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A LEAKY INTEGRATOR COMPUTATIONAL MODEL OF COGNITIVE RESOURCE UTILIZATION AND THE VIGILANCE DECREMENT

Robert Earl Patterson, Kathleen G. Larson, Anna M. Maresca, Samuel J. Johnston

711 HPW/RHXM
Human Analyst Augmentation Branch

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AIR FORCE RESEARCH LABORATORY
711TH HUMAN PERFORMANCE WING,
AIRMAN SYTEMS DIRECTORATE,
WRIGHT-PATTERSON AIR FORCE BASE, OH 45433
AIR FORCE MATERIEL COMMAND
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ROBERT E. PATTERSON, WUM
Human Analyst Augmentation Branch
Airman Systems Directorate
711th Human Performance Wing
Air Force Research Laboratory

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RICHARD D. SIMPSON, DR-IV, DAF
Human-Centered ISR Division
Airman Systems Directorate
711th Human Performance Wing
Air Force Research Laboratory

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ABSTRACT

Effective human-machine teaming can be significantly impacted by situations that require a human to sustain attention for a prolonged duration, which can cause a significant decline in his or her cognitive performance (i.e., 'vigilance decrement'). This paper presents a model of the vigilance decrement which is framed within a computational model of *human cognitive resource utilization*. The computational model of cognitive resource utilization was based on the concept of a *leaky integrator*, which takes the integral of input (cognitive resource replenishment) and leaks some amount over time (resource depletion). The leaky integrator model of cognitive resource utilization was simulated by employing the techniques of system dynamics modeling, which entails the use of numerical-integration techniques for modeling complex feedback systems. The computational modeling of human cognitive resources may be advantageous for creating effective human-machine teaming: such modeling theoretically could allow a future autonomous software agent to anticipate the needs of the human and compensate accordingly.

INTRODUCTION

A wide variety of problems (e.g., reducing labor or enhancing human abilities) are being solved by the action of autonomous machines. In most cases, the autonomous machine will interact with humans who will serve in supervisory or collaborative roles (Endsley, 2017). Thus, the development of successful autonomous machines may rely on human–machine teaming.

Effective human-machine teaming can be significantly impacted by situations that require a human to sustain attention for a prolonged duration, which can cause a significant decline in his or her cognitive performance. Such cognitive performance decrements are known to occur in industrial process/quality control, agricultural inspection tasks, medical settings such as electrocardiogram monitoring, and airport baggage inspection (Warm, Parasuraman & Matthews, 2008). This decline in cognitive performance due to sustained attention is referred to as the 'vigilance decrement' (e.g., Teichner, 1974; Warm & Jerison, 1984).

Developing effective human–machine teaming in general, and counteracting the vigilance decrement in particular, can be aided by the computational modeling of human performance. Such computational modeling can provide insight into how to improve the design of machines and interfaces, how autonomous machines should adapt to variation in human performance, and how human performance can be predicted within existing and future human-machine systems (Harriott & Adams, 2013). Accordingly, the present paper presents a model of the vigilance decrement which is framed within a computational model of *human cognitive resource utilization*.

BACKGROUND

Vigilance Decrement

Research on sustained attention, or vigilance, began after World War II when Mackworth studied the phenomenon following recognition of performance decrements by British airmen watching radar screens for prolonged durations. Employing a research paradigm that involved participants watching for signals defined as infrequent small jumps in a clock hand which moved around an unmarked face, Mackworth (1948) discovered that signal detections declined over the course of a 2-hour vigil. Subsequent research has shown that, under conditions of sustained attention, performance begins to fall off almost immediately, the major portion of the decrement typically appears within the first 15 minutes of watch, and the magnitude of the decrement—in terms of percent correct detection—can be 30% or greater (Jerison & Pickett, 1963; Nuechterlein, Parasuraman & Jiang, 1983, Teichner, 1974).

Several key factors that can determine whether sustained attention will lead to decrements in cognitive performance are: (1) capacity-demanding tasks that require information to be retained in working memory; (2) high rate of events which require processing; and (3) low probability of critical-signal occurrence (e.g., Davies & Parasuraman, 1982; Parasuraman & Davies, 1977; See, Howe, Warm & Dember, 1995; Warm, Finomore, Vidulich & Funke, 2015). The combination of working-memory load and a rapid rate of events creates a high demand for effortful attention allocation, which leads to a performance decrement.

The vigilance decrement arises from the depletion of people's limited attentional resources (Davies & Parasuraman, 1982; Fraulini, Hancock, Neigel, Claypoole & Szalma, 2017; Helton & Russell, 2017; Warm, Finomore, Vidulich & Funke, 2015). Evidence for cognitive-resource depletion comes from results showing that the decrement is accompanied by high levels of workload and stress (Fraulini, Hancock, Neigel, Claypoole & Szalma, 2017; Warm, Parasuraman & Matthews, 2008). Levels of epinephrine and norepinephrine, biomarkers for stress, are elevated in the bloodstream during the performance of a vigilance task (Lundberg & Frankenhaeuser, 1979). Neuroimaging studies using transcranial Doppler sonography show that cerebral blood flow velocity declines during the performance of a vigilance task, which signifies metabolic resource depletion (Shaw, Warm, Matthews, Riley, Weiler, Dember, Tripp, Finomore & Hollander, 2006; Shaw, Warm, Finomore, Tripp, Matthews, Weiler & Parasuraman, 2009). The vigilance decrement is not produced by a lack of arousal, which was one of the original explanations for the decrement (Warm, Finomore, Vidulich & Funke, 2015).

Sustained attention can produce a significant decrement in human performance. However, the impacts of such decrements could be alleviated via computational modeling which could help predict the occurrence of the decrement and thereby allow a future autonomous software agent to compensate accordingly.

Computational Model of the Vigilance Decrement

The present study developed a computational model of the vigilance decrement that was flexible enough to represent conditions that do not produce a decrement as well as those that do—that is, flexible enough to represent tasks of differing difficulty or different types of interruptions. In doing so, a computational model of *cognitive resource utilization* was created, which embraced a cognitive-resource depletion explanation of the vigilance decrement.

Our cognitive-resource utilization model of vigilance is consonant with a *cognitive energetics* approach. Hockey (1997) notes that a cognitive energetics approach combines energybased concepts with an information processing framework. Cognitive energetics emphasizes the close connection between behavior and its biological/motivational context, which can include factors like stress, emotion, fatigue, and adjustment to the demands of work (Hockey, 1997).

The model of cognitive resource utilization was simulated by employing the techniques of system dynamics modeling (Forrester, 1961, 1968; Sterman, 2000). System dynamics modeling entails the use of numerical-integration techniques for modeling complex feedback systems. Stock and flow diagrams are used: rectilinear boxes (called stocks) represent integrations, and solid arrows (flows) represent derivatives; dashed arrows denote information connections and feedback, while circles (convertors) represent variables, constants, conditional logic, or expressions. A set of interconnected symbols can be computer simulated as a complex feedback system.

The computational modeling of cognitive-resource utilization is covered next, followed by the discussion section. The last section offers concluding remarks.

COMPUTATIONAL MODELING

The point of departure for the model was a study by Giambra and Quilter (1987). Giambra and Quilter conducted an empirical investigation of the vigilance decrement and mathematically modeled their results.

Giambra and Quilter (1987) Model

Giambra and Quilter (1987) replicated the methods of Mackworth (1948) by employing a clock test in which a single black pointer moved in 100 small discrete steps around the face of an unmarked clock. Each participant's task was to detect the occurrence of targets which were defined as infrequent and unpredictable double jumps. There was a total of 23 targets presented within a 62-minute test period. A total of 613 participants served in the study.

The 23 points in time (in elapsed minutes) during which the targets were presented, together with the corresponding proportion correct detection given in parentheses, were: 2 minutes (0.91); 4 minutes (0.87); 7 minutes (0.82); 11 minutes (0.74); 13 minutes (0.73); 15 minutes (0.71); 19 minutes (0.71); 21 minutes (0.69); 23 minutes (0.67); 26 minutes (0.66); 30 minutes (0.64); 32 minutes (0.62); 34 minutes (0.64); 37 minutes (0.62); 41 minutes (0.60); 43 minutes (0.65); 45 minutes (0.63); 49 minutes (0.62); 51 minutes (0.64); 53 minutes (0.63); 56 minutes (0.66); 60 minutes (0.64); and 62 minutes (0.62). The proportion of correct target detections ranged from 0.91 to 0.60 across the test period. The decline of approximately 30 points represented a classic vigilance decrement.

Giambra and Quilter (1987) modeled the time course of this decrement in proportion correct detection as:

$$A[e^{-T1*time} + 1/(1 + e^{-T2*time})], \qquad (1)$$

where e is the base of the natural logarithm, A = 0.6419, T1 = 0.05319, and T2 = 0.04633 (T1 and T2 are each the multiplicative inverse of the time constant). Within the brackets, the first term, $e^{-T1*time}$, is initialized at 1.0 (i.e., when time is zero, $e^{-0} = 1/e^0 = 1/1 = 1.0$), which equals 0.64—to the nearest hundredth place—when multiplied by A. The first term then *decreases* with time and asymptotes at zero. The second term, $1/(1 + e^{-T2*time})$, is initialized at ½ (i.e., when time is zero, $1/(1 + e^{-0}) = 1/(1 + 1) = ½$), which equals 0.32 when multiplied by A. The second term—with the exponential being in the denominator—*increases* with time and asymptotes at 1.0, which equals 0.64 after being multiplied by A. Thus, the overall expression is *initialized at a value of 0.96 before time begins and over time decays to an asymptote of 0.64*. Giambra and Quilter state that the R^2 was 0.97 between their empirical data and their Expression 1 given above.

The system dynamics model of the Giambra and Quilter expression is shown in Figure 1. The model is composed of two decay mechanisms which are labeled 'Decay 1' and 'Decay 2'. The Decay 1 mechanism produces exponential decay multiplied by the constant A at function 'g'. This represents the first term $e^{-T1*time}$ in the Giambra and Quilter expression. The Decay 2 mechanism produces exponential decay which is entered into the 1/(1+Decay 2) expression and then multiplied by the constant A at function 'h'. This represents the second term $1/(1 + e^{-T2*time})$ in the expression.

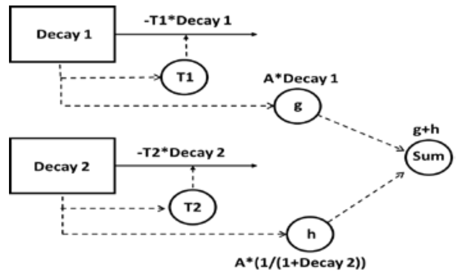

Figure 1. System dynamics model of the Giambra and Quilter expression. On the left, two stocks representing decay mechanisms (labeled 'Decay 1' and 'Decay 2') are shown. The Decay 1 mechanism produces exponential decay (computed as -T1*the quantity labeled 'Decay 1', where T1 = 0.05319) which is shown as a rightward pointing solid arrow (i.e., a rate or derivative). The decay is multiplied by the constant A (which equals 0.6419) at function 'g'. The Decay 2 mechanism produces exponential decay (computed as -T2*the quantity labeled 'Decay 2', where T2 = 0.04633) which is also shown as a rightward pointing solid arrow (i.e., a rate or derivative). This decay is entered into the 1/(1+Decay 2) expression which is then multiplied by the constant A at function 'h'. Finally, g and h are summed to produce the final simulated result.

The R^2 was 0.96 between Giambra and Quilter's empirical data and the results of the system dynamics simulation of their Equation 1. Thus, the system dynamics simulation is a faithful representation of Giambra and Quilter's data and model.

Giambra and Quilter discussed several concepts that their expression might represent. These authors suggested that their two terms might represent the interaction of two types of attentional processes, one controlled and the other involving automaticity. However, this seems unlikely given that automaticity develops only after several thousand training trials (Fisk & Schneider, 1981), a regime that was not undertaken in the Giambra and Quilter empirical study. These authors also discussed the possibility that their two terms might represent other dual processes, such as the interplay of two arousal systems (Eysenck, 1982). However, it is unlikely that arousal is an explanation for the decrement (Warm, Finomore, Vidulich & Funke, 2015).

Giambra and Quilter's framework of the vigilance decrement is limited: (1) it only considers the vigilance decrement; (2) it does not fully embrace the concept of cognitive resource depletion; (3) it does not consider the concept of cognitive resource replenishment; and (4) it cannot deal with situations involving rest or tasks of differing difficulty.

In what follows, a computational model of *cognitive resource utilization* is presented, which overcomes these limitations. Our computational model is based on a concept called a *leaky integrator*. However, before introducing our leaky-integrator model of cognitive resource utilization (which includes the vigilance decrement), we first discuss the notion of negative feedback. Consideration of negative feedback will help in understanding the leaky integrator. Following our discussion of negative feedback, we then present our leaky-integrator model.

Negative Feedback Model

A first-order negative feedback process is goal-seeking. The output is compared with a goal or set-point and the error emanating from the comparison is corrected. When the value of the output is below the goal, the comparison [goal-output] is positive and some amount is added. When the value of the output is above the goal, the comparison [goal-output] is negative and some amount is subtracted. The process of negative feedback is ubiquitous throughout the world. For example, a thermostat for controlling room temperature, cruise-control for controlling speed of an automobile, and a human's hypothalamus for controlling body weight all operate as negative feedback mechanisms with goals.

A system dynamics model of cognitive resource utilization can be implemented as a negative feedback process. The model is calibrated for yielding proportion correct detection, ranging from 0.96 to 0.64, as in Giambra and Quilter's model. Negative feedback with an explicit goal or set-point (CR') is implemented as the following (Figure 2):

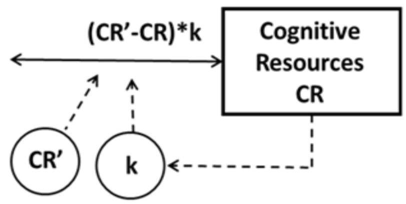

Figure 2. System dynamics modeling of cognitive resource utilization implemented as negative feedback. The model yields proportion correct detection. A stock represents the integration of cognitive resources (i.e., CR) and a solid bidirectional arrow represents a rate or derivative. The quantity CR is fed via dashed arrows to the comparison expression (CR'-CR)*k, where CR' = goal and k = gain of the loop (k = 0.1). Depending on starting value CR(0), the model produces exponential growth or decay of cognitive resources which asymptotes at the value of CR'.

When starting value CR(0) is greater than CR', the mechanism shown in Figure 2 produces exponential decay toward goal CR'. Analogous to Giambra and Quilter's (1987) framework, when CR(0) = 0.96 and CR' = 0.64 (and k = 0.1), exponential decay is produced which starts at a value of 0.96 and asymptotes at the value of 0.64 (Figure 3). The value of k was determined based upon a best-fit of the model to the Giambra and Quilter's empirical data. With these parameters, the R^2 was 0.98 between Giambra and Quilter's empirical data and the output (Figure 3) of the system dynamics simulation of this negative feedback process.

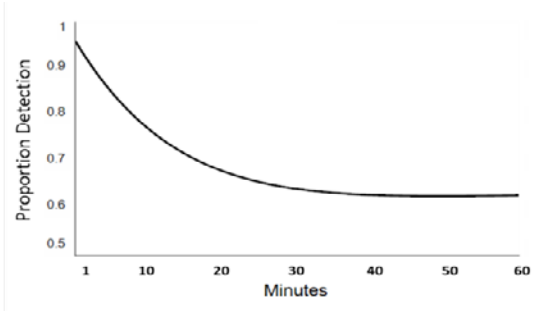

Figure 3. System dynamics simulation of negative feedback. Simulated proportion correct detection is shown for different elapsed times in the simulation. CR(0) = 0.96, CR' = 0.64, and k = 0.1.

When starting value CR(0) is less than CR', the mechanism shown in Figure 2 produces exponential growth toward CR'. For example, when CR(0) = 0.64, and CR' = 0.96 (again k = 0.1), the simulation result is shown in Figure 4.

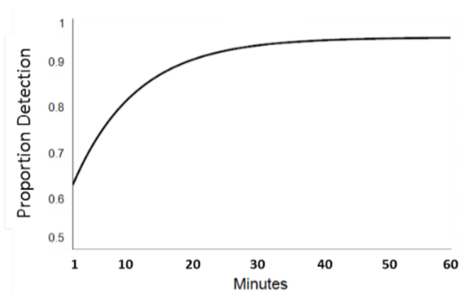

Figure 4. System dynamics simulation of negative feedback. Simulated proportion correct detection is shown for different elapsed times. CR(0) = 0.64, CR' = 0.96, and k = 0.1.

Of the two components that make up cognitive resource utilization, depletion or replenishment, the negative feedback model here models only one of them at a time. Separating the components of depletion and replenishment creates an intuitive model which enables researchers to better understand the two components of performance.

Leaky Integrator Model

The actions of a first-order negative feedback process can be mimicked with a *leaky integrator*, which is our computational model of cognitive resource utilization (which includes the vigilance decrement). The idea of a leaky integrator, which takes the integral of input, and leaks some amount over time, commonly appears in the literature in electronics and in neuroscience. A simple resistor-capacitor analog circuit, as well as the accumulation of charge from post-synaptic processes across a neuron's soma, can be modeled as a leaky integrator (Eliasmith & Anderson, 2003).

The leaky integrator represents cognitive resource utilization—*the input represents resource replenishment and the 'leak' represents resource depletion*. The leaky integrator model is calibrated for yielding proportion correct detection, analogous to Giambra and Quilter's model. The expression for the leaky integrator is a first-order linear differential equation (Patterson, Tripp, Rogers & Boydstun, 2009, Appendix B):

$$dCR/dt = w*k - CR*k \qquad (2)$$

where CR is cognitive resources, w*k is the input (replenishment), -CR*k is exponential decay or the 'leak' (depletion), and both terms are integrated by a stock. When k = 0.1, which is true of all simulations reported in this paper, the value of w determines the level at which CR asymptotes. The system dynamics model of the leaky integrator is shown in Figure 5.

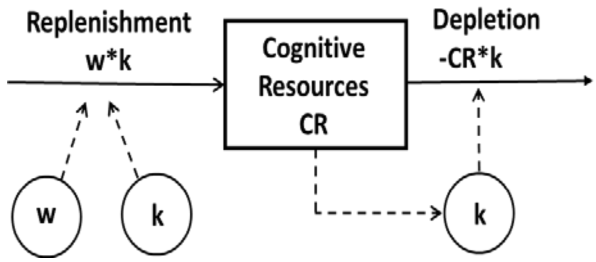

Figure 5. System dynamics model of the leaky integrator framework of cognitive resource utilization. Here, w*k is a constant input or replenishment and -CR*k is exponential decay or depletion. When k = 0.1, w determines the level at which a dynamic equilibrium is established. The model produces exponential decay of cognitive resources when CR(0) is larger than w, and the model produces exponential growth of cognitive resources when starting value CR(0) is smaller than w.

This leaky integrator framework is a reasonable embodiment of the concept of cognitive resource utilization because a first-order negative feedback response is mimicked by having a goal or set-point established via a *dynamic equilibrium*. A dynamic equilibrium is established when the input—replenishment—becomes exactly balanced out by the rate of decay—depletion—which occurs at some point during the mechanism's activation. Currently, the model is calibrated such that the value of w determines the level of the dynamic equilibrium in terms of proportion correct detection (when k = 0.1).

Thus, when starting value CR(0) is larger than w (therefore w is relatively small), depletion will dominate replenishment and cognitive resources CR will decay to a value at which point the low rate of decay balances out the low strength of the input and a dynamic equilibrium is established at the low value of w. For instance, when CR(0) = 0.96 and w = 0.64, correct detection performance will exponentially decay to a dynamic equilibrium of 0.64, thus simulating cognitive resource depletion. A low level of correct detection performance would reflect a low level of resources which, in turn, would reflect a *low level of replenishment relative to high task demands*. This set of parameters produces the exact function shown in Figure 3, thus the output of the leaky integrator replicates the output of the negative feedback process. The R^2 was 0.98 between Giambra and Quilter's (1987) empirical data and the output of this simulation of the leaky integrator.

When the starting value CR(0) is smaller than w (thus w is relatively large), replenishment will dominate depletion and cognitive resources CR will grow to a value at which point the high rate of decay balances out the high strength of the input and a dynamic equilibrium is established at the high value of w. For example, when CR(0) = 0.64 and w = 0.96, correct detection performance will exponentially grow to a dynamic equilibrium of 0.96, thus simulating recovery from performing a difficult task via cognitive resource replenishment (assuming that the individual's level of cognitive resources could be indexed via brief periods of testing). A high level of correct detection performance would reflect a high level of resources which, in turn, would reflect a *high level of replenishment relative to low task demands*. This set of parameters produces the function shown in Figure 4.

A dynamic equilibrium is established by the interplay between replenishment and depletion. This is what we think of when we consider the idea of cognitive resources—our recent rest and/or nutrients being metabolized help replenish our cognitive resources so that they can be drawn upon to help fuel the mentally-demanding tasks that we might be performing now or in the near future. Human cognitive resources are continuously being replenished (more so during sleep, less so during performance of a cognitively demanding task) while at the same time undergoing depletion (more so during performance of a cognitively demanding task, less so during sleep). This is the conceptual importance of our leaky integrator—the notion of a dynamic equilibrium between replenishment and depletion precisely captures the idea of a common resource being utilized.

Predictions. The advantage of modeling the vigilance decrement as a leaky integrator is that a mechanism exists for cognitive-resource replenishment and depletion. This, in turn, allows the modeling of situations involving rest or tasks of differing difficulties, predictions of which are given below. Future empirical research will determine the accuracy of these predictions and the calibration necessary for our model.

Such predictions are made about proportion correct detection, based on the use of parameters that yielded the close fit between Giambra and Quilter's (1987) empirical data and the results of the simulation of the leaky integrator model (Figure 3). In the case of rest, predictions are made about the level of performance that would be obtained if an individual's rest was briefly interrupted for testing in an attempt to index their level of cognitive resources. Future empirical studies will be needed to determine the degree of accuracy of the predictions made below.

Consider the hypothetical case in which an individual starts out resting after performing a mentally strenuous task. Their cognitive resources are largely depleted which over the next half hour get replenished. Following replenishment, the individual again engages in a mentally strenuous task for the subsequent half hour. In this case, $CR(0) = 0.64$ (starting out with depleted cognitive resources) and $w = 0.96$ for the first half-hour. At the 30 minute mark, CR approaches the asymptote of 0.96. Then the value of w changes to 0.64, and CR decays to near 0.64 over the second half-hour. Simulated results are shown in Figure 6.

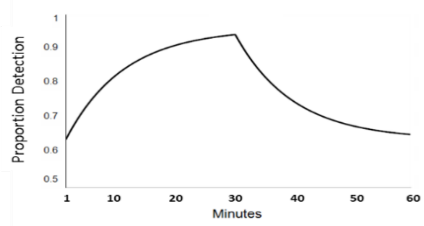

Figure 6. System dynamics simulation of a hypothetical case in which an individual starts out resting for a half hour after performing a mentally strenuous task, followed by the individual engaging in a mentally strenuous task for the subsequent half hour. Here, CR(0) = 0.64 and k = 0.1. If time < 30, w = 0.96 else w = 0.64.

Now consider the case in which an individual starts out performing a difficult task for 15 minutes after having had their cognitive resources replenished. Following this difficult task, the individual engages in a moderately strenuous task for the subsequent 45 minutes. In this case, CR(0) = 0.96 (starting out with replenished cognitive resources) and w = 0.64 for the first 15 minutes. Then, after 15 minutes, w = 0.75 over the remaining 45 minutes. See Figure 7.

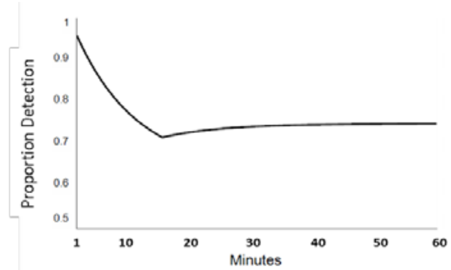

Figure 7. System dynamics simulation of a hypothetical case in which an individual starts out performing a difficult task for 15 minutes after having had their cognitive resources replenished. Following this difficult task, the individual engages in a moderately strenuous task for the subsequent 45 minutes. Here, CR(0) = 0.96 and k = 0.1. If time < 15, w = 0.64 else w = 0.75.

DISCUSSION

Most autonomous machines in current and future systems will interact with humans who will be serving in supervisory or collaborative roles (Endsley, 2017), thereby making the success of such machines dependent on human–machine teaming. Such teaming can be significantly impacted by situations that require a human to sustain attention for a prolonged duration, which can produce a decline in his or her cognitive performance, the so-called 'vigilance decrement' (e.g., Teichner, 1974; Warm & Jerison, 1984). The present paper presents a computational model of the vigilance decrement, which can enable a machine's estimation and prediction of human performance (Harriott & Adams, 2013) and thereby aid in the development of effective human–machine teaming.

The vigilance decrement likely arises from people's limited cognitive resources which get depleted over time (e.g., Fraulini, Hancock, Neigel, Claypoole & Szalma, 2017; Helton & Russell, 2017; Warm, Finomore, Vidulich & Funke, 2015), thus our computational model embraces the concept of *cognitive resource utilization*. This computational model of cognitive resource utilization is based on a *leaky integrator* framework, which takes the integral of input (cognitive resource replenishment) and leaks some amount over time (resource depletion).

Our leaky-integrator model of cognitive resource utilization, and thus of the vigilance decrement, can be placed within the context of *dual-process theory*, which has heretofore not been done. As will be argued below, our model of cognitive resource utilization, and of the vigilance decrement, is a model of *analytical cognition*.

Dual-Process Theory

Hundreds of scientific sources show that human reasoning and decision making are mediated by two distinct sets of cognitive processes or systems: analytical cognition versus intuitive cognition (see recent reviews by Patterson, 2017, and Patterson & Eggleston, 2017). *Analytical cognition* involves conscious deliberation that draws on working memory. Analytical cognition is voluntary, limited in capacity, effortful, slow, and it includes declarative memory and explicit knowledge. Analytical cognition can be encouraged with the use of symbols, rules, and/or algorithms. Because analytical cognition draws upon working memory which is limited in capacity, effortful, and slow, *analytical cognition is impacted by time pressure and workload*.

Intuitive cognition involves unconscious situational pattern recognition that is independent of working memory (Patterson, 2017; Patterson & Eggleston, 2017). Intuitive cognition is independent of conscious "executive" control, large in capacity, fast, and it likely entails procedural memory and implicit knowledge (Patterson, Pierce, Boydstun, Ramsey, Shannon, Tripp & Bell, 2013). Intuitive cognition can be encouraged with judgments requiring a quick grasp of the meaningful gist of information based on perceptual cues, without the use of symbology or precise analysis. Because intuitive cognition is independent of working memory, large in capacity, and fast, *intuitive cognition is relatively immune to time pressure and workload*. [Because intuitive cognition is independent of conscious executive control, it is easy to conflate it with the notion of "automaticity"—that performance on a given task can become unconscious and automatic due to a consistent mapping of stimuli to responses (Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977). However, intuitive cognition—unlike automaticity—refers to a reasoning and decision-making system based on situational pattern recognition, thus intuitive cognition should not be conflated with automaticity.]

Recall that the vigilance decrement involves capacity-demanding tasks that require working memory, high levels of stress, high levels of mental workload, a depletion of limited cognitive resources, and the typical use of artificial displays involving symbology. Now recall that analytical cognition is characterized as having a limited capacity linked to working memory, impacted by time pressure and workload, and it is encouraged with the use of symbols. Thus, *aspects of the vigilance decrement map well to the properties of analytical cognition*.

Recall that intuitive cognition is characterized as having a large capacity, independent of working memory, relatively immune to time pressure and workload, and it involves judgments based on perceptual cues without the use of symbology. Thus, *aspects of the vigilance decrement provide a poor match to the properties of intuitive cognition*. Evidence suggesting that the vigilance decrement does not occur with intuitive processing comes from findings that reveal that tasks involving stimuli that approximate perception in natural environments are resistant to the vigilance decrement, such as: biological motion cues (Thompson & Parasuraman, 2012), targets embedded in natural scenes (Szalma, Schmidt, Teo & Hancock, 2014), and changes in stereoscopic 3-D depth (Greenlee, Funke, Warm, Finomore, Patterson, Barnes, Funke & Vidulich, 2015), all of which convey a perception of three-dimensionality. Stimuli that consist of two-dimensional or 'top-down' perspectives do not appear to be resistant to the vigilance decrement (Finomore, Shaw, Warm, Matthews & Boles, 2013; Funke, Warm, Matthews, Riley, Finomore, Funke, Knott & Vidulich, 2010).

In short, the vigilance decrement is likely produced by a depletion of cognitive resources related to analytical cognition but not to intuitive cognition. *Our leaking integrator model of cognitive resource utilization, and by implication the vigilance decrement, is a theoretical representation of analytical cognition*.

CONCLUDING REMARKS

The computational modeling of human cognitive resource utilization should be advantageous to the development of human-machine teaming. Such modeling of the utilization of human cognitive resources can improve its understanding and prediction and thus theoretically allow a future autonomous software agent to anticipate the needs of the human and compensate accordingly. Because our leaky integrator model is a mathematical representation, its algorithm could be easily encoded into a computer which would then possess a computational model of the human. Future work will involve the modeling of additional components that may affect cognitive resources like motivation, stress, and emotion and their potential validation against empirical data.

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