Testing a Complex Training Task

Frank E. Ritter[†] **(frank.ritter@psu.edu)**
Farnaz Tehranchi[#] **(farnaz.tehranchi@psu.edu)**
Mat Brener[†] **(mib5292@psu.edu)**
Shan Wang[†] **(sxw820@psu.edu)**
† College of Information Sciences and Technology
# Department of Computer Science and Engineering
Penn State, University Park, PA 16802 USA

Keywords: Cognitive model; Cognitive architecture; Learning and retention curves; Complex task.

Introduction

Figure 1 shows a learning theory based on reviewing multiple learning theories (Kim, Ritter, & Koubek, 2013). This figure shows that learning (curve 1) follows a power law as the learner goes through a declarative stage, a mixed stage, and a procedural knowledge stage.

Retention follows three different curves as well. Retention in the declarative stage (curve 2) falls off fairly rapidly. Retention in the mixed stage (curve 3) falls off less rapidly, and in the procedural stage retention falls off (curve 4) much more slowly. These curves differ because of the three (or two) types of knowledge decay at different rates, with procedural knowledge most robust against decay. These curves have been matched by an ACT-R model of a complex spreadsheet task (Ritter, Tehranchi, & Oury, 2019).

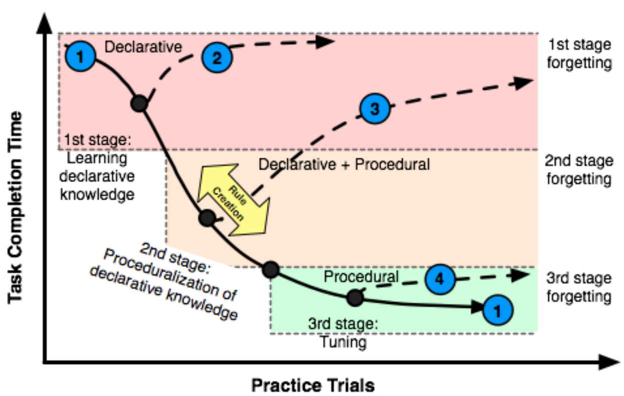

Figure 1. The KRK learning theory in a graph.

To test this set of curves, we needed a complex task that could be learned in an hour but productively practiced for several hours. We also wanted it to be related to troubleshooting and be instrumented.

We considered the Klingon Laserbank Task (KLBT) that has been used to study learning (Bibby & Payne, 1993; Friedrich & Ritter, 2009; Kieras & Bovair, 1984; Ritter & Bibby, 2008), but in 20 trials it can be done in under 10 s by most subjects. We report here a more complex task and an initial test of it.

The Ben-Franklin Radar Task

Ben Bauchwitz for a separate project found a radar that could be made by hobbyists. We modified its schematic to be similar to the KLBT but more complex. The schematic and interface are shown in Figure 2. This device has 36 components compared to the KLBT's 7 components. Colleagues at Charles River Analytics created it as a Unity program.

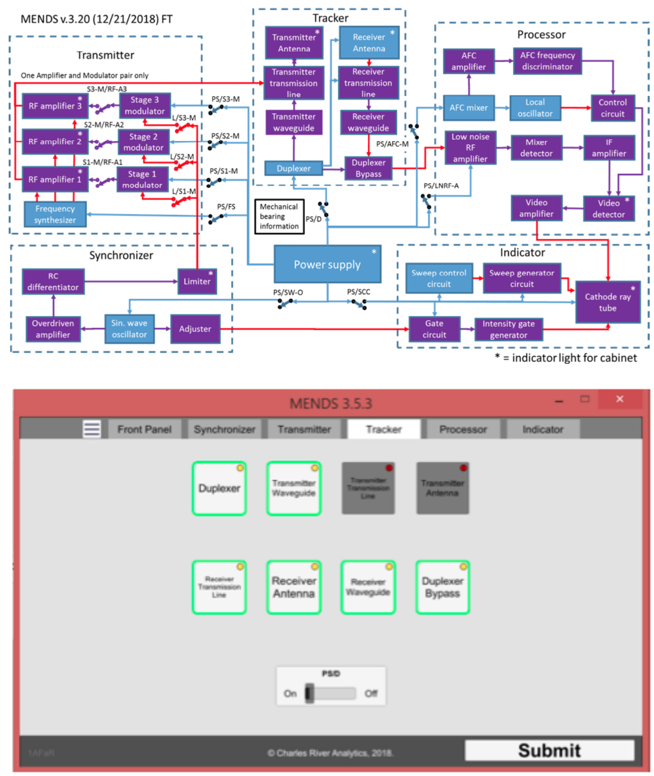

Figure 2. The Ben-Franklin Radar schematic (top) and interface (bottom).

Method

Subject

We had one subject, a 24-y.o. female, first-year master's student, with a BS in Psychology and Mathematics, without any engineering background. She had not seen the schematic before the study.

Materials

Materials included: a printed schematic, the simulation, a D2P2 tutor (Ritter et al., 2013) to teach them both; 1-fault problems for practicing with and without feedback; and 10 recall and 10 recognition questions. The tutor explains each subsystem and guidelines that teach how to do troubleshooting based on the Navy's 6-step troubleshooting approach with example practice problems.

Design and Procedure

In each session, the subject used the tutor and interacted with practice problems for 45 min. In the first four sessions (days 1 – 4), the subject had five minutes to study the printed schematic and then five minutes to draw it from memory. Next, the subject went through the tutor and solved practice scenarios with feedback. At the end of each session, the subject answered the schematic recall and recognition questions and then solved 5 problems. In the fifth session (day 14), the subject answered 10 recognition, 10 recall questions, and 20 troubleshooting questions without feedback.

Results

The subject was able to complete the task and got quite rapid in her responses. Figure 3 shows that over Sessions 1 to 4 her average time for the test problems dropped from 57.5 s to 10.7 s. After a 10 day delay in Session 5, her average time on the first 5 test problems was 13.0 s and on all 20 test problems was 7.9 s. (Her times within sessions followed a learning curve.) Her error rate was consistently low, 4%.

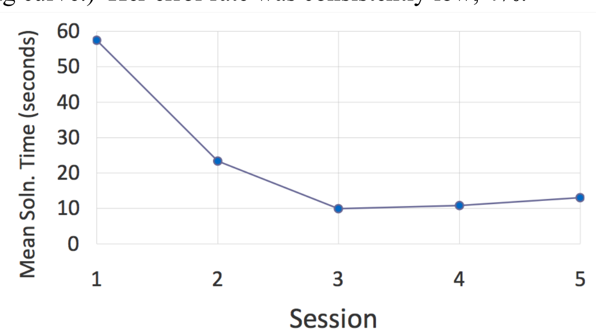

Figure 3. The learning curve for troubleshooting a fault by session (days 1 – 4). Session 5 is the retention test at day 14.

We can see several things from Figure 3. After one practice session, the task was doable and the time to find a fault was about a minute. The task time after three hours of practice also showed that the performance time did not decrease beyond the KLBT task times with 20 practices, so this task is much more complex initially, but approachable and learnable. Compared to the KLBT, the Ben-Franklin Radar task was about 3 times slower in the first test, but after practice, was about the same amount of time.

Another aspect is that the learning curve in sessions 1-4 approximated curve 1 in Figure 1. So, this task might be useful for studying learning and retention.

We saw that after a 10-day break between session 4 and 5, the subject's response time in the 5 test problems did not increase much (as per curve 4, Figure 1). If all 20 test problems are used, however, the average time actually decreased further to 7.9 s. This was on problems without direct feedback (but the interface did provide some indirect feedback). Further examination showed that the trial times kept improving over the 20 problems. So, to study retention of the procedural knowledge, 10 days was just enough to allow forgetting after 4 hours of study—if you do not ask too many questions! This suggests that including a larger number of test trials even without feedback leads to learning in this task, and might not be desirable in a larger study.

Conclusion and Further Research

We found that the task appears to support this study and found some limited support for the theory. We will be running more subjects to test the learning and retention theory.

Acknowledgments

This work was funded by ONR (N00014-15-1-2275). We wish to thank Ben Bauchwitz, Chungil Chae, Cesar Colchado, Josh Irwin, James Niehaus, Billy Manning, Ashley McDermott, William Norsworthy, Jr., Sarah Stager, and Peter Weyrauch for their assistance with developing the experiment. They can be seen as co-authors as well if there was space. Pooyan Doozandeh, Raphael Rodriguez, and Martin Yeh provided useful comments.

References

Bibby, P. A., & Payne, S. J. (1993). Internalisation and the use specificity of device knowledge. *Human-Computer Interaction, 8*, 25-56.

Friedrich, M. B., & Ritter, F. E. (2009). Reimplementing a diagrammatic reasoning model in Herbal. In *Proceedings of ICCM - 2009- Ninth International Conference on Cognitive Modeling*, 438-439. Manchester, England.

Kieras, D. E., & Bovair, S. (1984). The role of a mental model in learning how to operator a device. *Cognitive Science, 8*, 255-273.

Kim, J. W., Ritter, F. E., & Koubek, R. J. (2013). An integrated theory for improved skill acquisition and retention in the three stages of learning. *Theoretical Issues in Ergonomics Science, 14*(1), 22-37.

Ritter, F. E., & Bibby, P. A. (2008). Modeling how, when, and what is learned in a simple fault-finding task. *Cognitive Science, 32*, 862-892.

Ritter, F. E., Tehranchi, F., & Oury, J. D. (2019). ACT-R: A cognitive architecture for modeling cognition. *Wiley Interdisciplinary Reviews: Cognitive Science, 10*(3), Paper e1488.

Ritter, F. E., Yeh, K.-C., Cohen, M. A., Weyhrauch, P., Kim, J. W., & Hobbs, J. N. (2013). Declarative to procedural tutors: A family of cognitive architecture-based tutors. In *Proceedings of the 22nd Conference on Behavior Representation in Modeling and Simulation*, 108-113. Centerville, OH: BRIMS Society.