Team Neurodynamics
by The
Learning Chameleon, Inc.

Allocation of Time, EEG-Engagement and EEG-Workload Resources as Scientific Problem Solving Skills Are Acquired in the Classroom

Ronald Stevens
IMMEX Project / UCLA
5601 W. Slauson Ave #255
Culver City, CA 90292
ron@immex.com

Trysha Galloway
IMMEX Project / UCLA
5601 W. Slauson Ave #255
Culver City, CA 90292
trysha@immex.com

Chris Berka
Advanced Brain Monitoring
2237 Faraday Avenue, Suite 100
Carlsbad, CA 92008
chris@b-alert.com

Abstract

We have studied EEG-derived metrics of Workload (WL) and Engagement (E) as students developed and refined their problem solving approaches to determine the degree to which these are modulated as problem solving experience is gained. The problem solving tasks (IMMEX™) used for these studies were a series of science and mathematics online simulations designed for middle school students. Comparison of WL and E levels on IMMEX™ tasks and baseline cognitive tasks indicated that the simulations recruited high levels of both WL and E. Detailed second-by second analysis of these metrics during problem solving indicated they were dynamic with cycles of high and low values.

Aggregated comparisons of WL and E across students as they gained experience in problem solving showed rapid decreases in time on task while E and particularly WL showed little change. Performances where the solution was missed were significantly lower in WL than when the problem was solved. Analysis of WL and E of individual students showed fluctuations of E with practice with some students showing decreased levels with time and others showing increases. When the levels of WL and E were compared across strategies accounted to be novice or proficient by probabilistic modeling there were no significant differences.

These findings indicate that as students practice and refine their problem solving strategies the levels, and changes in the mental effort put into the process is not easily predicted by the changes in the speed of the task, by whether or not the problem was solved, or whether the resulting strategy is more novice or expert.

1 INTRODUCTION

Problem solving is often defined as 'what you do when you don't know what to do'. This is particularly true when students encounter a scientific problem space for the first time. Here, they will have little idea of the data representations to expect, the units the data will be expressed in, and the format in which they will appear. As problem spaces are explored, a linear model of the problem space exploration (i.e. episodic memory) is thought to evolve into a more navigation-based, (or semantic-memory) representation of the problem space as the student learns to distinguish useful from useless information (Dragoni & Buzaki, 2006). This process whereby an individual optimizes his or her performance in a situation that requires the operation of a number of cognitive, supervisory or controlling processes that are collectively called the brain's executive functions (Baddeley, 2003). This cognitive map perspective of problem solving suggests that there should be significant differences in cognitive state variables as experience is gained and skills are refined. For instance, the first time a piece of data is examined the student must understand and encode both the representation of the data (scales, axes, graph format), as well as the significance of the data within the context of the problem. Once the data representation is understood, the process of relating the data to the problem should dominate.

These general processes of skill acquisition are described as occurring in stages characterized by distinctive amounts of time and mental effort required to exercise the skill (Schneider & Shiffrin, 1977). Three stages have been identified: the initial cognitive stage requiring the assembling of new knowledge, the associative stage where newly assembled procedural steps gradually automate as they are practiced, and the autonomous stage where the task execution is automated and performed with minimal conscious mental effort. During the transition from the cognitive to associative stage, both speed and accuracy increase as subjects become less reliant on the declarative representations of knowledge (Anderson, 1995). Because the key distinction between the second and third stages of skill acquisition is a decrease in mental effort rather than a reliable difference in the accuracy of performance, application of neurophysiologic approaches such as electroencephalography (EEG) may be useful for providing objective evidence of the progression from stage 2 to stage 3 (Berka, 2004).

There are, however, conceptual, technical and logistical challenges associated with implementing methods such as real-time EEG monitoring in settings like high school classrooms. In these situations there is nothing like the experimental control that others working in the sensory, and motor systems have where defined stimuli are easily time locked to EEG readouts. Instead, students move through problem spaces at their own pace, choosing information in many different sequences, and developing competence and expertise in many different ways. Technical challenges to using neurophysiologic methods like EEG in classroom settings are being overcome with the availability of portable, easy to use and cost-effective methods to assess brain function (Berka et al., 2004, 2005), making it now more feasible to focus on the logistical and conceptual educational challenges: How does cognitive load change over the course of a problem solving episode, and how do such changes lead to different strategic behaviors? How can real-time feedback be linked to cognitive state changes and can responses to these changes help optimize engagement and workload during learning? Because data collection can occur without interfering with normal task-driven cognition, such assessments of cognitive load will not be confounded by strong measurement effects, and in the future could be used to guide classroom learning in novel and engaging ways.

In this study we have begun addressing the logistical and conceptual challenges by measuring the overall changes in cognitive workload (WL) and engagement (E), as defined by the B-Alert system (Berka et al., 2004, 2005), as problem solving tasks are practiced, and skills are acquired in high school and university classrooms.

1.1 EEG Indices of Cognitive States

Heart rate variability, oculomotor activity, pupilometry, functional near infrared imaging (fNIR) and galvanic skin response have been employed to detect cognitive state changes; however, the electroencephalogram (EEG) is the only physiological signal that reliably and accurately reflects subtle shifts in alertness, attention and workload that can be identified and quantified on a millisecond time-frame. Significant correlations between EEG indices of cognitive state changes and performance have been reported based on studies conducted in laboratory, simulation and operational environments (Berka et al., 2004; Brookhuis & de Waard, 1993; Makeig & Jung, 1995; Sterman, 1993). The conventional methods employed to analyze the EEG generally involve computation of the power spectral densities within the classically defined frequency bands including alpha, beta, theta, delta and gamma or ratios between these frequency bands (Gevins & Smith, 2005; Wilson, 2005). Several investigators have reported EEG measures of attention, engagement and mental workload that reflected differences in task-related cognitive resource allocation, task mastery and task overload (Kramer et al. 1996; Parasuraman, 2003). The EEG variables employed in the conventional models to monitor workload included alpha suppression, increased beta, increased frontal midline theta and ratios such as beta/alpha plus theta and alpha plus theta/beta. Alternatively, the amplitudes of the N100 and P300 components of the event-related potential (ERP) have been employed in some cognitive assessment models (Kramer, 1996). The use of ERPs for naturalistic applications has several limitations; the requirement for introducing "probe" stimuli into real-world tasks to elicit the potentials, the requirement for precise time-locking of the stimulus presentation to the EEG and the difficulty of extracting relevant cognitive state information from single-trial ERPs in real-time.

The EEG data was acquired from the wireless headset developed by Advanced Brain Monitoring, Inc. that uses an integrated hardware and software solution for acquisition and real-time analysis of the EEG. It has demonstrated feasibility for acquiring high quality EEG in real-world environments including workplace, classroom and military operational settings. The system contains an easily-applied wireless EEG system that includes software designed to identify and eliminate multiple sources of biological and environmental contamination and allow real-time classification of cognitive state changes even in challenging environments. To monitor workload and engagement using the B-Alert 4-class model, participants wear a wireless sensor headset that includes the following bi-polar sensor sites: F3-F4, C3-C4, Cz-PO, F3-Cz, Fz-C3, Fz-PO. EEG metrics (values ranging from 0.1-1.0) for "engagement" and "mental workload" are calculated for each 1-second epoch of EEG using quadratic and linear discriminant function analyses of model-selected EEG variables derived from power spectral analysis of the 1-Hz bins from 1-40Hz. Bi-polar recordings were selected to reduce the potential for movement artifacts that can be problematic for applications that require ambulatory conditions in operational environments. Limiting the sensors (seven) and channels (six) ensures the sensor headset can be applied within 10 minutes. Simple baseline tasks are used to fit the EEG classification algorithms to the individual so that the cognitive state models can then be applied to increasingly complex task environments, providing a highly sensitive and specific technique for identifying an individual's neural signatures of cognition in both real-time and offline analysis. These methods have proven valid in EEG quantification of drowsiness-alertness during driving simulation, simple and complex cognitive tasks and in military, and industrial simulation environments (Levendowski et al., 2003; Stevens et al., 2006), quantifying mental workload in military simulation environments (Berka et al., 2004), distinguishing spatial and verbal processing in simple and complex tasks (Berka et al., 2005) characterizing alertness and memory deficits in patients with obstructive sleep apnea (Westbrook et al., 2004), and identifying individual differences in susceptibility to the effects of sleep deprivation (Makeig, 1993). The model system has also been integrated into real-time, automated computing systems to implement dynamic regulation and optimization of performance during a driving simulation task and in the Aegis C2 and Tactical Tomahawk Weapons simulation environments (Berka et al., 2005b).

2 METHODS

2.1 Tasks and Subjects

The tasks used for these studies were IMMEX^{TM} problem solving science simulations that have been performed by thousands of middle school, high school and university students' worldwide (Stevens et al., 2002). One sample IMMEX^{TM} task is a mathematics simulation *Paul's Pepperoni Pizza*, where students must decide how many pizza's to buy for the team based on the number of players, costs, etc. Students navigate a hierarchy of menus and submenus to select different pieces of information which are each available at a cost. This form of task structure and subtask boundaries would be expected to elicit different levels of cognitive engagement as students explore and seek out relevant information (Iqbal & Bailey, 2006). Each IMMEX^{TM} problem set also contains many instances of the problem where the menu, submenu and cost structures are the same, but where the data behind each one varies to adjust the task. For example, in a case of *Paul's Pepperoni Pizza* subjects are required to find how many medium pizza's to order when the team wins, while another case will require finding how many small pizza's to order. Hidden in the problem are clues whether or not the coach or mascot will eat, or if one of the team members has food allergy. These real-world uncertainties give the problems more depth than simple math problems.

Unlike tasks often used for EEG studies of mental effort, IMMEX^{TM} problems have no externally imposed time constraints or defined stimulus prompts, essentially creating a very loosely coupled problem space. We have previously shown that as students solve a series of cases of an IMMEX problem set the time needed to solve each case decreases. While not directly following the Power Law of Practice (Newell & Rosenblum, 1981), students deriving correct solutions show exponential decreases in performance time whereas students who get interrupted by making mistakes show more linear decreases in speed (Stevens et al., 2003).

Classroom observations have indicated that IMMEX^{TM} problems are engaging and challenging for students eliciting a sense of 'presence' similar to that described for virtual environments (Slater, 1998; Sadowski & Stanney, 2002). This engagement most likely results from the ease of interaction and consistency of the user interface, as well as the wide range of options the user has to explore the problem space, providing a high sense of control. It is also cognitively complex with the majority of utterances during verbal protocols being mapped to cognitive and meta-cognitive components (Chung et al., 2001). One final unique and powerful feature of this online simulation system is the associated machine learning performance modeling techniques, providing real-time capability to model the relative expertise of a student on a particular task based on the strategy employed (Stevens et al., 2004, 1996).

University students (n = 12) and Advanced Placement high school students (n = 6) each performed three cases of middle school science problem solving tasks. The choice of the problem set difficulty and level of student expertise was chosen to maximize the likelihood that students would improve across cases, and that their strategies should be efficient after three performances. This design deliberately sought to remove the potential confounders of frustration, guessing or confusion that are more characteristic of novices. As we will show later, these design goals may not have been totally achieved. All subjects were presented with the goals of the project and the logistics and constraints (regarding excessive talking, movement, etc.) of EEG monitoring as per approved Institutional Review Board protocols. They then performed a single 30-minute baseline EEG test session to adjust the software to accommodate individual differences in the EEG (Berka et al., 2004).

2.2 Procedure

In order to identify EEG patterns that detect the onset and duration of important task-related cognitive activities, it is critical to capture and label events of interest within the task environment in an event log that is time-synched with the EEG file with millisecond accuracy. The event logs can then be used to identify patterns of EEG associated with key task demands and student responses and to develop and validate new EEG indices to answer questions relevant to educators.

One approach we have tried for addressing these challenges is to align the EEG output metrics with the problem solving actions using software (Morae, Techsmith, Inc.) that captures output from the screen, mouse click and keyboard events as well as video and audio output from the users (Figure 1). Each of these events are time stamped at 10ms intervals and can be used to identify both when the student requested the data (intent) as well as when the data appeared (response). The database from Morae is then integrated in Matlab with that of the B-Alert system allowing precise alignment of events with EEG responses. With these combined data architectures we can model from the 10ms level upwards making different levels of analysis possible.

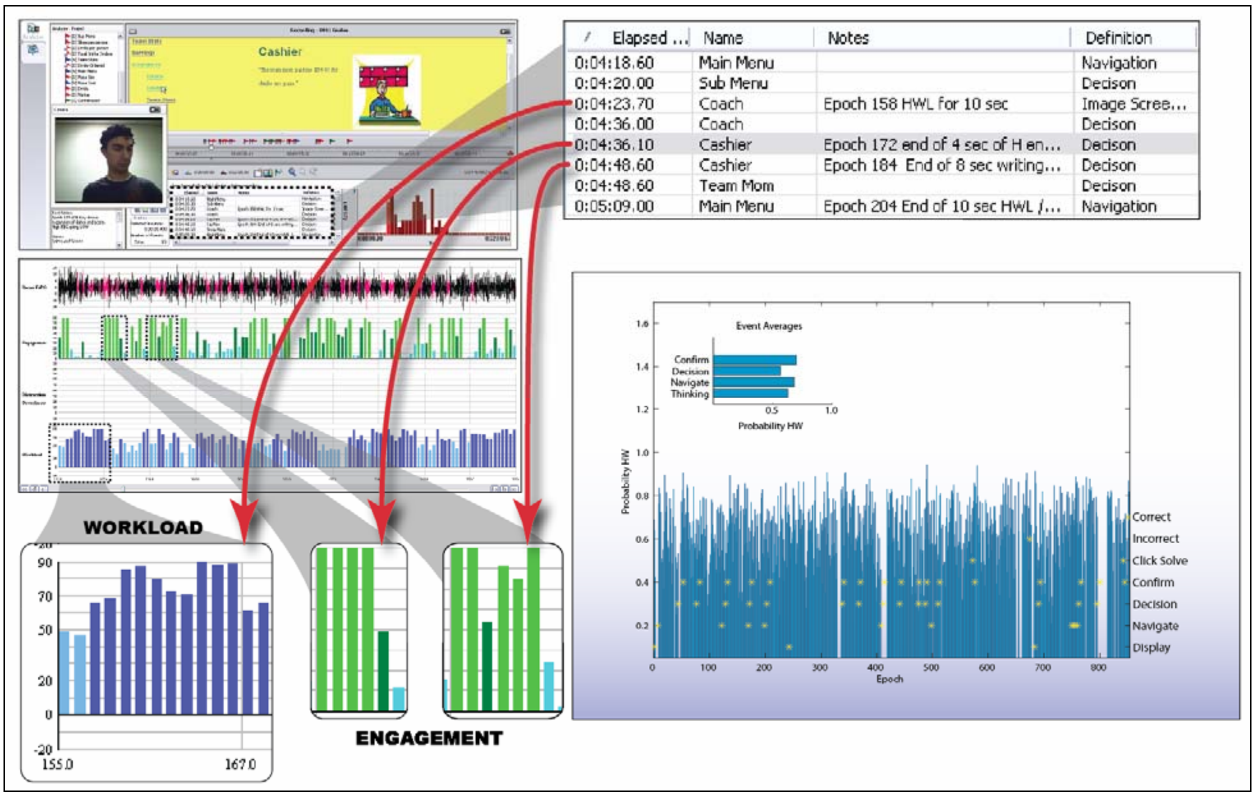

Figure 1. Integrating EEG workload and engagement indexes with problem solving events. The upper left figure shows a user engaged in problem solving while keyboard and mouse events are simultaneously recorded. The figure below shows the real-time output of the B-Alert cognitive indexes where samples of the workload and engagement data streams have been linked with specific events in the log. On the lower right, timestamps of IMMEX data requests and displays are integrated with the EEG workload indices and then plotted for the one-second epochs of the task.

3 RESULTS AND DISCUSSION

3.1 Dynamics of E and WL During Problem Solving

Using the above approaches we examined the dynamics of E and WL in relation to specific user actions in the simulation (Test Selections row) for each second of the simulation. Figure 2 shows four performances of *Paul's Pepperoni Pizza* for subject # 379. Within each performance there is a dynamic cycling of E and to a lesser extent, WL during problem solving indicating variable application of attention / engagement and workload across the different tasks. The epochs between performances 1 and 2 showed areas where both WL and E decreased substantially suggesting that during the problem solving process itself the students were working hard. Also shown in this figure are two trend lines for E and WL over the four performances which showed constant WL and slightly decreasing E over the session. A more detailed analysis of each performance indicated that elevated levels of E were often near the boundaries where tests appeared on the screen (i.e. after the values of .4 in the Test Selections panel) suggesting visual engagement with the appearance of new information (data not shown).

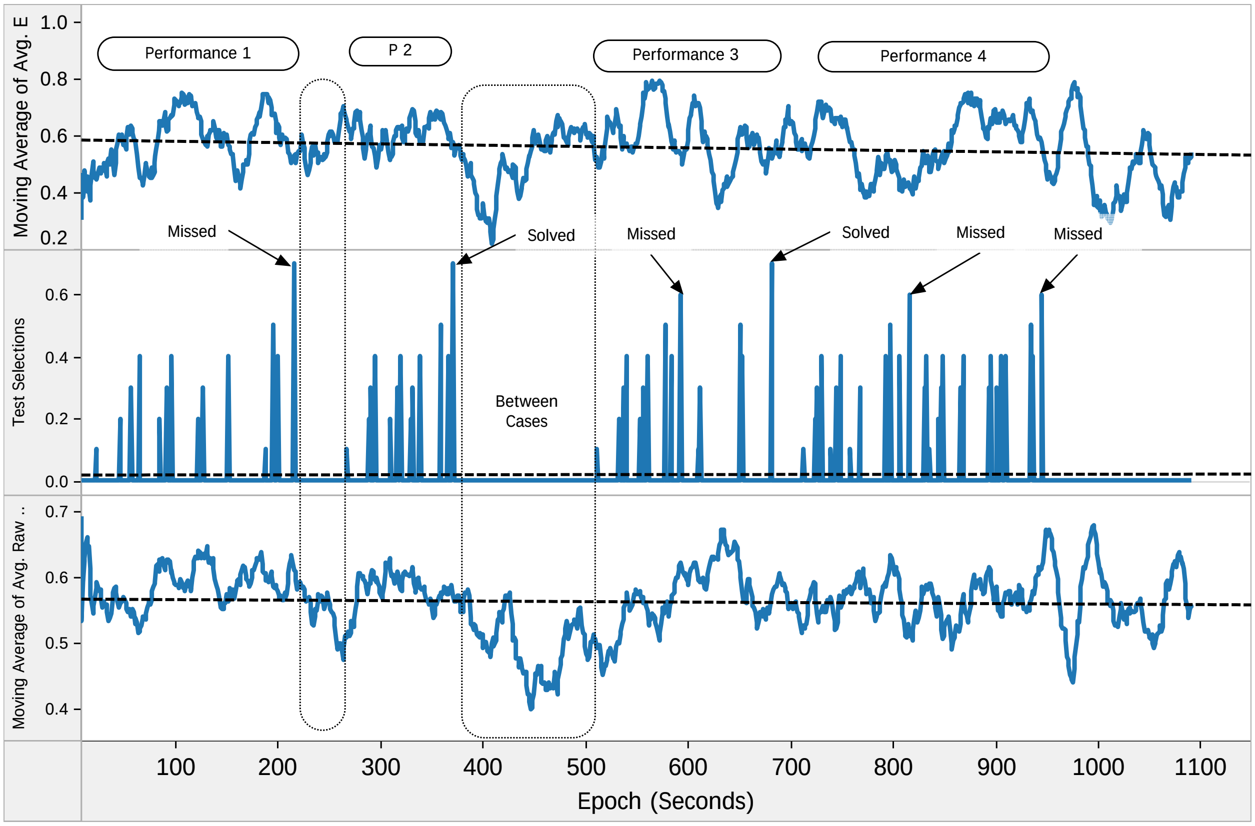

Figure 2. Dynamics of E and WL across problem solving tasks. The levels of Engagement (top panel) and Workload (lower panel) are shown for each second of effort and are linked to different categories of test selections (middle panel). The values for the test selection histograms were: .1 = opening prologue, .2 = Main Menu items, .3 = Submenu Items, .4 = Confirm test, .5 = Attempt to Solve, .6 = Missed, .7 = Solved.

3.2 Changes in WL, E and Task Time as Skills Develop

Having shown that the levels of E and WL dynamically change within performances, we reviewed how these levels changed as students gained experience. We have previously shown that students deriving correct solutions show exponential decreases in performance time whereas students who get interrupted by making mistakes show more linear decreases in speed (Stevens et al., 2003) and speed therefore was one measure of improvement. We have also shown that student strategies change in a predictable way as students become more proficient problem solvers (Stevens et al., 2004). Our approach, therefore, was to have students solve a series of cases in an IMMEX^{TM} problem set and monitor the changes in performance time and the E and WL cognitive measures, the strategy used and whether the problem was solved.

We first wished to determine how difficult IMMEX^{TM} problems are for our subjects. E levels are based on a calibrated standard and may be directly compared across individuals as well as across tasks. An example of such a comparison is shown in Figure 3 for baseline tasks and for a series of IMMEX^{TM} tasks. To situate IMMEX^{TM} problem solving within the context of the cognitive indices defined by ABM, we compared the WL and E values for three baseline tasks, the psychomotor vigilance task (PVT), and the eyes open (EO) and eyes closed (EC) target identification paradigms. PVT is a simple visual reaction task that requires continuous attention to detect randomly occurring stimuli and sensitively reflects circadian rhythm and sleep need (Sforza et al., 2004). The EO and EC tasks require the subject to respond to visual or auditory stimuli presented at regular intervals on the computer. As shown in Figure 2, individual levels of E ranged from nearly 0 on the EC task up to over 0.6 for some individuals on IMMEX™, giving some sense of the fluctuations that can be expected. The average E levels on IMMEX™ tasks were routinely higher that the levels seen with the baseline tasks indicating that problem solving requires sustained attention, and develops a sense of presence in the student (Sandowski & Stanney, 2002). In this example subject 251 showed normal E levels across the baseline tasks but were below normal for the IMMEX™ task; suggesting a lack of engagement / attention; the opposite was seen for subject 379. A similar across-individual comparison is not possible for WL as the maximum levels are individual specific, i.e. a WL value of 0.6 for one individual may be equal to a value of 0.7 for a second individual (G. Davis, personal communication).

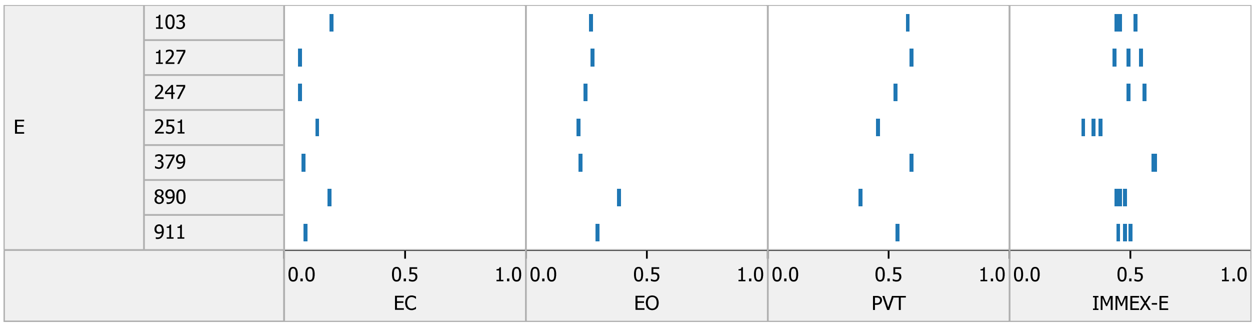

Figure 3. Engagement comparisons across baseline tasks and IMMEX™ performances.

While it is not possible to directly compare levels of WL across individuals the data can be aggregated across a series of the same tasks to look for differences in whether or not a case was solved, or for changes with skill development. Seven subjects performed three or more cases of *Paul's Pepperoni Pizza*, where students must decide how many pizza's to buy for the team based on the number of players, costs, etc. There were no significant differences in E whether or not the problem was solved but WL was significantly lower when the solution to the problem was missed twice (0.59 ± 0.02 vs. 0. 64 ± 0.02, p = .002).

For each of the performances we measured the time (seconds) needed to solve the case, as well as the overall WL and E. As shown in Table 1, while the time needed to complete the task rapidly decreased, there were no significant group decreases in either WL or E.

Table 1. Changes in Time on Task, WL and E With Problem Solving Experience

Performance	Speed (seconds)	WL	E
1	**422 ± 234**	**.629C .07**	**486 ± .09**
2	**241 ± 126**	**.625 ± .08**	**.469 ± .08**
3	**136 ± 34**	**.648 ± .06**	**.468 ± .09**

Given the literature of skill acquisition (Ericsson, 1995) and the Power Law of Learning (Lacroix & Cousineau, 2006) these results were unexpected. We then disaggregated the data to more closely examine changes in WL, E and speed as individuals performed the series of problems (Figure 4).

All subjects decreased their performance speed as they performed the cases, although with quite different trajectories (Figure 4A). The levels of E (Figure 4B) also changed with practice but the dynamics were variable for each student. For some students there was a trend towards decreasing levels of E with practice (subjects 127, 247). There were also instances where levels of E increased with practice (subjects 103, 911), and other where the levels were constant (subject 379). All subjects except # 127 missed at least one of the three cases performed.

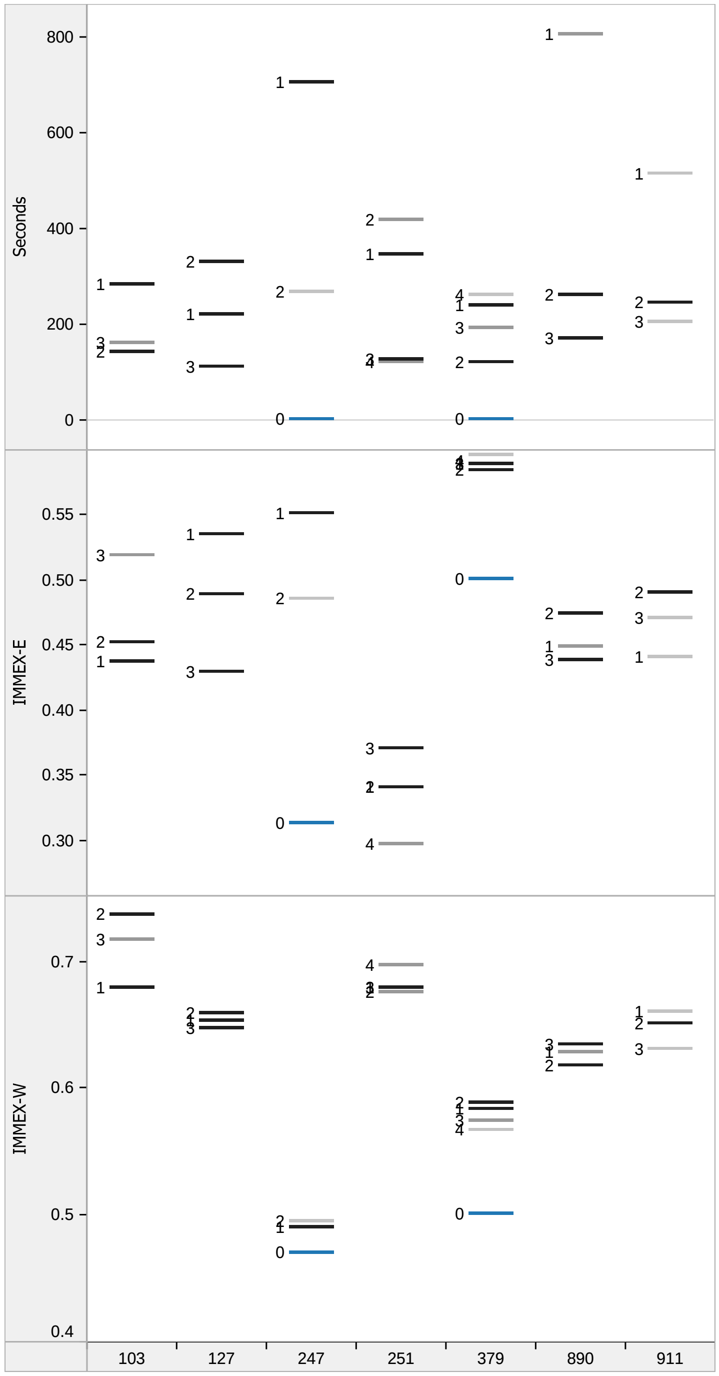

Figure 4. Changes in Time, WL and E as Students Gain Problem Solving Experience. Each horizontal bar represents a student performance and they have been color-coded to indicate whether the case was solved (black) or missed (gray). The numbers next to the bars indicate the performance number. For subjects 247 and 379 there are also values from between the cases, i.e. ‘resting’, and these are coded as ‘0’.

To obtain a more strategic perspective of the levels and fluctuations of WL and E, we related them to the sophistication of the strategy used. This approach uses machine learning models of skill acquisition that dynamically model the transitions from novice to expert (Stevens et al., 2004). The categories of novice and proficient are derived from artificial neural network and Hidden Markov Modeling models of thousands of student performances, and they reflect how a student performed on any particular problem solving episode as well as how the strategies have been changing as experience developed.

Figure 5 shows the distribution of speed, E and WL across these two strategic levels separated by subject, with color-coded performance numbers. The levels of E and WL were not significantly different across strategy groups although there was greater variance in the WL across subjects. Only one subject, however, made a clear transition from a novice to proficient strategy (# 247).

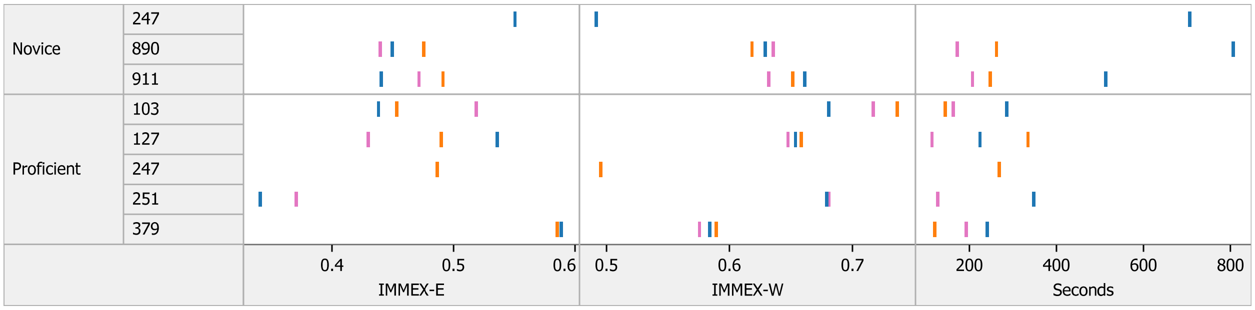

Figure 5. Separation of WL and E into novice and proficient strategies. Following the problem solving session the strategies the student's used were determined by artificial neural network analysis using trained unsupervised neural networks from 7345 student performances. The nodes were aggregated into Novice and Proficient categories based on the solve rates of the different strategy categories and learning trajectory data from Hidden Markov Modeling. The colors represent the different performance numbers with blue = performance 1, orange = performance 2 and purple = 3.

4 DISCUSSION

The goal of these studies was to determine how WL and E were modulated as students refined their strategies and became more proficient problem solvers. To ensure that students would improve their strategies across performances, we chose a middle school mathematics problem set as the task and university / advanced placement students as the subjects. This was to help control the potential confounders of frustration, guessing or confusion when students struggle with tasks beyond their abilities. While we successfully avoided these confounders, other, more subtle confounders appeared which illustrate the challenges of conducting studies in ecologically valid situations.

The tasks were engaging and challenging for the students as indicated by the high levels of E and WL when compared with simpler baseline tasks, and consistent with our previous findings (Stevens & Palacio-Cayetano, 2003) all students improved their performance times across the three simulations, one hallmark of problem solving skill improvement.

Unfortunately, for the purpose of the study the problems proved more challenging than expected as only one of the seven students we studied in detail solved all three of the cases attempted. This student, #127 however, showed progressive decrease in E, but not WL with each performance, consistent with the idea that he / she was better understanding the problem space, displays, etc. as he / she practiced the cases. The remaining students missed at least one of the three cases. Our previous results have shown that missing problem solutions has an effect on performance times, and our current studies show an association between missing a problem and low WL. For our studies it would therefore have been useful to have more students who solved all three cases as subjects to reduce the possible effects of missing a solution.

Another confounder for the study was that only one of the students # 247 showed a transition from a novice strategy to a proficient strategy by probabilistic modelling. The other students either started off proficient and remained proficient (while decreasing performance time), or started and remained using novice strategies (while decreasing performance time). This lack of wide strategy shifts with practice makes it difficult to say with certainty that our subject population made a clear transition from novice to proficient.

Although the aggregated levels of E and WL changed little as the performance times decreased, the confounding factors of solve rates and strategy shifts leave the question open as to how they relate to skill acquisition. These studies indicate that the sensitivity of EEG to multiple aspects of problem solving performance may begin to redefine the studies of the dynamics and complexity of skill acquisition.

5 REFERENCES

Anderson, J. R. (1995). *Cognitive psychology and its implications* (4th ed.). New York: Freeman.

Baddeley, A. (2003). Working Memory: Looking Back and Looking Forward. *Nature Reviews| Neuroscience 4*, 829-839.

Berka, C., Levendowski, D., Davis, G., Lumicao, M., Ramsey, C., Stanney, K., et al. (2005). EEG indices distinguish spatial and verbal working memory processing: Implications for real-time monitoring in a closed-loop Tactical Tomahawk Weapons Simulation. *International Conference on Human Computer Interaction*, July, Las Vegas, NV.

Berka, C., Levendowski, D. J., Olmstead, R. E., Popovic, M. V., Cvetinovic, M., Petrovic, M. M., et al. (2004). Real-time analysis of EEG indices of alertness, cognition, and memory with a wireless EEG headset. *International Journal of Human-Computer Interaction, 17*(2), 151-170.

Berka, C., Levendowski, D. J., Ramsey, C. K., Davis, G., Lumicao, M. N., Stanney, K., et al. (2005, May). Evaluation of an EEG-workload model in an Aegis simulation environment. *SPIE Defense and Security Symposium: Biomonitoring for Physiological and Cognitive Performance during Military Operations* (pp. 90-99).

Berka, C., et al. (2004). Real-time analysis of EEG indexes of alertness, cognition and memory acquired with a wireless EEG headset. *International Journal of Human-Computer Interaction, 17*(2), 151-170.

Brookhuis, K. A., & de Waard, D. (1993). The use of psychophysiology to assess driver status. *Ergonomics, 36*(9), 1099-110.

Dragoi, G., & Buzsáki, G. (2006). Temporal encoding of place sequences by hippocampal cell assemblies. *Neuron, 50*, 145-157.

Gevins, A., & Smith, M. E. (2005). Assessing fitness-for-duty and predicting performance with cognitive neurophysiological measures. Biomonitoring for physiological and cognitive performance during military operations. *SPIE - The International Society for Optical Engineering* (pp. 127-138).

Iqbal, S. T., & Bailey, B. P. (2006, April 22-27). Leveraging characteristics of task structure to predict the cost of interruption. *CHI 2006 Proceedings: Using Knowledge to Predict & Manage*. Montreal, Canada.

Kramer, A., & Parasuraman, R. (2005). Neuroergonomics --Application of neuroscience to human factors. In J. Cacciopo, L. G. Tassinary, & G. G. Berntson (Eds.), *Handbook of psychophysiology* (2nd ed.). New York: Cambridge University Press.

Makeig S, & Jung, T. P. (1995). Changes in alertness are a principal component of variance in the EEG spectrum. *Neuroreport, 7*(1), 213-216.

Makeig, S. (1993). Auditory event-related dynamics of the EEG spectrum and effects of exposure to tones. *Electroencephalography and Clinical Neurophysiology, 86*(4), 283-293.

Parasuraman, R., & Rizzo, M. (2005). *Neuroergonomics: The brain at work*. New York: Oxford University Press.

Sadowski, W., Jr., & Stanney, K. (2002). Measuring and managing presence in virtual environments. *Virtual environment handbook.* Lawrence Erlbaum Assoc.

Shiffrin, R. M., & Schneider, W. (1977). Controlled and automatic information processing: II. Perceptual learning, automatic attending, and a general theory. *Psychol Review, 84*, 127-190.

Sforza, E., Haba-Rubio, J., De Bilbao, F., Rochat, T., & Ibanez, V. (2004). Performance vigilance task and sleepiness in patients with sleep-disordered breathing. *Eur Respir J, 24,* 279-285.

Sterman, M. B., Mann, C. A., & Kaiser, D. A. (1992, June 25). Quantitative EEG patterns of differential in-flight workload. *Space Operations, Applications, and Research Proceedings* (pp. 466-473). Sepulveda VA Medical Center: NASA Conference Publication.

Sterman, M. B. (1993). Application of quantitative EEG analysis to workload assessment in an advanced aircraft simulator. *Proceeding of Human Factors Society*.

Stevens, R., & Casillas, A. (2006). Artificial neural networks. In R. E. Mislevy, D. M. Williamson, & I. Bejar (Eds.), *Automated scoring* (pp. 259-312). Lawrence Erlbaum.

Stevens, R., Johnson, D. F., & Soller, A. (2005). Probabilities and predictions: Modeling the development of scientific competence. *Cell Biology Education*, *4*(1), 42-57.

Stevens, R., & Palacio-Cayetano, J. (2003). Design and performance frameworks for constructing problem solving simulations. *Cell Biology Education*, *2*(1), 162-179.

Stevens, R., Soller, A., Cooper, M., & Sprang, M. (2004) Modeling the development of problem solving skills in chemistry with a web-based tutor. In J. C. Lester, R. M. Vicari, & F. Paraguaca (Eds), *Intelligent tutoring systems* (pp. 580-591).

Stevens, R., Wang, P., & Lopo, A. (1996). Artificial neural networks can distinguish novice and expert strategies during complex problem-solving. *Journal of the American Medical Informatics Association*, *3*(2), 131-138.

Team Neurodynamics

by The
Learning Chameleon, Inc.