The Roles of Modeling, Microanalysis and Response Strategy in a Skill Acquisition Task

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Abstract

Researchers (see Siegler, 1987; Newell, 1973) have demonstrated the dangers of aggregating data over strategies. In this paper, we provide a current demonstration of this point using our recent work in the study of cognitive skill acquisition as a case study. Moreover, we call particular attention to the relation between cognitive modeling and microanalysis as driving forces toward a more thorough understanding of the role of strategies in cognitive skill acquisition.

Overview

We begin by reviewing the general results of our prior skill acquisition research. Following this summary, we put forth the rationale for performing a microanalysis of these data, which describes our latest effort at modeling skill learning in the experimental paradigm introduced in Anderson and Fincham (1994) and extended in Anderson, Fincham and Douglass (1997). We describe the main results of our microanalysis and finally conclude with a discussion of the importance of performing such analyses in this domain, particularly with regard to the research problem that emerges when multiple strategies, both within and between subjects, can be employed in a particular task.

Background

Anderson & Fincham (1994) and Anderson, Fincham & Douglass (1997) introduced a paradigm designed to understand the process and time course of skill acquisition. At issue in this work were two seemingly opposing theories of skill acquisition. One view was that the transition to skilled performance in a task progressed from the use of abstract rules to a reliance on retrieval of specific instances (Logan, 1988; Logan & Klapp, 1991). The other view characterized the development of skill as progressing from initially using examples to the development and use of abstract rules (Anderson, 1993). Anderson, et al. (1997), proposed a theory that is essentially a melding of these two views. The proposal describes a four stage model of skill acquisition. These (unordered, possibly overlapping) stages, ordered by increasing efficiency, characterize skill acquisition as attributable to the use of (a) analogy to examples, (b) declarative abstractions, (c) procedural rules and (d) retrieval of examples. While this four stage theory seems to be a reasonable qualitative account of the data, our goal is to elaborate the theory with a more quantitative account.

Modeling and Microanalysis Motivation

The goal of our current work is to generate a well specified, mechanistic account of the transition that occurs when moving from the novice level toward the skilled level of performance in our skill acquisition task. In particular, our intent is to develop a simulation model for the above described paradigm using ACT-R (Anderson & Lebiere, 1998; Anderson, 1993), a general cognitive modeling architecture. Developing a mechanistic account of this transition process serves several purposes. First, it is proof in principal that the qualitative account outlined above can be described by and achieved through a more formally specified process. Second, it allows us to quantify the theory in such a way that we can then use the model to make specific, testable predictions about behavior in novel tasks. Third, we hope that the modeling effort will provide additional insight into the underlying mental processes that are involved in the skill acquisition process. Finally, the act of generating the model should provide insights into subtle nuances that may exist in this specific task or within the ACT-R modeling architecture. In essence, the devil is in the details.

Serendipitously, we had recorded detailed individual mouse clicking data from Experiment 2 in Anderson, et al. (1997). In order to facilitate modeling our skill acquisition task at the atomic level of granularity outlined above, the heretofore dormant mouse clicking data were analyzed. In what follows, we will outline the general method for our task and present new results that this phase of our efforts has yielded. To foreshadow, we have found that participants employ multiple strategies when performing this task. Upon doing separate analyses for the two most common strategies, we have managed to (1) provide more compelling empirical evidence for two components of the proposed stage theory of skill acquisition and (2) identify at the mouse click level what we believe to be the atomic components involved in the execution of the task.

The Task

In the first part of these experiments participants commit to memory 8 specific facts such as "Skydiving was practiced on Saturday at 5 PM and Monday at 4 PM." Although participants were not informed of it at the time, they were learning examples of eight different rules about the time relationship between the two events for each sport. In the current example, the rule is that the second skydiving event always occurs two days later and one hour earlier than the first skydiving event. We denote this rule as "+2,-1". After successfully memorizing these eight examples, participants were told of the nature of the underlying rules associated with each sport. Participants were then tested with novel problems over a period of five days in an interface like that illustrated in Figure 1. Participants were given either the first or second time (day and hour) and had to compute the other time using the rule associated with the given sport. Figure 1 shows a training trial where the skydiving stimulus is the first time (Friday at 3) and they would have to predict that the target was Sunday at 2. They made their prediction by clicking the relevant buttons in the boxes below. We were interested in the speed and accuracy with which they could do this. The example in Figure 1 involved going from the first time to the second time but Anderson and Fincham (1994) trained participants on 8 sports and half of them involved going from the second time to first time. On each of the five days, participants practiced 8 rules 32 times each in one direction (four with the times presented on the left hand side of the display and four presented with the times on the right hand side). Two of these rules were then tested in the other ("unpracticed") direction (also 32 times each) beginning on day 2, two more starting with day 3, two more starting with day 4, and the final two starting on day 5. We were interested in whether participants would be faster in the more practiced direction. We found more asymmetry (a greater latency advantage for rules in the more practiced direction) for rules that were reversed after more practice in one direction.

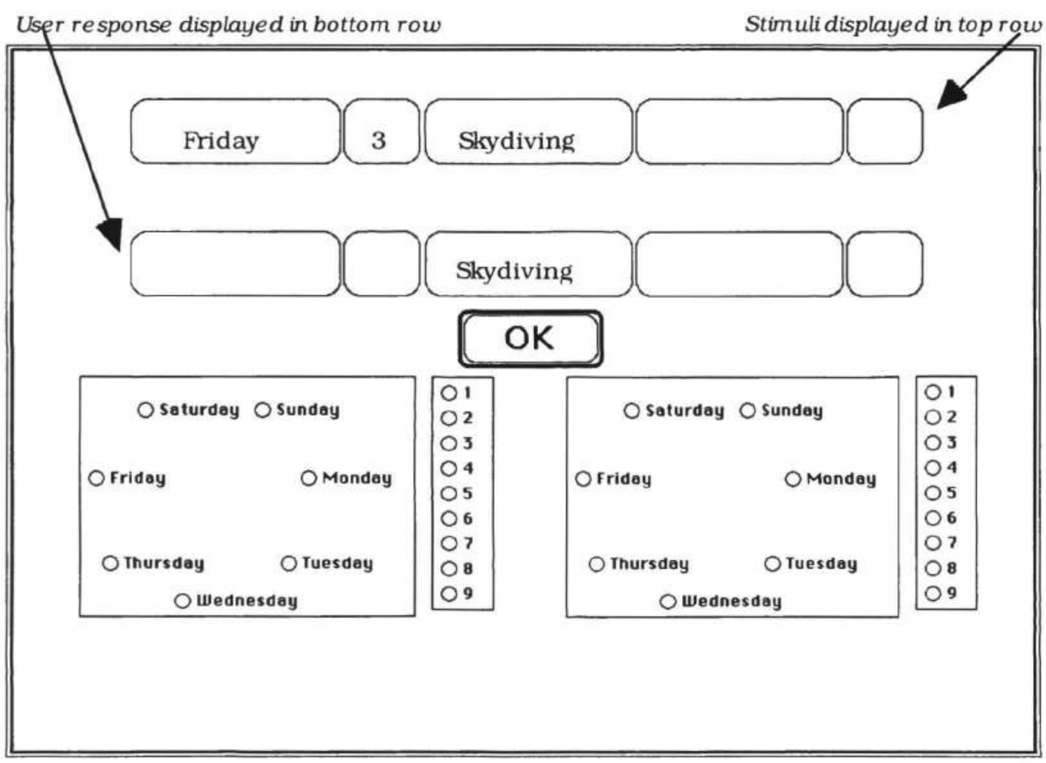

Figure 1. User interface for Anderson & Fincham skill acquisition task.

Table 1. Strategy counts as determined by response mouse click sequence for stimuli presented on the left side and right side of the display. The labels A, B, C and D represent responses of the leftmost day, leftmost hour, rightmost day and rightmost hour in the experimental interface, respectively.

Response Strategy	Ss	Left Side (A B S x x)	Right Side (x x S C D)
ST (stimulus then target)	16	ABCD	CDAB
LR (left side then right side always)	8	ABCD	ABCD
DH(st) (days then hours, stim side first)	1	ACBD	CADB
DH(lr) (days then hours, left side first)	4	ACBD	ACBD
HD(lr) (hours then days, left side first)	1	BDAC	BDAC
ST(fast) (stimulus then target, efficient mousing)	2	ABCD	DCBA
Other	15	----	----
Total	47		

Response Strategies

Using their detailed mouse clicking data, participants were classified according to the predominant response strategy they employed. The classification was performed by examining the mouse clicking patterns they exhibited on the final day of the experiment. The classification criterion for a particular strategy was that the mousing sequence was consistent for at least 80% (Siegler & Taraban, 1986) of the trials for each of the eight rules in both directions. Table 1 shows the result of this classification scheme. Remember that participants were required to fill in all four cells in the user response row (see Figure 1). Consider, for example, the response sequence we refer to as the Stimulus to Target (ST) strategy in Table 1. When employing this response strategy, participants move the mouse to the location of the stimulus, click the radio-buttons to copy the givens and then move to the opposite side of the display and enter the target transformation. Thus, when the stimulus was presented on the left, they would respond by clicking the leftmost response buttons to copy the givens followed by movement to the right side of the display and clicking the rightmost response buttons to indicate the target transformation (click sequence ABCD in the table). Conversely, when the stimulus was presented on the right, they would respond by clicking the rightmost response buttons to copy the givens followed by movement to the left side of the display and clicking the leftmost response buttons to indicate the target transformation (click sequence CDAB in the table).

The predominant response strategy was the above described ST strategy with 16 of the 47 participants using this method. The second most popular strategy (8 Ss) was the Left to Right (LR) strategy whereby participants consistently entered responses in a strictly left to right order across the display, independent of the location of the stimulus.

In order to demonstrate the importance of discovering varied strategy use by our participants, we will now present a small subset of the analyses of the two predominant strategies within the context of specific issues raised in our earlier work.

Directional Asymmetry

We have previously argued (Anderson, et al., 1997) that the emergence of a directional asymmetry in response latency is evidence for the formation of production rules, stage (c) in our skill acquisition model. In our previous work, we have shown that indeed there exists a directional asymmetry between practiced and unpracticed rules. Overall, sports tested in the more practiced direction were on average slightly (250ms) faster than when tested in the less practiced direction. While this was a significant effect, we noted that indeed it seemed relatively small.

However, we have in the past ignored the possibility of the existence of the multiple response strategies that we have currently identified. Thus, we inadvertently averaged over these strategies when performing our analyses. To correct for this problem, we have reanalyzed the latency data of the current experiment.

A repeated measures ANOVA with a single between factor of strategy (ST or LR) and within factors of day (4) and practice (practiced and unpracticed direction) was performed. There was no main effect of strategy, $F(1,19) = 1.47$, $MSE = 62.95$, indicating there is no overall latency advantage for one strategy over another. More interesting is the fact that strategy interacted only with practice, $F(1,19) = 5.05$, $MSE = 2.97$, $p<0.05$. As can be seen in Figure 2, the LR strategy shows no latency difference when applying rules in the practiced versus unpracticed direction. On the other hand, the ST strategy shows a clear asymmetry between the practiced and unpracticed directions, with the rules in the practiced direction showing about a 470ms advantage over rules in the unpracticed direction.

At first blush, it is curious that the LR strategy did not exhibit the predicted asymmetry between practiced and unpracticed rules. Yet another examination of the data sheds some light on this issue. Of the eight LR participants, only two of them adopted the LR strategy consistently from the onset of the experiment, while all ST participants

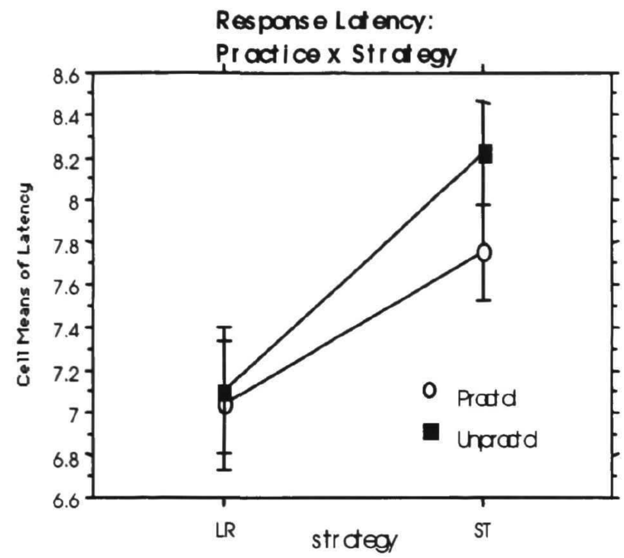

Figure 2: Response latency as a function of practice and strategy.

consistently applied their strategy throughout the experiment. In fact, it was not until the last day of the experiment that the remaining six LR participants consistently applied the strategy. Over the course of the experiment, these participants gradually changed their strategy choice from an initial ST strategy to a mixture of both ST and LR and finally entirely to the LR method. We take this then as further evidence that proceduralization goes hand in hand with asymmetry of access. Given that most of the LR group were inconsistent in their strategy choice, they were unable to develop proceduralized embodiments of the declarative versions of the rules they were applying and hence the corresponding lack of asymmetry exhibited in the latency data.

It seems clear that by taking the role of strategy into account we have managed to obtain much stronger evidence for, given substantial practice, the formation of production rules that encapsulate specific, directional transformations, stage (c) of our skill acquisition model.

Localization of Learning

To get to the heart of the atomic components involved in this task, we performed a repeated measures ANOVA of the latency data for the individual mouse clicks of user responses. This analysis allows us to examine the mouse click response profiles within strategy. Factors are day (4), practice (practiced versus unpracticed direction), mouse click sequence (ABCD or CDAB, see Table 1) and click position (first through fourth). We will only consider the data from the ST subjects here.

As we have noted, the mouse click response profile is of particular interest for the present discussion. There was a significant main effect of click position, $F(3,39) = 43.57$, $MSE = 165.95$, $p<0.0001$. Figure 3 displays this result.

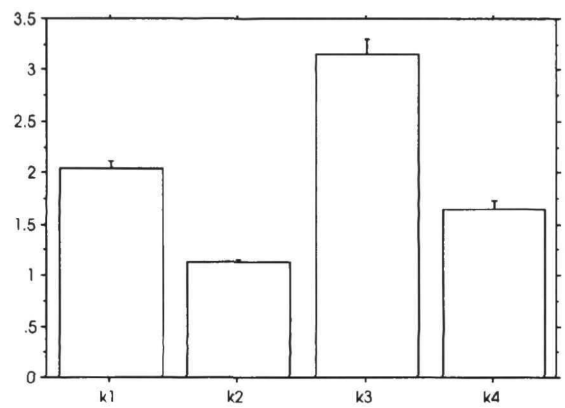

Figure 3: Mouse click latency as a function of position for the ST strategy.

The first mouse click latency corresponds to the time it takes for ST participants to orient to the stimulus and copy the given day. The second item corresponds to the copy hour operation. We see that the third item in the response carries with it the greatest latency. This is where the participant must compute and respond with the appropriate day transformation. Finally, the fourth item is where the participant must compute and respond with the appropriate hour transformation.

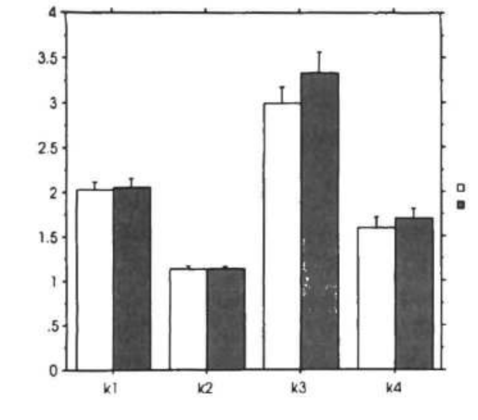

Figure 4: Mouse click latency as a function of mouse click position and practice for the ST strategy.

Note there is a subtlety here that is not necessarily obvious. Because there are two distinct mousing sequences within the ST strategy (ABCD and CDAB), we aggregated the mouse clicking data into these categories. Had we not done so, we would have missed the clear effects we have demonstrated in the mouse click response profile.

Where is the asymmetry?

There were significant interactions between practice and mouse click position, $F(3,39) = 8.87$, $MSE = 0.36$, $p<0.0001$, and between mouse click sequence and click position, $F(3,39) = 12.98$, $MSE = 1.20$, $p<0.0001$. These are shown in Figure 4 and Figure 5, respectively.

Figure 4 shows that the latency advantage for practiced over unpracticed rules reported earlier (470ms) is almost entirely driven by the third mouse click in the response sequence. Given that the third mouse click corresponds to the computation required for performing the target transformation of the day (and possibly the hour as well), we have further converging evidence that this computation has been proceduralized as per stage (c) of our skill acquisition model.

Figure 5 shows that a speed advantage for moving left to right in the response sequence is also almost entirely driven by the third mouse click in the response sequence. This is due the fact that when processing the right side of display first, the mouse must be moved from the far right of the display to the far left of the display to enter the target response.

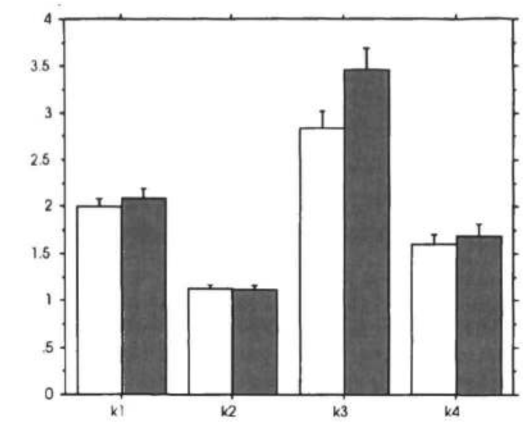

Figure 5: Mouse click latency as a function of mouse click position and response sequence (ABCD vs. CDAB) for the ST strategy.

By virtue of examining the mouse clicking data, we have discovered several previously unknown features of this particular task. The general response profile is consistent with a task analysis enumerating the procedure for solving these problems using the ST strategy, thus constraining potential models of the task. Further, we have identified the third mouse click as the predominant source of the procedural asymmetry result. Finally, we have also identified a potential problem with the current user interface employed in our skill acquisition paradigm. It simply takes longer responding from right to left across the display when compared to moving in the left to right direction when using the ST strategy.

Conclusions

We have provided here only a very small window into our efforts at generating an ACT-R model of learning in our skill acquisition task. Through this window, we hope to have shown that there is a symbiotic relationship between modeling, microanalysis, theory and empirical research methods. Indeed, the importance of this interrelationship has been characterized by others as well (Carpenter & Just, 1999).

The goal of constructing a quantitative model served as the impetus to perform a microanalysis of the task at hand. In so doing, we discovered a plethora of previously unconsidered strategies. Because we were inadvertently averaging over these strategies, we attenuated effects in support of our general skill acquisition model. Finally, we have uncovered a potential problem with the interface used in our studies that also serves to attenuate the effects in which we are most interested.

As a result of this effort, we have been able to constrain our ACT-R model of this task. Further, this research has spawned another study in which we control for response strategy and eliminate potential problematic interface problems.

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