that may vary in different situations [11]. Its intrinsic degree of uncertainty and subjectiveness are hard to model and we propose a simple *subjective arousal taxonomy* where different types of arousal, such as curiosity, motivation, anxiety, psychological stress, are organised in a multi-level tree. A *subjective arousal taxonomy* is a 3-tuple $< A, W, R >$, composed by vertexes $A$ connected as a tree by unidirectional weighted edges, defined in $R$, by using the weights in $W$. Each vertex has at most one parent, except the root node $A_{root}$ which has no parent and represents the final level of arousal that influences cognitive effort.

$$A : \{a | a \in \{[0..1] \in \Re\}\} \quad W : \{w | w \in \{[0..1] \in \Re\}\}$$
$$R : \{\forall\ a_i \in A\ \exists!\ r\ |\ r :\ A \times A\ \rightarrow W,\ r : (a_i,\ a_p) = w\}$$
$$A^{leaf}_{explicit} \cup A^{internal}_{aggregated} = A; \quad \forall\ a_i \in A\ \exists!\ path(a_i, a_{root})$$

All the nodes have a path towards the root node: this property guarantees the non-presence of cycles. Leaf nodes (node without children) are values explicitly provided by an agent: they indicate the related degree of a given type of arousal (eg. 0 is not motivated at all, 1 is highly motivated). Internal nodes represent aggregation nodes and like the root node's value are inferred by the relationship with their children defined in $R$ along with the related strength in $W$. In particular, each internal node's value is the weighted sum of its $c$ children's values:

$$a^{leaf}_{explicit} = [0..1] \in \Re, \quad a^{internal}_{aggregated} = \left( \sum_{z=0}^{c} (a_z \cdot w_z) \right) \leq 1$$

Finally, the root node is a special internal node with weight $w_{root} = 1$ and, as it has no parent, its relation $r_{root} = \emptyset$. The weights $w$ in the arousal taxonomy may be derived from the literature or learnt while the explicit values $a^{leaf}_{explicit}$ represent an individual's subjective status before starting a task. An example of a possible *subjective arousal taxonomy* is depicted in figure 1. Based on the level of arousal, we may adopt the descriptive Yerkes-Dodson law [21] which empirically studied the relationship between performance and arousal. For example, the authors discovered that increasing the intensity of a shock administered to mice facilitated the learning of brightness discrimination, up to a point. However, further increases of shock intensity caused learning deteriorate. These conclusions, appear to be valid in an extraordinarily wide range of situations. The law is usually modeled with an inverted U-shape curve which increases the level of performance at low level of arousal and then decreases with higher levels of arousal. The law is task-dependent: different tasks require different levels of arousal for optimal performance thus the shape of the curve can be highly variable. The first part of the curve, which increases, is positively affected by the strength of arousal while the second part, which decreases, is influenced by the negative effect of arousal on cognitive effort. The law is useful to study the maximum performance an agent can achieve based on his subjective status before performing a task. As each task may have a different complexity and as the law is task-dependent, we propose to introduce a *task dictionary* formally described as a tuple $< TS, A, P, TP, D, YD, \delta_{yd}, \delta_d, \delta_{tp} >$:

· $TS \subseteq \aleph$ is the set of possible tasks;
· $A, P, TP, D \subseteq \{[0..1] \in \Re\}$ are the possible set of values for Arousal, Performance, Time-pressure, Difficulty;
· $YD \subseteq \{f_{yd} : A \rightarrow P\}$ is the set of possible functions that model the Yerkes-Dodson law. Each of them takes an arousal level and return a performance value;
· $\delta_{yd} : TS \rightarrow YD$ assigns to a task a Y.D. law function;
· $\delta_{tp} : TS \rightarrow TP$ assigns to a task a degree of time-pressure.
· $\delta_d : TS \rightarrow D$ maps for each task a level of difficulty.

A task dictionary example is depicted in table 1. Here the YD laws associated to each task are for descriptive purposes but in reality they may be approximated with experiments via numerical analysis. Once we have the *subjective arousal taxonomy* for a subject and the *task difficulty dictionary*, we are able to study the effect of arousal on cognitive effort. The derived performance is the maximum level of attention that a subject can elicit on a certain task. Formally, given a task

**Table 1.** Tasks dictionary with descriptive YD equations

| Description | D | TP | YD law ($a \in A$) |
|---|---|---|---|
| math equation | 0.8 | 0.9 | $f_{yd}(a) = e^{-a^2}$ |
| reading/summary | 0.6 | 0.7 | $f_{yd}(a) = -a^2 + a$ |
| reading | 0.3 | 0.2 | $f_{yd}(a) = -2a^2 + 2a$ |
| dictate | 0.4 | 0.8 | $f_{yd}(a) = e^{-(a-2)^2}$ |
| memorising poetry | 0.7 | 0.6 | $f_{yd}(a) = -3a^2 + a$ |

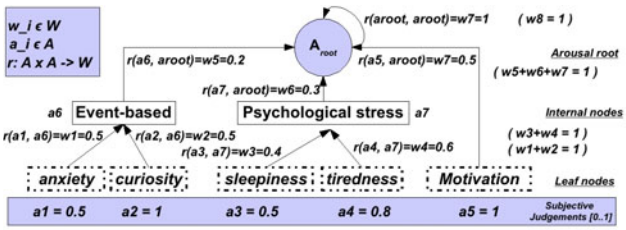


**Fig. 1.** A possible Subjective Arousal Taxonomy

$ts \in TS$, the max performance $p$ on the task $ts$ is derived from the associated Yerkes-Dodson law with an input level of arousal $a$, that means $p = (\delta_{yd}(ts))(a)$.

**Intentions.** A subject's intentions have an important role in determining the amount of cognitive effort while performing a task. As with arousal, this is an individual, subjective concept that may be split into short-term and long-term intentions, and that may be modelled with real values. We refer to short-term intentions or momentary intentions with $I_{st}$ and to long-term intentions with $I_{lt}$. Those are subjective judgments in the range $[-1..1] \in \Re$ (-1: no intention at all; 1: highly intentioned). The overall degree of intentions $I$ is the average of the above values and may have a negative, positive or null influence on cognitive effort:

$$I : [0..1] \in \Re^2 \rightarrow [-1..1] \in \Re,\ I_{ST}, I_{LT} : [-1..1] \in \Re$$
$$I(I_{ST}, I_{LT}) = \tfrac{2}{3} I_{ST} + \tfrac{1}{3} I_{LT}$$

This model deals with intentional shades: an individual may be momentarily intentioned to success in a IQ test without any future intention.

**Involuntary Context Bias.** Several external factors may influence cognitive effort as pseudo-static and unpredictable biases. The former refers to biases that are almost static and depend on environmental aspects. For instance, there is a large difference across ethnic groups and geographic areas in the available knowledge: people living in poor African countries have a reduced access to knowledge compared to their counterpart in occidental countries so they may find a question dependent on access to information to be more difficult to answer. Another pseudo-static bias is the task's difficulty. Even though it is hard to exactly estimate the complexity of different tasks, it is not unfeasible perhaps to claim that reading a newspaper demands less cognitive effort than resolving a math equation. Unpredictable context biases represent involuntary context biases such as a phone ringing, questions from colleagues, e-mail delivering in a working context. These involuntary distractions and environmental aspects, in comparison to arousals and intentions, are easier to embed in a formalism as they are not individual-dependent. We propose real fuzzy values to model contextual available knowledge and unpredictable bias, while the level of task difficulty is obtained from the task dictionary. Knowledge availability is a positive factor, that means it elicits less cognitive effort, while task-difficulty and unpredictable bias are negative as they require more cognitive effort as value increases. The higher the value of contextual bias is, the more a subject has to concentrate allocating more cognitive effort on a task. To model how context bias negatively affects attention, we take the complement of knowledge availability:

$$CB : [0..1] \in \Re^3 \rightarrow [0..1] \in \Re, \quad {\scriptstyle C_{know}, T_{diff}, U_{bias}:\ [0..1] \in \Re}$$
$$CB(C_{know}, T_{diff}, U_{bias}) = \frac{[1 - C_{know}] + T_{diff} + U_{bias}}{3}$$

where $CB$ is the total context bias, $C_{know}$ is the contextual knowledge availability, $T_{diff}$ is the task difficulty and $U_{bias}$ is the unpredictable bias.

**Perception.** The same task may be perceived differently by two subjects. In literature there is evidence suggesting that perceived difficulty is higher when individuals are presented with a new task: they may not know what the optimal amount of effort is, given a particular difficulty level [20]. We propose to model this concept as a simple real fuzzy value $P_{diff} = [0..1] \in \Re$ where values close to 0 indicate a task perceived highly complex. Perception is connected to cognitive ability and skill acquisition. Intermediate students may perceive the resolution of math equations to be difficult compared to university students due to their limited experience, preparation and background. Perception has a negative effect as a subject who perceives a task to be difficult needs to allocate more resources eliciting higher cognitive effort.

**Time.** Time is a crucial factor that must be considered in modelling cognitive effort. Temporal properties are essential because performing a task is not a single-instant action, rather is an action over time, therefore cognitive effort's influencing factors need to be considered over time. Our environment is dynamic and, consequently, time-related: the temporal dimension is an important aspect of perception necessary to guide effective action in the real world [12]. Several temporal theories are available in the literature of computer science but less effort has been spent on the temporal-related aspect of cognitive effort.

Firstly, we take into consideration time as a single stimulus that influence attention. We refer to this as time-pressure which is sometimes imposed by explicit instruction to hurry and sometimes by intrinsic characteristics of the task. The former may me modelled as a fuzzy value $T_{press}^{explicit} : [0..1] \in \Re$. For instance, a student may resolve a task within an interval of 10 minutes. In this case we need to estimate or learn the maximum time to perform a task (mapped to 1) and transform 10 minutes in the scale [0..1]. The latter may be modelled as a fuzzy value $T_{press}^{implicit} : [0..1] \in \Re$ and we propose to adopt the task-related time-pressure value from the task-dictionary previously proposed that underlines the intrinsic pressure imposed by a certain task. For instance, a student may resolve an integral equation which requires an auto discipline and rigorousness in performing the task. He must keep track of the initial problem, partial results, the next step, requiring greater cognitive effort: slowing down or even stopping for just an instant of time may force the student to start again. The more difficult arithmetic problems require more storage, the more they impose high time-pressure eliciting greater cognitive effort [11]. The final degree of time-pressure is modelled as the average of the above values:

$$T_{press} : [0..1] \in \Re,\ T_{press} = \tfrac{1}{2} T_{press}^{explicit} + \tfrac{1}{2} T_{press}^{implicit}$$

Everyday experience suggests that time intervals also play an important role in directing our attention to the external world. Cognitive effort may vary while performing a task due to the variation on the degree of focused attention and sustained attention. The former is referred to as the ability to respond discretely to specific visual auditory or tactile stimuli while the latter refers to the ability to maintain a consistent behavioural response while performing a certain task [11]. The modelling of focused, and sustained attention, is not easy at all and these properties are individual-dependent. However, taking into consideration a certain task, a trajectory that describes how the degree of sustained attention would likely behave for most of the people on that task would be useful. To deal with this we propose an extension for our task-dictionary by adding an estimation of the time needed to complete a certain task. This value may be learnt through experimentations by using unsupervised techniques and is needed to estimate the end of a certain task in order to model the focused attention function. This function likely has a S-shape that increases quickly at the beginning reaching the maximum peak of attention, then decreases very moderately during the sustained attention time-interval, and decreases quicker until the estimated time for the completion of the task. Yet, this function may be approximated by applying numerical analysis and should model the fact that, at the beginning, people elicit almost the highest degree of attention, which is the maximum performance level obtained by the Yerkes-Dodson law of a task $ts$ with a given arousal $a$ defined before ($p = (\delta_{yd}(ts))(a)$); from here it follows an interval of time in which individuals perform well, maintaining a high level of sustained attention. Then the curve starts to decrease towards the estimated end-point of the task from which the function persists but at very low levels, underlying that a small amount of cognitive effort is dedicated to the task. Formally, we add to the task-dictionary:

· $T \subset \Re$ is the domain of time;
· $AT \subseteq P$ is the set of possible degrees for attention;
· $SA : \{f_{fa} : T \rightarrow AT\}$ is the set of possible functions that models the concept of focused attention for tasks;
· $\delta_{fa} : TS \rightarrow SA$ is the function that maps a S-shaped function from the domain SA to a given task;

· $\delta_{TE} : TS \rightarrow T$ is the function that assigns to a task a completion estimated time.

The completion time would be useful for understanding whether an agent performed similarly to others or required further time to complete a task or even before giving up.

Taking into account the explanations so far, we are now able to provide a general formula to compute cognitive effort of an agent on a given task along with a formalism summary depicted in figure 2.

$$CE : [0..1] \in \Re^5 \times [-1..1] \in \Re \times TS \times T^2 \rightarrow \Re$$
$$CA' = CA(G_{th}, G_r, t),\ A' = (\delta_{yd}(\alpha))(A_{root}),\ PD' = PD$$
$$t' = t_{press},\ I' = I(I_{st}, I_{lt}),\ CB' = CB(C_{know}, T_{diff}, U_{bias})$$
$$CE(CA', A', I', CB', PD', t', \alpha, t_0, t_1) =$$
$$\int_{t_0}^{t_1} \Big[\delta_{fa}(\alpha)\Big](x)\left(\frac{CA' + A' + I' + CB' + PD' + t'}{6}\right)dx$$

where CA is *cognitive ability*, A represents *arousals*, I is *intentions*, CB is *contextual bias*, $t_{press}$ is the *time pressure*, $t_0$ is the start time and $t_1$ the time spent on the task $\alpha$.

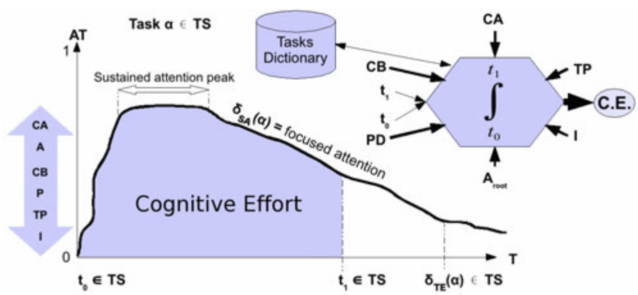


**Fig. 2.** The Cognitive Effort's formalism

## 5 A Multi-agent Application

In this section we take the viewpoint of an agent $\alpha$ situated in an open environment trying to choose the best interaction partners from a pool of potential agents $A$ and deciding on the strategy to adopt with them to resolve an effort-full task $T$ in an optimal way. Our heuristic, based on cognitive effort, represents a possible strategy to select reliable partners. Each agent in the system has certain cognitive properties such as experience, motivation, intentions, cognitive ability, and it is realistic to assume that they operate in environments with different constraints and biases. Furthermore, we assume each agent acts honestly and provides real information about its cognitive status. An agent $\alpha$ may split the

**Table 2.** Agents, influencing factors and Cognitive Effort

| Factor | $a_1$ | $a_2$ | $a_3$ | $a_4$ | $a_5$ |
|---|---|---|---|---|---|
| $G_{th}$ (Growing Threshold) | 85 | 85 | 85 | 85 | 85 |
| $G_R$ (Growing Rate) | 22 | 22 | 22 | 22 | 22 |
| $Age$ (Years) | 18 | 25 | 28 | 40 | 55 |
| $CA$ (Cognitive Ability) | 0.25 | 0.37 | 0.43 | 0.62 | 0.82 |
| $I_{ST}$ (Short-term Intentions) | 0.4 | 0.6 | -0.5 | -1 | 0.5 |
| $I_{LT}$ (Long-term Intentions) | 0.6 | -0.3 | -1 | 0 | 0.2 |
| $I$ (Intentions) | 0.47 | 0.3 | -0.67 | -0.67 | 0.4 |
| $P_{diff}$ (Perceived Difficulty) | 0.7 | 0.7 | 0.6 | 0.5 | 0.7 |
| $TP$ (Time Pressure) | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| $C_{know}$ (Context Knowledge) | 1 | 1 | 0.9 | 0.8 | 1 |
| $T_{diff}$ (Task Difficulty) | 0.8 | 0.8 | 0.8 | 0.8 | 0.8 |
| $U_{bias}$ (Unpredictable Bias) | 0.6 | 0.3 | 0.4 | 0.6 | 0.7 |
| $CB$ (Contextual Bias) | 0.47 | 0.37 | 0.43 | 0.53 | 0.5 |
| $ar_1$ (Anxiety) | 0.5 | 0.7 | 0.5 | 0.4 | 0.3 |
| $ar_2$ (Curiosity) | 0.7 | 0.3 | 0.5 | 0.8 | 0.4 |
| $ar_3$ (Sleepiness) | 0.3 | 0.3 | 0.5 | 0.7 | 0.4 |
| $ar_4$ (Tiredness) | 0.4 | 0.3 | 0.6 | 0.2 | 0.5 |
| $ar_5$ (Motivation) | 0.6 | 1 | 0.8 | 0.6 | 0.3 |
| $A_{root}$ (Arousal Root) | 0.67 | 0.81 | 0.72 | 0.67 | 0.37 |
| $f_{yd}(A) = e^{-A^2_{root}}$ | 0.64 | 0.52 | 0.59 | 0.64 | 0.87 |
| $t_0/t_1$ (secs) | 0 / 55 | 0 / 40 | 0/45 | 0/40 | 0/50 |
| C.E. (Cognitive Effort) | 18.30 | 14.32 | 11.00 | 11.87 | 22.63 |

task $T$ in partial sub-tasks $t_1...t_n$ with the same estimation of required effort. We suppose he has direct connections with 5 agents, $a_1$ .. $a_5 \in A$ , and it forwards to each of them one of the 5 sub-tasks $t_1..t_5$.. Now, each agent starts to resolve the sub-task of competence by using its own resources, skills and experience. Once the sub-task is completed, they send back to $\alpha$ their subjective status of arousals, their intentions, cognitive ability, perception, involuntary context bias and the start/stop time needed to complete the assigned sub-task. Let's assume the agent $\alpha$ adopts the first task (math equation) of the task-dictionary depicted in table 1 and uses the *subjective arousal taxonomy* depicted in figure 1 with the explicit values ($ar_i$) provided by each agent and showed in table 2. The Yerkes-Dodson law associated to the task is $\delta_{yd}(\alpha) = f_{yd}(a) = e^{-a^2}$ while the task difficulty is $\delta_d(\alpha) = 0.8$. The time pressure is $\delta_{tp}(\alpha) = 0.9$ and the focused attention trajectory is: $\delta_{fa}(\alpha) = f_{fa}(t) = [1 + e^{(bt-a)}]^{-1}$.

The parameter $b$ shrinks the S-shaped curve while $a$ shifts the function to the right. We set $b = \frac{15}{100}$ to model sustained attention at the beginning of $\alpha$ for around 20 seconds, and $a$ to effectively start from the 0 of the time line (x-axis) with attention at high level (1). The function decreases quickly after 20 seconds reaching low levels of around 50 ($\delta_{TE}(\alpha) = 50$) seconds which is the estimated time we set for the completion of $T$. $\alpha$ uses our heuristic formalism as a potential decision-supporting tool useful to generate an index of cognitive effort for each partner: the results obtained are presented in table 2. It may forward remaining sub-tasks in proportion of the elicited agents' cognitive effort, it may deliver more sub-tasks to agents that showed less cognitive effort (eg. $a_3$, $a_4$) in completing assigned work. Furthermore, $\alpha$ has a knowledge of its partners' skills, their subjective status and over time it can infer something about their behaviour. For instance, information about the learning rate may be learnt, as $\alpha$ might assume that its partners, over time, should acquire experience, get more skilled therefore manifesting less cognitive effort in performing similar tasks.

## 6 Open Issues and Future Challenges

Cognitive effort is a subjective phenomenon and its formalisation for a virtual agent is not a trivial problem. In this paper we tackled the problem by analysing current state-of-the-art in psychology, cognitive and neuro-science to build a formalism that is extensible and open to further refinements. The heuristic proposed here can be embedded in an artificial agent providing it with a cognitive effort-based decision supporting system. The computational model is an aggregation of a subset of the possible presumptions or factors influencing cognitive effort such as cognitive ability, arousals, intentions, contextual bias, perception and time. We intend this to be the starting point of an active discussion among researchers in social and computer science fields.

In this work we have considered each factors' influence being the same but a simple aggregation is not subtle enough to provide good estimates of cognitive effort. Argumentation theory provides a framework for systematic studying how cognitive effort influencing factors may be combined, sustained or discarded in a computable formalism towards a robust approximation of the concept. In our opinion, cognitive effort shares some of the properties of a non-monotonic concept by which we mean that adding a factor to the overall formalism never produces a reduction of its set of consequences [2]. Adding a new argument and reasoning on its plausibility/combination with previous ones increases the robustness of the overall formalism. A new factor may attack or support an existing one therefore amplifying or diminishing its strength. The consideration of mutual relationships among arguments is fundamental in assessing an index of cognitive effort, therefore a future challenge might be the investigation of the strength of each argument and their mutual influence by using non-monotonic logics such as the defeasible reasoning semantic proposed by Pollock [13].

It remains to demonstrate this aspect of computation of cognitive effort. In terms of evaluation, popular frameworks such as the NASA-TLX [8] and SWAT [14] may be useful for comparisons. Furthermore, our framework, as conceived to be open and adaptable to different contexts, may be applied in operational environment and, for instance, populated by physiological-based argument related to neuro-science equipment such as fMRI, EEG and other types of physiological scanner.

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