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HUMAN LEARNING OF SCHEMAS FROM EXPLANATIONS IN PRACTICAL ELECTRONICS

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Training materials in practical electronics appear to follow a building blocks approach in which common simple circuits are presented and then combined into more complex circuits. Each circuit is presented in the form of a circuit diagram and an explanation of how the circuit works in terms of a causal chain of events. Such materials suggest that learning electronics consists of learning schemas for the building block circuits; complex circuits can then be understood as combinations of these simpler schematic circuits. The process of learning appears to be based on extracting schemas from the explanations. This report presents human experimental results based on earlier artificial intelligence work in this project. Engineering students learned building block circuits and then learned complex circuits; the time required to understand the explanations and answer questions about the circuit behavior were compared to an AI system that learned from explanations and a model of question-answering. Generally, learning the schematic building block circuits facilitated performance, and the AI system and question-answering model could predict the amount of facilitation. However, the benefit of learning circuit schemas under these conditions was surprisingly mild.

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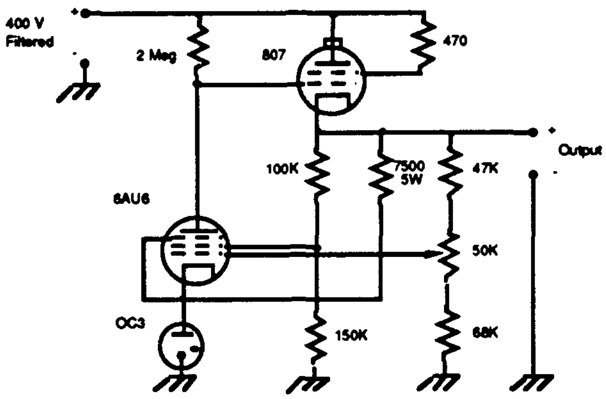
Abstract

Training materials in practical electronics appear to follow a building blocks approach in which common simple circuits are presented and then combined into more complex circuits. Each circuit is presented in the form of a circuit diagram and an explanation of how the circuit works in terms of a causal chain of events. Such materials suggest that learning electronics consists of learning schemas for the building block circuits; complex circuits can then be understood as combinations of these simpler schematic circuits. The process of learning appears to be based on extracting schemas from the explanations. This report presents human experimental results based on earlier artificial intelligence work in this project. Engineering students learned building block circuits and then learned complex circuits; the time required to understand the explanations and answer questions about the circuit behavior were compared to an AI system that learned from explanations and a model of question-answering. Generally, learning the schematic building block circuits facilitated performance, and the AI system and question-answering model could predict the amount of facilitation. However, the benefit of learning circuit schemas under these conditions was surprisingly mild.

Introduction

Explanations and Schemas in Electronics

Practical electronics textbooks, such as those used for training in the Navy (e.g., Van Valkenburgh, Nooger, & Neville, Inc., 1955), seem to be organized in terms of what can be called a *building blocks approach.* These textbooks present a series of circuit types, each of which performs a specific function, and which are then combined into more complex circuits. Each circuit is introduced with a diagram and explanatory text; the text typically explains how the circuit performs the stated function. Often the explanation takes the form of a causal chain of events that starts from some perturbation to the circuit, such as a change in the input signal, and finishes at a statement of the desired effect. Figure 1 gives an example of such a circuit and a fragment of the explanatory text from *The Radio Amateur's Handbook* (1961) .



When the load connected across the output terminals increases, the output voltage tends to decrease. This makes the voltage on the control grid of the 6AU6 less positive, causing the tube to draw less current through the 2-megohm plate resistor. As a consequence the grid voltage on the 807 series regulator becomes more positive and the voltage drop across the 807 decreases, compensating for the reduction in output voltage.

Figure 1. A sample circuit, a voltage regulator, and excerpt from the explanatory text.

These building blocks constitute *schemas* – each is a basic, frequently appearing unit; complex circuits can be analyzed into a hierarchy of these simpler circuits. The learner is supposed to learn each circuit schema by understanding its explanation, and then is expected to apply this new schema to understanding the subsequent more complex circuits. As an example of how more complex circuits can be viewed in terms of circuit schemas, Figure 2 shows a complex circuit parsed into schematic subcircuits. The behavior of this circuit as a whole can be understood by combining the behaviors of each of the schematic subcircuits.

The process of learning from such materials seems to be naturally explained in terms of how schemas are learned and applied, and how learning them can be done from explanations. Thus, this domain is a natural place to apply the concepts of schemas and explanation-based learning as they have appeared in psychology and in artificial intelligence.

The circuits studied in this work have been DC vacuum tube circuits, such as that shown in Figure 1. These are a good choice because: (1) They are well documented – this is a thoroughly mature technology with considerable instructional material having been written. (2) At this time vacuum tubes are unfamiliar to even technically sophisticated college students, so prior knowledge on the part of experimental subjects is less of a problem. (3) The DC circuits are very simple; circuits involving alternating current and multiple-state devices such as capacitors and inductors are much more complex (See Mayer, 1990).

Judging from these training materials, research on such materials has value both for instruction and AI. The schematic building blocks approach must be instructionally important; there must be a shared belief that this is a good way to convey technical content. If we could understand how people learn from this approach, we could make better choices of the content and sequence of building blocks. There is also a possibility of automated knowledge acquisition for building AI knowledge bases. That is, considerable technical knowledge is already in textbooks which are complete enough for humans to learn technical domains from this material from explicit instruction. It is possible that large knowledge bases for AI systems could be constructed by developing mechanisms to read and understand such textbook knowledge.

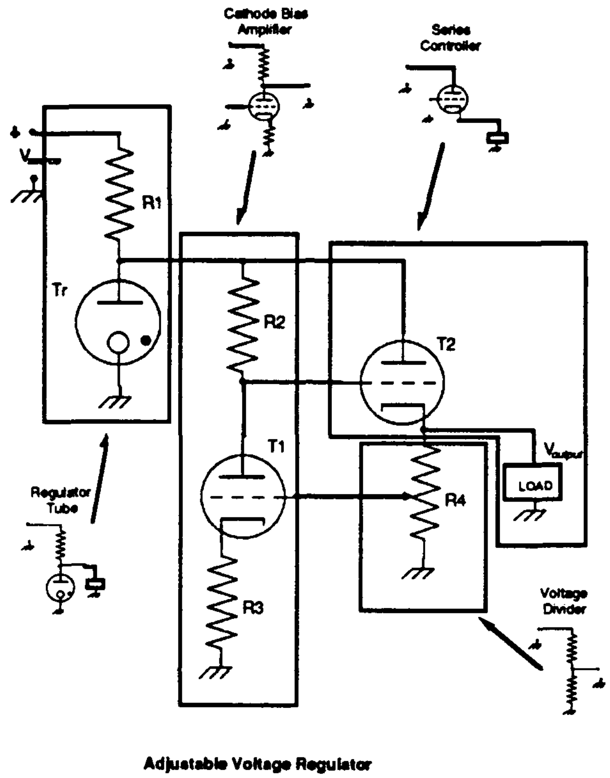


Figure 2. An analysis of a complex circuit in terms of schematic building block circuits. The basic form of each circuit schema is shown.

The goals of the project responsible for the work in this report were (1) to develop a simple AI system that learns from diagrams and text, and (2) compare it to human learning performance. The ultimate goal was to go on to explore the effects of the choice of content and sequence of explanations, but as will become more clear below, experimentation in this domain is very difficult, and some of the basic premises of this kind of learning can be called into question.

An AI System for Learning Schemas from Explanations

The AI system was developed by John Mayer as his dissertation (Mayer, 1990). Figure 3 shows the system organization and processing in Mayer's system. The AI system will not be described in detail because it is very thoroughly documented in Mayer (1990). The system is a combination of standard approaches to text comprehension, common sense reasoning, schema instantiation and construction, and explanation-based generalization. The AI system processes explanations using schemas, and then forms a schema for the new circuit described in the explanation.

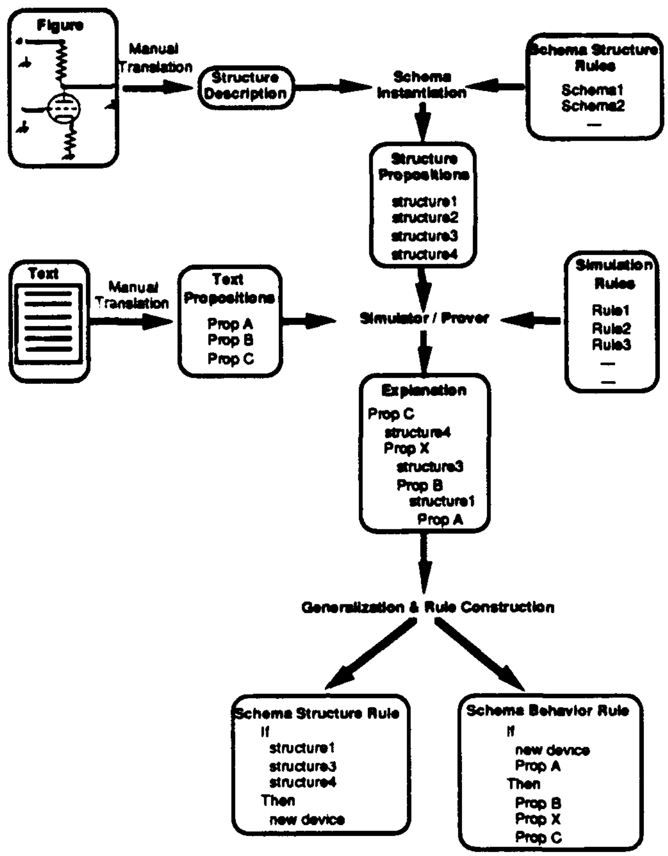


Figure 3. Organization and processing of Mayer's AI system for learning circuit schemas from diagrams and text.

The basic idea underlying the AI system is that an explanatory text constitutes an incomplete proof that the circuit performs the stated function. The explanation is a proof in the sense that it states a chain of causally-related events that concludes with the desired circuit behavior. The proof is incomplete because the explanation typically does not spell out each link in the causal chain that lies between the initial perturbation and final effect that corresponds to the circuit function; some of the intervening steps in the chain have been left out. Comprehending such a text thus consists of completing the proof, and learning from the text consists of generalizing the proof to extract a new schema for the circuit. The schema consists of two rules: one is a *structure rule* for when and how to instantiate the schema, based on the structure of the circuit; and the other is a *behavior rule* for how the schematic circuit behaves, given a triggering event. In Mayer's system, the first event described in the explanation is used as the trigger condition of the behavior rule. When this event happens, the rule is fired, and asserts all of the subsequent behaviors that appeared in the original explanation.

System processing. The process is shown in Figure 3. The system is presented with a diagram and the explanatory text. The diagram information consists of a hand-translated propositional description of the structure of the circuit. The schema instantiation process matches previously known schemas against the structure description and instantiates the appropriate schemas. The final result is a set of propositions about the circuit structure. The text information consists of hand-translated propositions about events in the circuit, listed in the order of appearance in the text. The simulator/prover component takes each text proposition and proves its truth in the circuit structure using the simulation rules. The simulation rules are either first-principle rules in the domain theory of basic electricity and electronics, or schema behavior rules from previously learned schemas. The simulator/prover does a forward simulation of the state of the circuit until it arrives at an event described by the circuit that matches the event described by the input text proposition. Then it moves on to the next input proposition, and repeats the process. When it has matched the last proposition in the text, the explanation has been completed. As shown in Figure 3, the simulator/prover may have had to infer other propositions to complete the proof, such as proposition X, which intervenes between the text propositions B and C.

The explanation is then used in a generalization process to arrive at the new structure and behavior rules. The schema instantiation rule is based on the portions of the circuit structure that were referred to in the proof. The behavior rule is formed by including the presence of the new schematic structure and the first event proposition (A) in the condition, and the assertion of all other event propositions (shown as B, X, and C) in the action.

Special properties of schema processing. It is important to note that the input and outputs of a schematic subcircuit are not distinguished, nor is the overall circuit strictly partitioned into the subcircuits. The substructure of the schematic circuit is still visible, and the simulation rule constructed for the schematic subcircuit contains all of the inferences made about the internal behavior of the schematic subcircuit. Thus, although the schema provides a short cut to the inferences about the circuit, reasoning from first principles can still go on, and behaviors internal to the schema can play a role in the reasoning.

The process of constructing the structure rule has a further important property. One function of an explanation in learning is to distinguish important features in the training instance from irrelevant ones. Thus, the only components included in a schema instantiation rule are the components that were referenced in the course of constructing the proof from the explanation. This principle had some odd effects in Mayer's system. The system recognized a cathode-biased amplifier as just the configuration consisting of R2 and T1 in Figure 4. As it happened, the original explanation of the cathode-biased amplifier schematic circuit did not involve the cathode resistor, which thus was not considered to be a mandatory component of a cathode-biased amplifier. In retrospect, this was probably not a good approach; a clearer picture of the nature of these circuits seems to result from taking the entire presented circuit as the structure of each schema. Mayer suggests that this approach would be justified by the fact that these circuits are designed to be economical, so each component that appears in the graphic accompanying the text must be necessary, regardless of whether the explanation contacts it or not.

Benefits of schema availability. Mayer's system learns each circuit schema in terms of the already-acquired schemas. If relevant schemas have been previously learned, learning a new circuit is faster because the event propositions in the text can be proved sooner. The schema behavior rules will immediately add all of the schema inferences to the explanation, resulting in an earlier match to the text proposition to be proven. Thus, instead of the system having to construct the causal chain step-by-step using first-principle rules, the schemas will skip ahead to the end results. Thus the proof can be arrived at more quickly, and the simulator/prover should do less processing when applicable schemas have been previously learned.

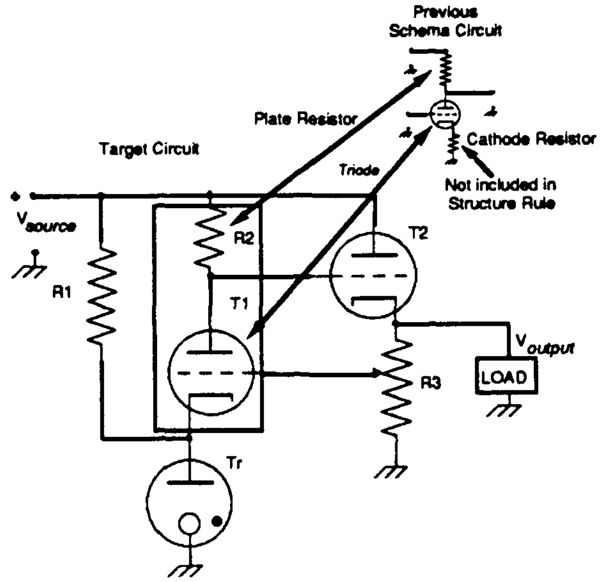


Figure 4. An example of how the AI system does not require a match of the complete building block circuit structure when instantiating a schema.

Mayer demonstrated such an effect of schema availability for the set of materials diagramed in Figure 5. Starting with a basic voltage divider schema, the system studied and formed schemas for the building block circuits of a triode amplifier, series controller, regulator tube circuit, and cathode-biased amplifier. Then it processed explanations for a set of *target* circuits: a two-stage amplifier, a basic voltage regulator, a stabilized voltage regulator, and an additional circuit, the vacuum tube voltmeter circuit. Compared to learning the targets without the building blocks, the processing effort on the target circuits should be less if the system has already learned the building block schemas.

Mayer considered different measures of processing effort, some of which are relevant to AI technology concerns, such as CPU time. Mayer found that in terms of CPU time, the pattern matching required to instantiate schemas can overwhelm the savings from the faster processing of explanations. In addition, since even if a schema behavior rule applies, the system still makes first-principle inferences, and so can end up doing more overall processing when the schemas are available, resulting in a longer run time than when they are absent. But Mayer also considered a psychologically relevant metric, the number of *cycles* of forward simulation that had to be done while processing the explanation. Under this metric, the AI system is very similar to a production-rule cognitive model; each cycle of simulation consists of applying all of the simulation rules, both first-principle and schema rules, to deduce one set of new inferences about the circuit state. In most psychological production system models, it is assumed that the conditions of all the rules are matched in parallel, and so having additional rules in the system does not slow processing down. Thus the number of cycles performed by the AI system is a measure of processing effort which is not sensitive to underlying details of the implementation, and resembles common cognitive theoretical measures of processing time.

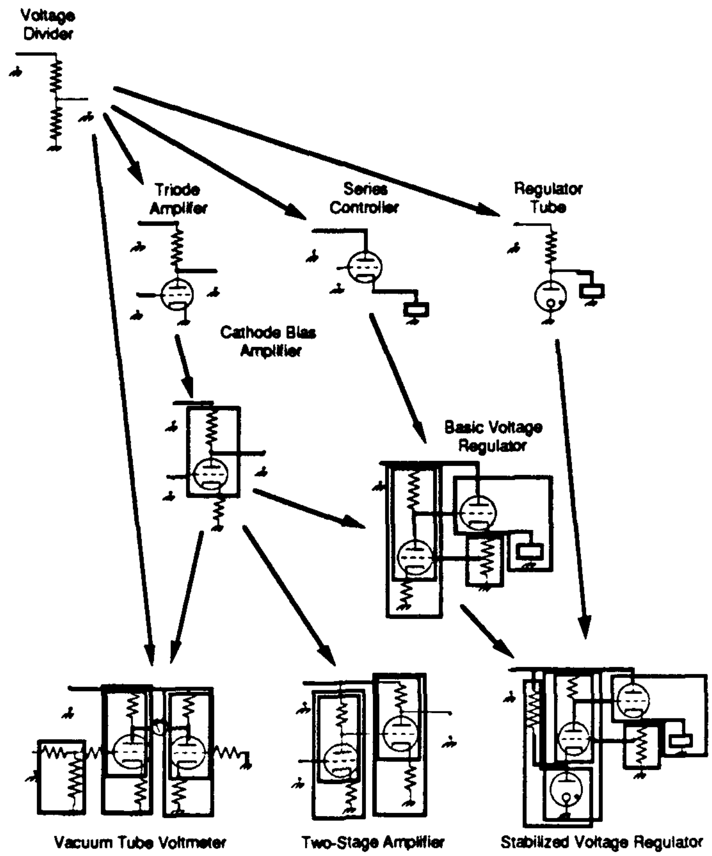


Figure 5. The schema relationships between circuits studied by Mayer and used in Experiment 1.

Figure 6 shows the number of cycles in the simulator/prover required to process the text event propositions for each of the target circuits. The voltmeter circuit is a special case in Mayer's system. The explanation of the voltmeter takes the form of two descriptions of a steady state, rather than a description of how a change propagates through the circuit. Mayer's system therefore verifies the text propositions using its rules for reasoning about voltage relationships (see Mayer, 1990) rather than verifying using the simulation rules. Thus Mayer's system always requires zero cycles of simulation to process this circuit.

But for the other three target circuits, the number of cycles is less when the schemas are available than when they are not. In addition, the system could learn a schema from the basic regulator circuit and apply it to the subsequent stabilized regulator circuit. Thus, the AI system can learn schemas from the explanations, and then can use these schemas to more quickly process future explanations.

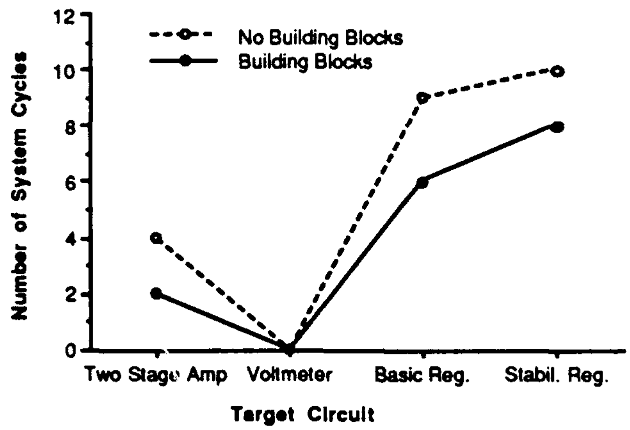


Figure 6. The number of cycles of processing needed by the simulator/prover to process each explanation.

Do Humans Use Schemas in Learning Electronics?

It helps the AI system to have schemas, at least measured in terms of a psychologically-relevant measure of processing effort. The psychological question is whether it helps people to have schemas. That is, can people understand the target circuits more easily if they have already learned the schematic building blocks? If so, the analysis of learning from these materials in terms of schematic building blocks would be verified, and the instructional value of the building blocks approach would be confirmed.

This question is especially relevant to the psychological theory of schemas. There has actually been very little evidence that schemas benefit acquisition processing, as shown by online measures, although this has always been claimed as an important advantage of schema knowledge (e.g., see Rumelhart, 1980; Rumelhart & Ortony, 1977). More generally, the basic claim that it is easier to learn about things one already has knowledge of is difficult to demonstrate (see Johnson & Kieras, 1983). But most of the empirical work demonstrating the use of schemas has been done in the context of recall or recognition paradigms. For example, subjects are asked to classify various stimuli, and then these classifications seem to be governed by schema or prototype representations. Or, subjects tend to make errors in memory for stories that are based on the assimilation of a story into a schema structure. But there are relatively few studies that actually demonstrate a benefit during online processing. For example, two such studies on reading comprehension time are Haberlandt, Berian, & Sandson (1980), and Graesser, Hoffman, and Clark (1980). Also, Kieras (1982) reported some results that suggest that devices seemed to evoke schemas immediately upon presentation, and subjects' descriptions of the presented device seemed to be organized in terms of schema knowledge for devices of that class. But clearly more evidence is needed that schematic knowledge has immediate processing time benefits.

Furthermore, it is not clear whether schematic knowledge can be effectively acquired and used in the time spans characteristic of classroom training of technical content. That is, within a single hour or a single day, which typically separates one lesson from the next, students are expected to form a schema for a particular type of circuit, and then are expected to apply this new knowledge to the next, more complex, circuit that they study. However, one common notion about schema knowledge is that it takes considerable exposure to develop a schema; this would accord with the general definition of a schema as being a *well-learned* familiar pattern or configuration of information. But the context of classroom study consists of brief, single, or few exposures to a concept, followed by its immediate use in a new context. The explanation-based learning work in artificial intelligence, and specifically Mayer's system, show that it is possible to acquire and make use of schemas in this single-exposure manner. But the question remains about whether this characterization is psychologically accurate. Two experiments will be described that seek to demonstrate a schema availability effect corresponding to that obtained by Mayer for the AI system.

Experiment 1

This first study was simply an attempt to determine whether providing building block information to learners would enable them to understand target circuits more readily. The experiment had three groups: the *No Building Blocks* group studied the target circuits without any prior study of the building blocks; the *Building Blocks* group studied the building block circuits before the targets; the *Descriptions* group studied the building block circuits and were given a description with the target circuits about how the schemas should be instantiated in the target circuits. The rationale for this third group was to ensure that these subjects not only know the schemas, but would also know how to apply them to the target circuits. After studying each circuit explanation, all subjects answered a set of multiple-choice questions about the circuit. The expected results were that learning and answering questions about the target circuits should be facilitated by having previously studied the building block circuits; the descriptions might produce further facilitation, depending on whether the Building Blocks subjects recognized and applied the schemas on their own.

Method

Materials and design. There were three groups. Each group studied the introductory training material. The No Building Blocks group then went directly on to study the target circuits. The Building Blocks and Descriptions groups studied the building block circuits and then went on to the target circuits. There was a deliberate confound of schema availability with the amount of practice (the number of circuits studied); this first study was simply to see if a schema availability effect would appear.

The DC vacuum tube circuit materials were based on actual textbook content, but were simplified in order to get a reasonable variety of circuits presented in a short amount of time. The training materials first reviewed the basic concepts of voltage, current, resistance, and voltage dividers, and then introduced the electronic components that were used in the circuits, such as resistors, variable resistors, voltage regulator tubes, and triode vacuum tubes. The building block and target circuits are shown in the Figure 7; the arrows connecting the circuits show how the circuits are assumed to be related in terms of their schema composition.

Accompanying each circuit was a diagram which was always present during reading, and two pieces of textual information. The first piece was an introduction that gave the name and the basic function of the circuit, the schematizing description (if appropriate), and the static facts about the circuit, such as voltage relationships which were constant. The second piece contained the explanation of the behavior of the circuit; this was a series of sentences that started with a perturbation to the circuit and continued through to the final behavior corresponding to the circuit function. Examples are shown in Figure 8, which shows a typical introductory screen for a building block circuit, and Figure 9, which shows an example building block explanation screen. Figure 10 shows the introductory screen for a target circuit, and Figure 11 shows the explanation screen for the same target circuit.

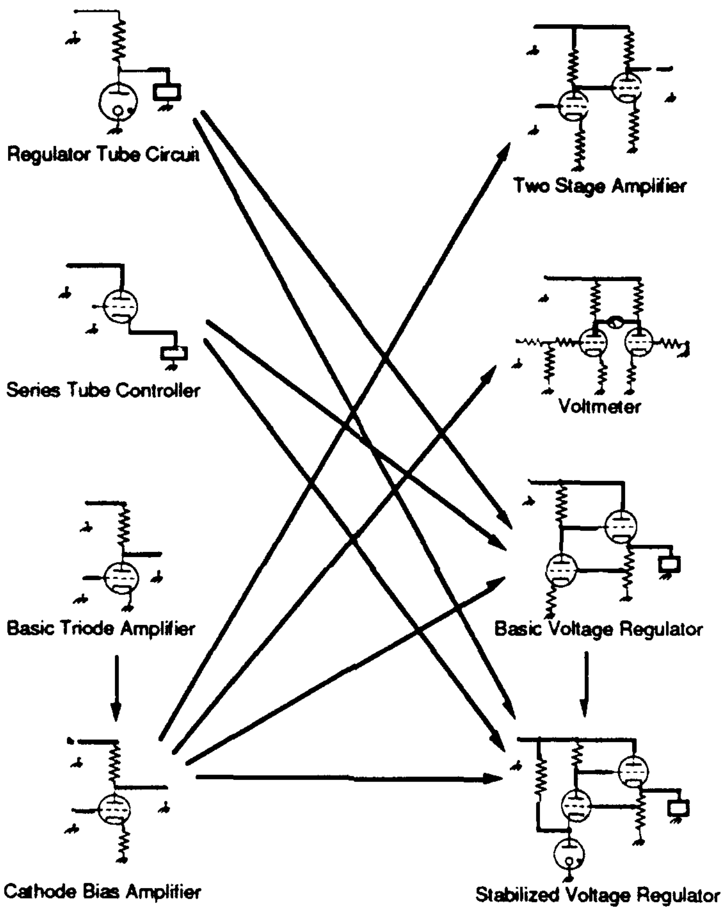


Figure 7. Circuits used in Experiment 1, with schema instantiation relationships. The building block circuits are on the left; target circuits on the right.

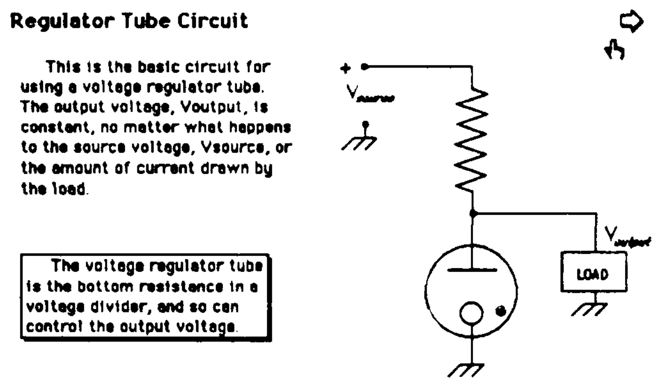


Figure 8. A sample introduction screen for a building block circuit.

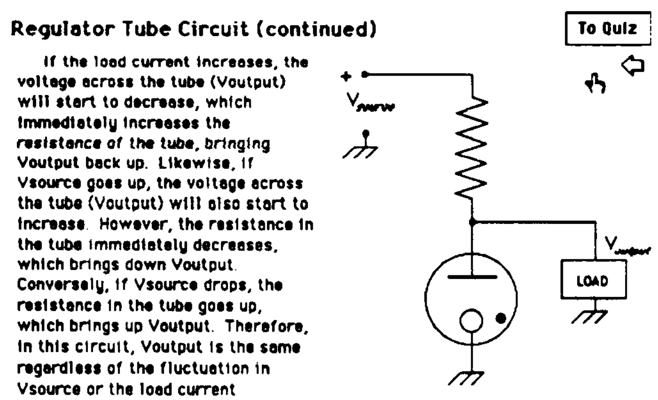
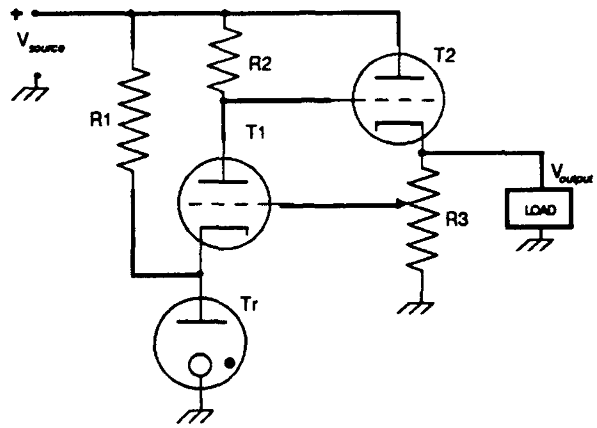


Figure 9. A sample explanation screen for a building block circuit.

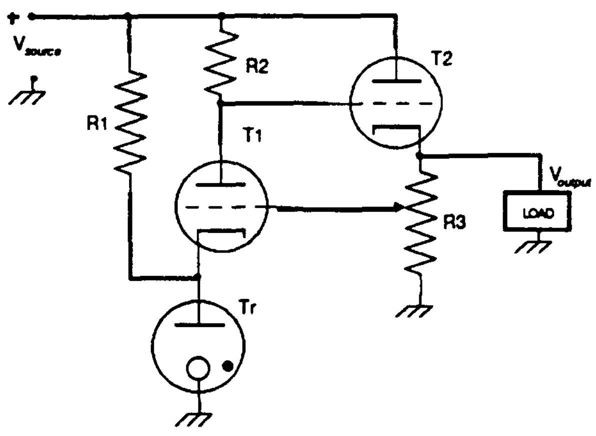


Stabilized Vacuum Tube Voltage Regulator Circuit

This circuit maintains a constant output voltage, regardless of changes in either the load current or the source voltage.

R1 and Tr form a regulator tube circuit. R2 and T1 is a cathode bias amplifier with Tr serving as the cathode resistor. T2 is a series controller tube. The output of the regulator tube circuit is used as the cathode bias voltage of T1. The output of the amplifier is the input for the series controller circuit. The input of the amplifier is the voltage across the load, reduced by the voltage divider R3.

Figure 10. An example target circuit introduction.



Stabilized Voltage Regulator Circuit (continued) | To Quiz |

If more current begins to flow through the load, the output voltage begins to decrease. This makes the voltage on the grid of T1 more negative relative to the cathode, causing less current to flow through T1. The grid of T2 then becomes less negative, decreasing the resistance of T2, and thus keeping the output voltage the same. If the load draws less current, the output voltage rises, and the opposite effects occur. The variable resistor R3 is used to set the circuit for the desired output voltage by changing the grid voltage of T2.

If the source voltage decreases, the output voltage and the voltage on the grid of T1 will start to decrease. However, the voltage on the cathode of T1 is kept constant by the voltage regulator tube Tr. Thus, the grid of T1 will become more negative relative to the cathode, causing the grid of T2 to become less negative, and the output voltage to remain constant.

Figure 11. A sample explanation for a target circuit.

Subjects. The subjects were engineering students without specific electronics coursework, but with background in electricity concepts. They had taken at least one physics course, and so were familiar with the basic concepts of voltage, current, resistance, electron flow and so forth, but they had not taken any courses specifically on electronic circuits. It was very difficult to selectively recruit such subjects; eventually eighteen in each of the three groups were obtained. Subjects were randomly assigned to groups.

Equipment. The experiment was run on a Macintosh computer running SuperCard (a HyperCard-like program) on a two-page display. The first nineteen of the subjects were run using an ordinary Macintosh Plus computer; due to the small screen, the larger diagrams were on paper and constantly available to the subjects. The remaining subjects were run with a Macintosh IIx with a two-page display, with the circuit diagrams constantly present on the screen.

Procedure. The materials were divided into a series of segments in which subjects would study the material and then answer a set of quiz questions. They would go on to the next segment if they got all questions correct, or go back to reread the segment if not. This was intended to ensure that subjects understood the material before they went on. The initial material on basic electricity and each component consisted of several segments, and each of the building block and target circuits was a separate segment. The computer software recorded how long the subjects studied the introductory screen and the explanation screen for each target circuit, and the latency and answer to each question. The circuits were presented in a fixed order of increasing complexity, as shown in Table 1, which lists the training segments in the order presented. The experiment took 1 – 2 hours to complete.

Table 1
Order of Presentation of materials in Experiment 1.

- Basic electricity
  - Electricity, Current, Voltage
  - Ohm's Law
  - Voltages are Relative, Voltage Law
  - Representing Circuits with Diagrams
- Components
  - Resistors
  - Variable Resistor
  - Voltage Regulator Tube
  - Vacuum Tube Triode
  - Power Supplies and Loads
- Voltage Divider
- Building Blocks
  - Regulator Tube Circuit
  - Series Controller
  - Triode Amplifier
  - Cathode Bias Amplifier
- Target Circuits
  - Two-stage Amplifier
  - *Vacuum-Tube* Voltmeter
  - Basic Voltage Regulator
  - Stabilized Voltage Regulator

Results

Only data from the target circuits will be presented, because this is where the predictions of the AI system are relevant. Analysis of variance were computed for each measure. Due to the data being very noisy, few effects were significant at conventional levels.

Figure 12 shows the time spent studying the explanation screen on the first exposure, not including any time spent rereading the material after answering questions. This is the data that should be most related to the amount of processing done by the AI system. There appears to be a general decreasing trend with increasing schema availability, but the effect is statistically weak. The main effect of group in nonsignificant ($p > .3$), but is rather marginally significant if only the No Building Block and Description groups are compared ($F(1, 34) = 2.13$, $p = .15$). Generally, study of the building blocks resulted in faster reading, and the presence of the schematizing descriptions helped further. As confirmed by an individual t-test, the stabilized regulator is clearly much faster than the basic regulator, suggesting that there is transfer between these two circuits.

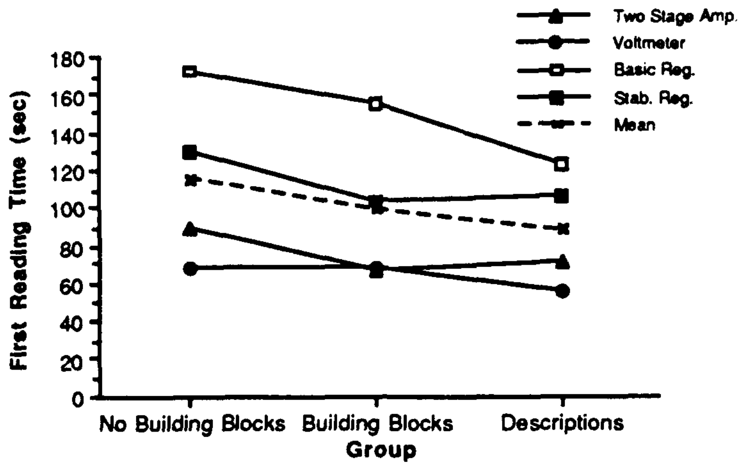


Figure 12. Mean time spent reading the explanation screen on first appearance for each circuit and each group.

Figure 13 shows the mean number of tries that subjects took to answer a question successfully, where one try means that the subject got the question right the first time, while four tries means that the subject is obviously guessing because these questions had four alternative answers. The fairly large number of tries shows that subjects were making many guesses. The main effect of group was significant (F 2, 51) = 334, p = .04); increasing schema availability resulted in fewer guesses. Also, the interaction of group and circuit was significant (F (6, 153) = 2.07, p = .02). The questions for the two-stage amplifier are much easier than the others, and show no effect of schema availability. A closer examination showed that these questions can be answered directly from the explanation without any reasoning about the circuit behavior. There is also no effect for the basic regulator. This circuit had only three questions, one of which was the

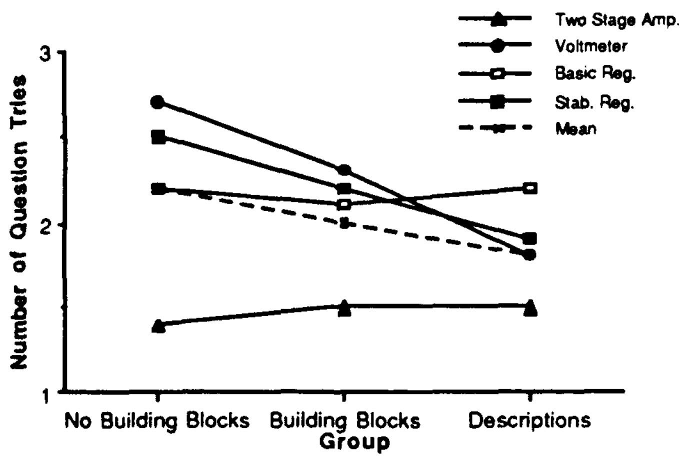


Figure 13. Mean number of attempts to answer questions for each circuit and group.

only reference to the variable resistor component that could easily have been forgotten from the initial training, and another question did not involve knowledge of the schemas. However, there are clearly strong effects for the voltmeter and stabilized regulator circuits for which the questions appeared to rely more heavily on schema knowledge.

The total reading time, shown in Figure 14, is the total time that subjects spent looking at the explanation screen, both the first time they read it and when rereading it after missing questions. This measure reflects both explanation difficulty and question difficulty. The main effect was marginal in the analysis of all three groups (F (351) = 2.26, p = .11). For just the No Building Blocks and Description groups, the main effect just missed conventional significance (F (1, 34) = 4.04, p = .052). Total time tends to decrease with increasing schema availability; subjects that had the building block knowledge tended to spend less total time reading the explanation than subjects without the building blocks, and subjects given the schematizing descriptions were even faster. The stabilized regulator is studied for much less time than the basic regulator which was previously learned. The effect of schema availability is quite small for the two-stage amplifier.

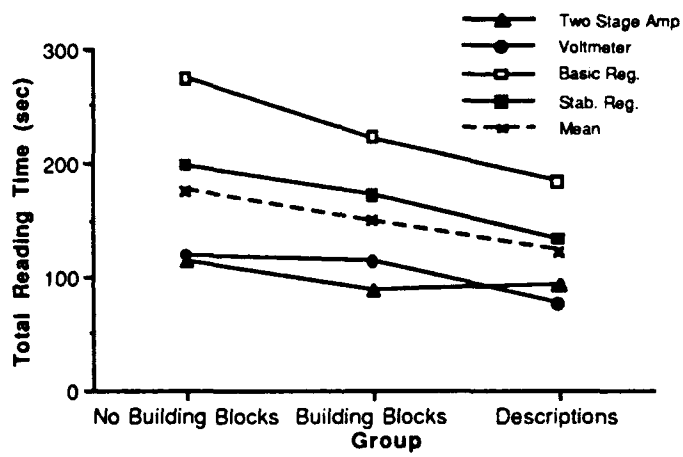


Figure 14. Mean time spent reading explanations, totaled over all rereadings, for each group and each circuit.

Comparison to the AI System

The number of simulation cycles performed by the AI system represents how much processing is performed, and so should be positively related to processing time for subjects (cf. Kieras,1984; Thibadeau, Just, and Carpenter, 1982). The number of simulation cycles was used as a predictor variable in a regression analysis with the total reading time as the predicted variable. Only the data for the No Building Blocks group and the Descriptions group (building blocks with schematizing descriptions) were used. This subset of the data corresponds most closely to the comparison in Figure 6.

Figure 15 presents the results of the regression analysis in a scatter plot showing reading time as a function of the number of system cycles. For clarity, the data points corresponding to the same circuit under the two different conditions are connected by arrows, with the tail of the arrow at the No Building Blocks condition and the the head at the Description condition. The line shown is for the regression equation :

$$Reading\ Time\ (sec) = 59.5 + 8.7 * Cycles.$$

While there are only eight data points, 79% of the variance is accounted for, which is significant ($p < .05$.). The human total reading time and the AI system cycles depend on the amount of material processed in each explanation; typically simpler circuits take less processing than the more complex circuits, but the amount of processing also depends on the savings due to schemas from previous learning. The Description (at arrow heads) condition is normally faster than the No Building Block condition on the same circuit. Thus the AI system and human readers are clearly related in terms of the amount of processing they do on individual explanations, and in terms of the savings resulting from previous learning of schematic subcircuits.

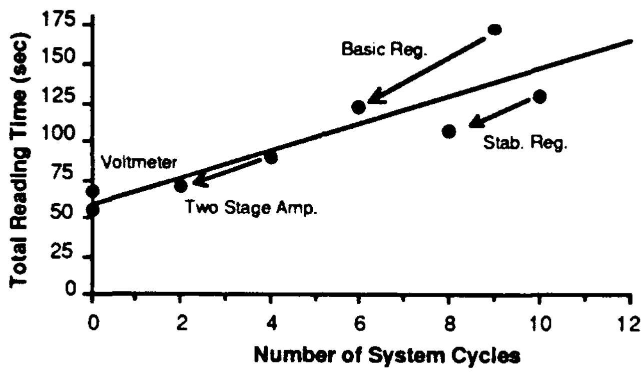


Figure 15. Scatter plot showing relation between AI system cycles and observed reading times. The arrows connect points for a circuit in the No Building Blocks condition (at tail of arrow) with the same circuit in the Descriptions condition (at head of arrow).

Discussion

Problems with the experiment. The results of the experiment were problematic due to some problems in the materials and paradigm. The materials turned out to be fairly difficult for the subjects, even though they were relatively highly selected undergraduates in technical fields. The paradigm apparently allowed subjects to adopt a strategy of muddling through the experiment simply by attempting to answer the questions and if they got it wrong, going back and either rereading or just guessing again.

The experiment was designed under the assumption that the important data would be the time spent reading the explanatory material, and so the purpose of the questions was simply to encourage the subjects to read carefully. However, the subjects made many errors on the questions and so did considerable rereading of the explanations. Thus the reading times on the explanations are not very clean measurements of how difficult it was to understand the explanations. The questions were not very uniform in content or difficulty. Some of the questions could be answered simply by direct matches to the explanation text; that is, the subject could sometimes find a similar set of statements in the explanation, and answer the questions without making any deeper analysis of what was happening in the circuit. Other questions could be answered simply by reversing the statements made in the explanation, for example, by having a voltage increase rather than decrease. But a more subtle and interesting problem, discussed more below, is that the questions sometimes required reasoning which was not based on the circuit schemas overall behavior of a circuit schema, but rather required reasoning inside the schematic subcircuits.

Finally, some of the questions required the subject to remember some aspect of a component that had been presented early in the experiment and not mentioned subsequently. For example, the variable resistor was mentioned late in the questions, but was presented very early in the training. Since the experiment had a built-in confounding between whether the building blocks were present and how many circuits the subjects studied, this could have differentially affected the two groups. Many of the questions queried several intermediate states in the circuit, so that subjects had to verify the accuracy of a whole chain of events. These were very confusing, appearing to be a "word salad."

Summary of the results. The expected results were that the performance on the target circuits should be facilitated by increasing the schema availability; this result did appear, but the data is fairly noisy; they were both time and accuracy effects, and the effects were not uniform across circuits. There should be facilitation on the second regulator circuit due to schema transfer from the first regulator circuit, this appeared quite clearly. The amount of facilitation should have some correspondence to the AI system processing effort, this correspondence does seem to be present.

This first study shows strong suggestions of the expected effects, but clearly much cleaner data is needed for a definitive answer to the basic question of whether studying the schematic subcircuits improves the understanding of later more complex circuits. The materials and training used in this experiment were reasonable, though surprisingly difficult, but there were definite problems with the paradigm and the questions.

How applicable are schemas to the materials? A detailed examination of the materials and questions from the point of view of the AI system reveals a new issue, that of *schema applicability*. The questions and the explanations vary in the extent to which knowledge of the subcircuit schemas suffices to process the explanation or to answer the questions. At the level of the circuit itself, some of the target circuits parse cleanly into schematic subcircuit schemas while others do not. For example, as shown in the upper panel of Figure 16, the basic regulator can be parsed into discrete subcircuit schemas, and the entire circuit can then be simplified by replacing each circuit with a "black box" for each subcircuit, as shown in the lower panel of the figure. The circuit behavior is then just the composition of the behavior of the black-box subcircuits. In contrast, as shown in Figure 17, the stabilized voltage regulator cannot be parsed completely into discrete subcircuit schemas; the triode T1 does not correspond to a cathode-biased amplifier. Thus there is a fundamental problem with the materials; in some of the circuits, the schemas are not fully applicable. It would seem that the benefit of learning the schematic subcircuits would be greater if the circuits could be understood in terms of the black-box behavior of the schematic subcircuits.

The explanations also did not fully make use of schema knowledge that subjects might have. That is, the explanations often were in terms of events that would happen "inside" the schemas, instead of treating the schemas as black boxes. For example, in the explanation for the two-stage amplifier (see Figure 18), the line of reasoning is that if the input voltage increases, the cathode-to-plate resistance of T1 goes down, and the resistance of T2 goes up. But in the original explanation of the amplifier schema circuit, the change of the cathode-to-plate resistance of the triode is a subsidiary event; the black box behavior of the amplifier is that if the input voltage changes, the output voltage changes in the opposite direction and by a larger amount.

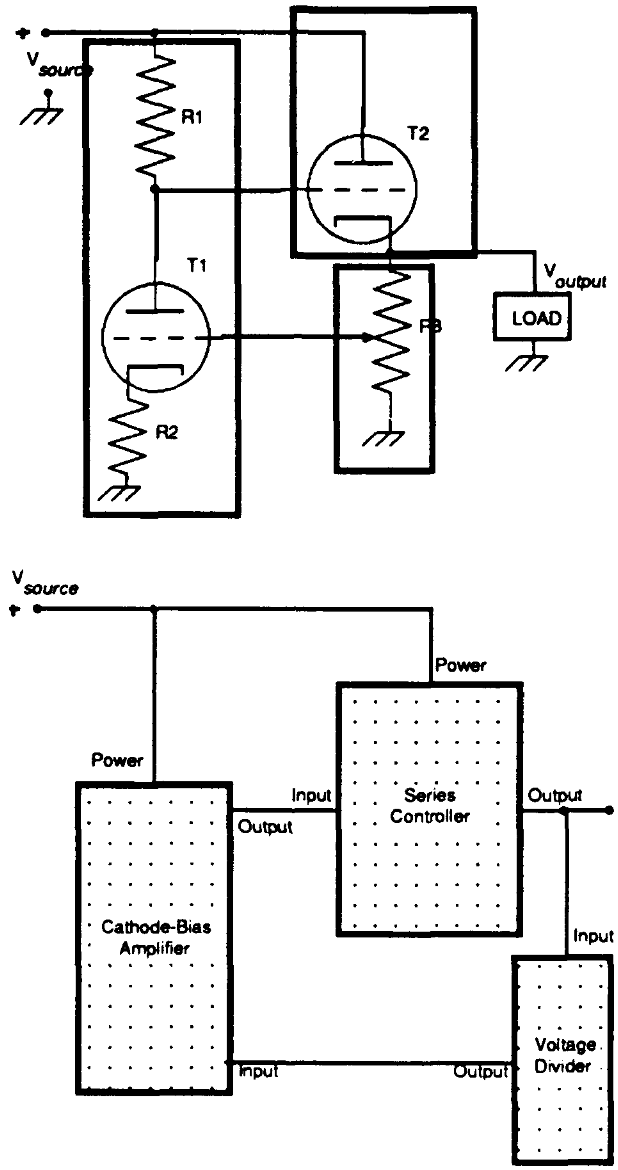


Figure 16. An example of a circuit that can be fully parsed into schema subcircuits.

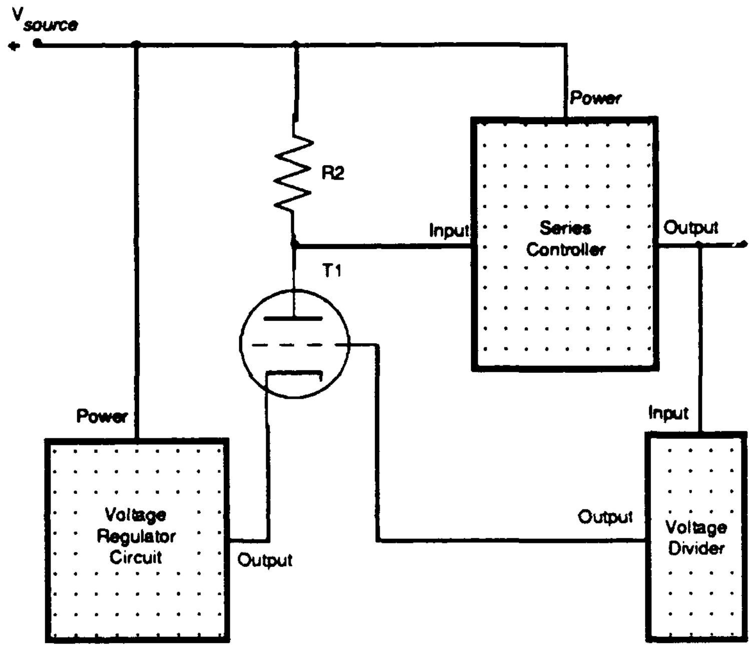


Figure 17. A circuit that cannot be fully analyzed into subcircuit schemas, assuming that schemas require complete structure matches.

Thus, with the presented explanations, if subjects knew the subcircuit schemas, they usually could not simply shortcut their analysis of the explanation, but instead would have to verify each behavior of the circuit mentioned in the explanation, which included internal schema events. For this reason, when Mayer's AI system instantiated a schema and triggered the behavior rule, it simply added all of the internal propositions to the system's knowledge base, which could result in immediate verification of schema-internal events contained in the explanation. But what would happen if the explanations were simply in terms of the black box behavior of the schema circuit? For example, in the same two stage amplifier circuit (Figure 18), a purely black-box schema line of explanation would be that if the input voltage increases, the voltage on T1's plate goes down, and the voltage on T2's plate goes up. In this case, a reader with schema knowledge could simply verify the main behaviors predicted by the schemas, whereas a person without the schema knowledge would have to make the individual inferences required to go from the input voltage change to the final output voltage change. Thus there should be a larger benefit of schema knowledge, if the explanations could be understood directly in schema terms. In a similar way, the questions used in the experiment often involved reference to events happening "inside" the schemas. For example: if the input voltage goes up, what happens to T2's resistance? Again one would predict a larger benefit of having schemas if the questions were posed strictly in terms of the schematic behavior of the circuit. For example: if the input voltage goes up what happens to T2's grid voltage?

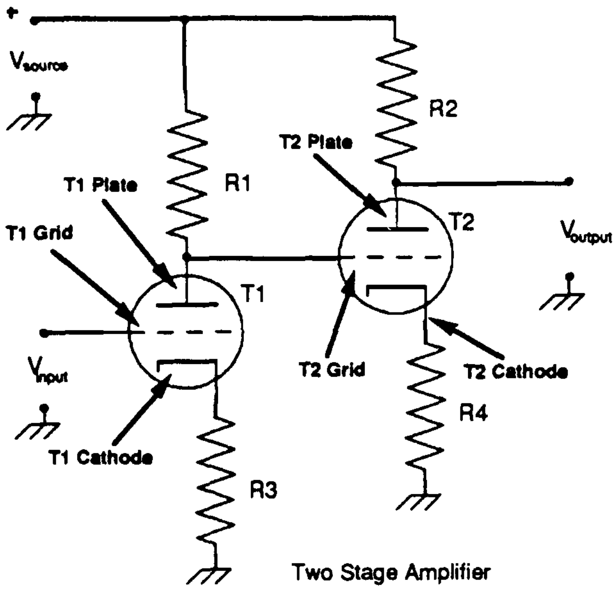


Figure 18. Reasoning based on an amplifier schema in the two-stage amplifier would refer only to voltages on the plates and grids of the triodes, not the cathode-to-plate resistance changes.

Can a circuit be understood in terms of black-box schemas, or do the schemas have to be unpacked into internal structure and behavior? The AI system does not black-box the schematic subcircuits, but also suffers from not doing so. On the other hand, schemas would seem to be most valuable if the schematic subcircuits can be treated as black boxes and reasoning done about a larger circuit only in terms of the external input/output behavior of the subcircuits. Thus the value of circuit schemas may depend on the extent to which the circuits, explanations, and questions involve black-boxed schemas versus reasoning about events inside the schemas.

Experiment 2

The basic problem with the first study is that the presence of the building blocks was confounded with the amount of practice (number of circuits studied) that subjects received. There was also the problem with the experimental paradigm that allowed subjects to adopt a strategy of guessing their way through the questions, and not enforcing a careful reading of the circuit explanation on the first try. In addition, some of the circuits and questions may have been too difficult for the subjects, further encouraging them to guess repeatedly. Also, as mentioned above, the circuits, explanations, and questions may not have allowed subjects to take full advantage of having schema knowledge, and so the benefit of studying the schema circuits may have been weakened.

The second study was designed to produce a clean and definitive effect of the availability of schemas. This was done by rewriting all of the materials used in Experiment 1 and adding new circuits, so that as much as possible, the schema knowledge was fully applicable.

Method

Design and materials. The experiment had two groups. The *Irrelevant Building Blocks* group studied building block circuits that were irrelevant to the later target circuits; these could not be instantiated as subcircuits in the target circuits. The *Relevant Building Blocks* group studied the same schematic subcircuits as in the first experiment, which were then instantiated in the target circuits. The target circuits were changed so that they could all be rewritten in the form of a black box parse with the building block circuits. However, there is much less variety in the circuits than in Experiment 1. Figure 19 shows the relevant building blocks and targets, with the arrows connecting the building blocks to their instantiation in the target circuits. Figure 20 shows the irrelevant building blocks and targets.

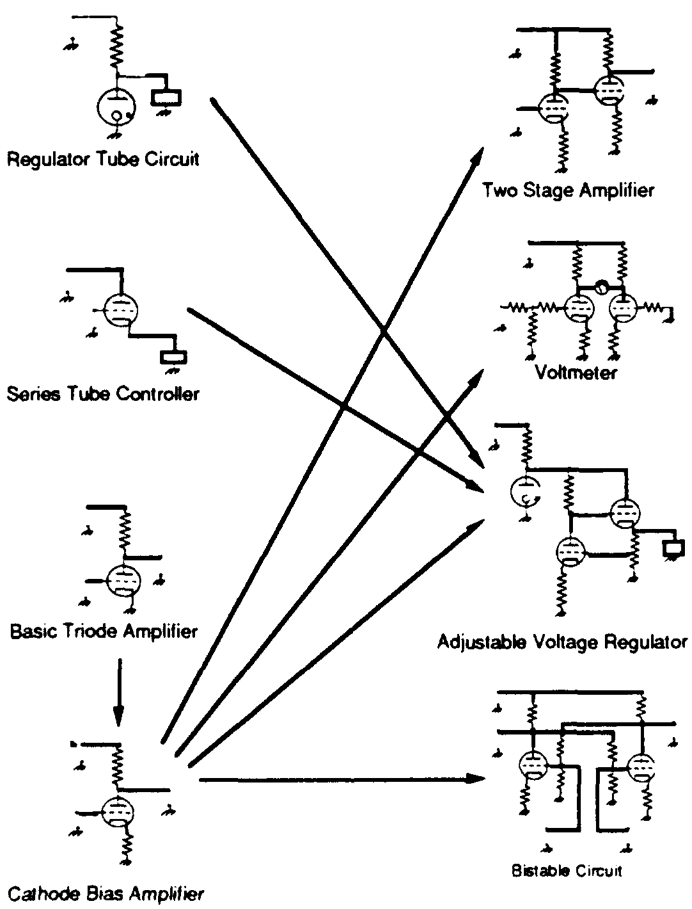


Figure 19. Relevant group materials used in Experiment 2, with schema relations shown.

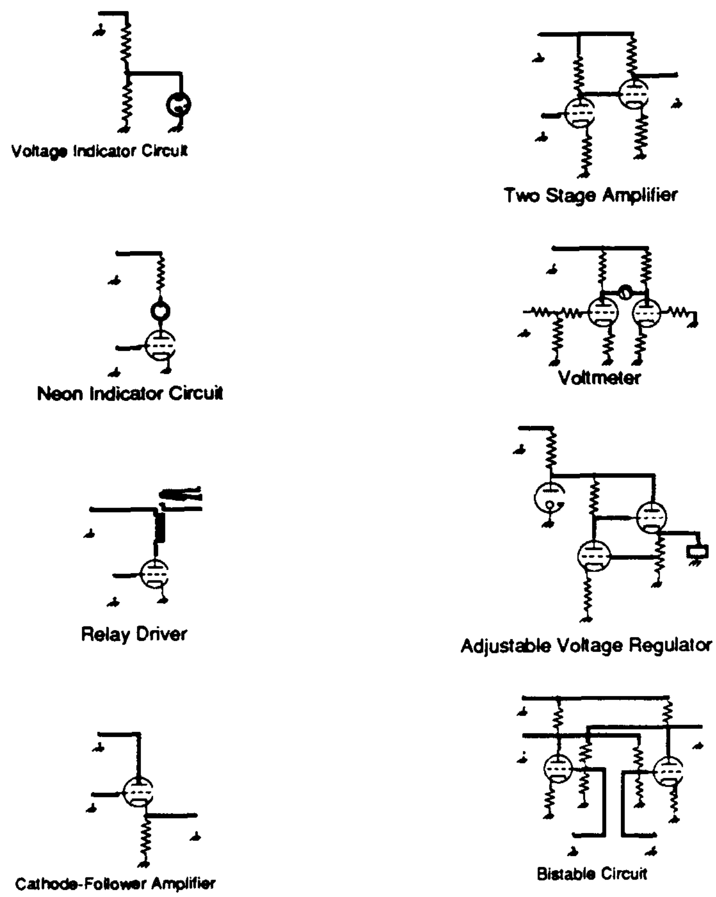
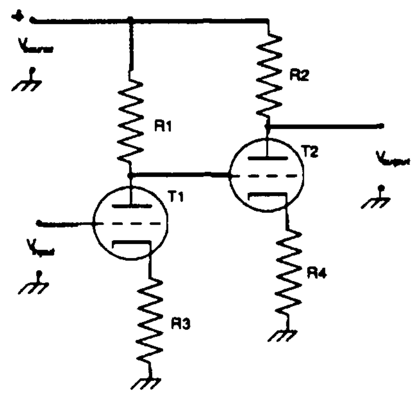


Figure 20. Irrelevant group materials; note the absence of any schema instantiations of the building blocks (left side) with the target circuits, which are the same as in the Relevant group (see Figure 19).

In addition, both groups received a description in the introductory screen, similar in format to the schematizing description in Experiment 1, thus controlling for the presence of prominent additional information. Figure 21 shows the introduction and diagram for the two stage amplifier target circuit. Figure 22 shows the two types of descriptions used. The Relevant Building Blocks group received a schematizing description as in the first study, in which the circuit is described in terms of the subcircuit schemas. The Irrelevant Building Blocks group got an irrelevant description, containing a statement of a correct technical fact or aspect of the circuit, but which had no bearing on the explanation.



The two-stage amplifier is used to get a greater amplification effect than is possible for a single triode amplifier. The values of the resistances are chosen so that the grids of both tubes are always negative with respect to their cathodes.

Figure 21. A sample target circuit introduction from Experiment 2.

Schematizing Description

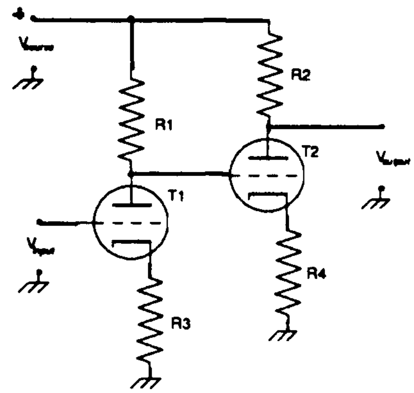
There are two cathode bias amplifier circuits: T1, R1, R3, and T2, R2, R4. They are connected so that the output of the first is the input of the second.

Irrelevant Description

This circuit is actually used very rarely, because it is difficult to arrange so that the grids are always negative with respect to the cathodes. But the corresponding circuit works very well with transistors, due to their different electrical properties.

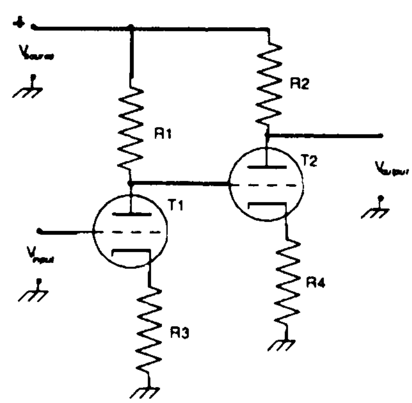
Figure 22. Example of the description boxes used in introductions in Experiment 2.

Figure 23 shows an example explanation that illustrates how the chain of events always referred to the input/output behavior of the circuit schemas. Likewise, the example question for the same circuit shown in Figure 24 illustrates the homogeneous form of the questions used in this experiment. The question presents a perturbing event, and the answers are a choice of a voltage that either increases, decreases, or stays the same.



If the input signal, Vinput, increases, the voltage on the plate of T1 and the grid of T2 goes down, causing the output voltage, Voutput, to increase. The changes in plate voltage of T1 are much greater than the changes in Vinput, and the changes in plate voltage of T2 are even greater. Thus, the total amplification effect is much greater than for a single triode.

Figure 23. A sample explanation from Experiment 2.



If V_{input} decreases, what happens to V_{output}?

- Increases
- Decreases
- Stays the same

Figure 24. Example target circuit question used in Experiment 2.

Procedure and apparatus. The overall paradigm was very similar to that in Experiment 1. During the training portion of the experiment, subjects were required to repeat the material and questions on basic electricity, components, and the building blocks, until they answered all questions correctly. But during testing on the target circuits the subjects were allowed only one try on each question. The subjects were warned very explicitly that they would be allowed to read the target circuit explanations only once, and would not get a chance to answer a question again if they got it incorrect. The basic measures were the time to study the target circuit introduction and explanation, and the latency and answer for each question. As in Experiment 1, a Macintosh IIx with two-page display was used. The experiment required 1 -2 hours to complete.

Subjects. As in Experiment 1, the subjects were engineering undergraduate students who had studied electrical concepts in physics courses, but who had not taken any specific coursework in electronics. Again recruiting subjects was very difficult, but fifteen were obtained in each group.

Results

Like Experiment 1, the data were very noisy, and performance was poor; 40% of the subjects got two thirds or more of the questions incorrect on the target circuits. In some of the statistical analyses to be reported, either data from these poor subjects, or times for questions that were answered incorrectly, were removed from the analysis.

Figure 25 shows the mean time spent on the introduction screen for the four different circuits. Surprisingly, more time was spent on the introduction screen if the subjects had studied the relevant building blocks. The main effect was nonsignificant ($p > .13$), but the interaction of circuit with condition was significant ($F(3, 84) = 7.32, p = .002$). The effect is present on most of the circuits. Removing poor subjects from the analysis produces a significant main effect ($F(1, 16) = 5.05$ $p = .037$) and interaction ($F(3.48) = 5.04, p = .004$), with an overall mean of 65 sec on the irrelevant building blocks, and 86 sec on the relevant building blocks. This effect is reminiscent of the disadvantage of schemas in Mayer's system being the extra computation time required to instantiate them.

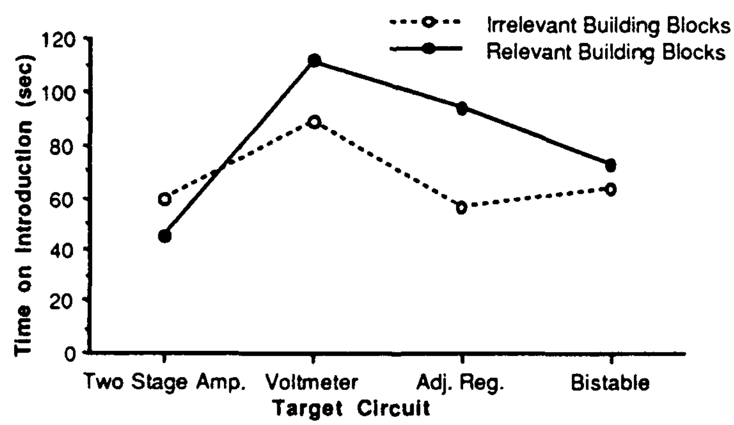


Figure 25. Mean time spent reading the introduction screen for each circuit and each group.

Figure 26 shows the mean time spent on the explanation for each circuit. There is an overall trend in the desired direction, in that the mean time for subjects who studied the relevant building blocks is less than those who studied the irrelevant ones. However both the main effect and interaction are nonsignificant ($p > .2$) and removing poor subjects does not improve the statistical situation. Comparing this figure with the reading time figures from the first experiment (Figure 12 and Figure 14) shows that the overall time spent on reading the explanations is substantially less than the times spent on the explanations in the first experiment. Perhaps again, subjects were not reading carefully, or perhaps these explanations are much simpler than those in the first experiment, resulting in a ceiling effect.

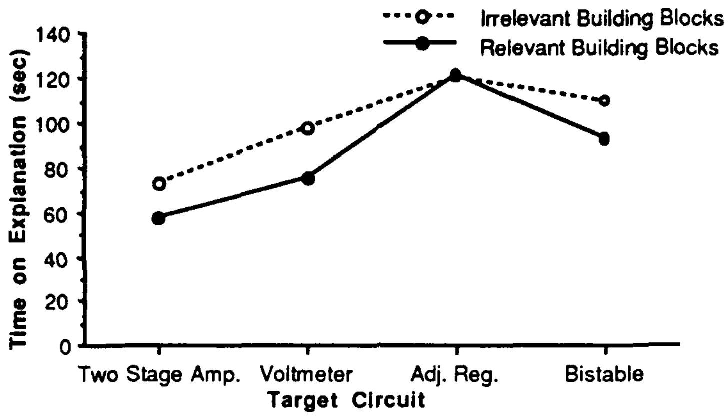


Figure 26. Mean time spent reading the explanation in each group.

Figure 27 shows the mean proportion of questions answered correctly for each circuit for the two groups. Clearly there is no effect of schema availability. Notice also that the level of accuracy is fairly low; the questions had three alternatives, so the chance level of performance would be 0.33, but one of the alternatives would often be easy to eliminate (i.e., the choice *stays the same*). Thus while the average level of accuracy is greater than chance, it is not impressively so.

Figure 28 shows the latency of choosing the question answers, averaged over both correct and incorrect answers. The main effect is nonsignificant ($p > .1$), but the interaction is significant ($F(3, 84) = 3.68$, $p = .016$); the effect appears for all but the bistable circuit. Removing poor subjects does not change the situation statistically, and the same overall pattern appears if incorrect question times are removed from the analysis as well. If the bistable circuit is not included, then the main effect is significant ($F(1, 28) = 4.84$, $p = .036$). The question of why the bistable circuit is different is interesting – perhaps the greater graphic complexity kept subjects from seeing it in terms of schemas, regardless of the schematizing description.

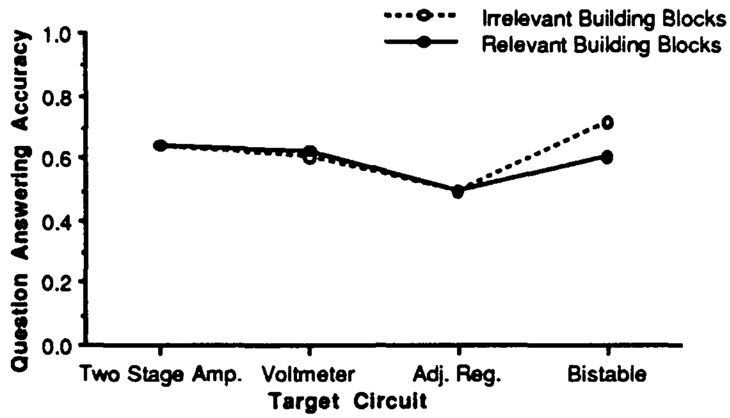


Figure 27. Mean proportion of correctly answered questions in each group.

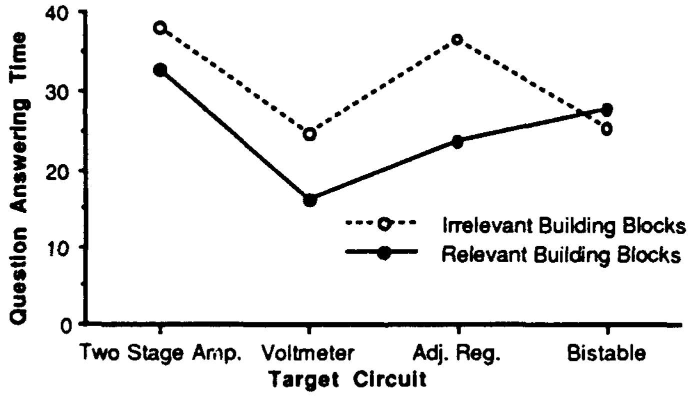


Figure 28. Mean time required to answer questions averaged over both correct and incorrect answers.

Discussion

It is clear that the methodological problems of experimentation in this domain are still unsolved. Apparently the subjects can not be depended upon to read the explanations carefully enough, or to perform well in answering the questions. Rather than an effect on the time spent processing the explanation, there is an effect on the time spent answering the questions, and this effect depends strongly on the circuit involved. Since the major effect of schema availability in this experiment is on question answering times, the issue is now whether this effect can be explained by mechanisms for using schemas during answering the questions. The next section presents a simulation model for schema use in answering questions.

A Model for a Schema-based Question-Answering About Circuit Behavior

Overview of the Model

The model is an ACT-class model, consisting of declarative knowledge represented with propositions, and procedural knowledge represented with production rules (see Anderson, 1983), and is similar to the simulation of a mental model for a simple device described in Kieras (1988). The circuit structure is represented with propositions assumed to be available constantly from the diagram, while the state of the circuit is represented with propositions in working memory. For convenience, shorthand notation is used for the propositions: no claim is being made of a specific propositional representation notation.

The production rules in the model "run" the mental model, performing the inferences and controlling the processing. The rules of most interest are those that represent the first principles in the domain theory, and those that perform schema recognition and schema-based inferences. The basic approach in the model is as follows: The question states a perturbation or change, such as to the input of the circuit. The model propagates the change through the circuit, and waits for a proposition that answers the question to appear in working memory. To simulate the Irrelevant Building Blocks condition, the rules for instantiating and making use of the subcircuit schemas are disabled; the Relevant Building Blocks condition is simulated by enabling the schema rules.

Before a comparison with the data was made, two models were developed that reflect two different overall processing strategies. The stages of model processing in both models are: (1) instantiate any schemas that might be present, (2) analyze the voltage relationships in the circuit, (3) accept the input, (4) propagate the changes until the processing is completed, (5) determine the answer. In the *terminating model,* flowcharted in Figure 29, the process of propagating the changes is terminated as soon as a proposition answering the question appears in working memory. If no more changes can be propagated, the question is answered using whatever propositions are available. This is the typical case if the correct answer to the question is that a voltage stays the same. The predictor of the time to answer the question is the number of production-system cycles that elapses between when the input is accepted and when the answer is determined (shown in Figure 29). According to the terminating model, there should be a large benefit of having schema knowledge, because the changes will propagate more rapidly and the answer will be computed faster than if schemas are not available.

The exhaustive model, flowcharted in Figure 30, continues the propagation of the input change until quiescence (no more changes propagated), whereupon the question is answered using the available propositions about the circuit state in working memory. The predictor for the time to answer the question is again the time between when the input is accepted and when the answer is determined (shown in Figure 30). This model predicts a mild effect of schemas, because the model may well spend many cycles propagating irrelevant changes long after the answer to the question has been determined.

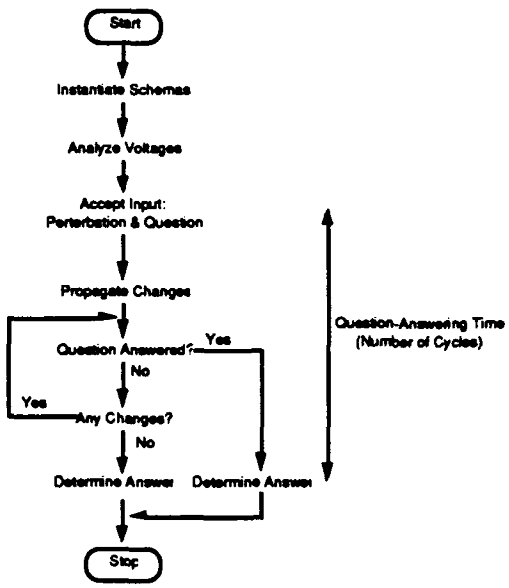


Figure 29. Flowchart of processing in the terminating model.

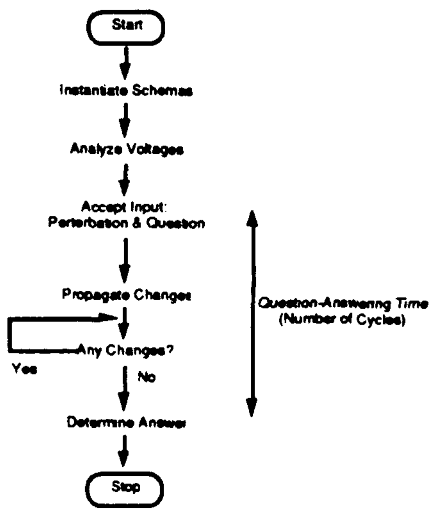


Figure 30. Flowchart of processing in the exhaustive model.

Model Details

To give more details of the models, Table 2 shows how the structure of the cathode-biased amplifier is represented. Each individual component (which includes the input and output terminals) is described with simple ISA and HAS propositions, while a shorthand notation is used to describe basic voltage and resistance properties of the circuit or its components. The connections between the components are described by a series of CONNECTION propositions; note that each connection is one-way, so connection propositions in both directions are necessary.

Table 2
Sample circuit description.

```
;*CATHODE-BIAS-AMPLIFIER-STRUCTURE

(ISA VS POWER-SUPPLY)
(ISA HOT-PORT VOLTAGE-SOURCE)
(HAS VS HOT-PORT)
(HAS VS COLD-PORT)
(VOLTAGE AT HOT-PORT IS POSITIVE FIXED HIGH)

(ISA R1 RESISTOR)
(HAS R1 R1-PORT1)
(HAS R1 R1-PORT2)
(HAS R1 RESISTANCE)
(RESISTANCE BETWEEN R1-PORT1 R1-PORT2 IS R1R)

(ISA R2 RESISTOR)
(HAS R2 R2-PORT1)
(HAS R2 R2-PORT2)
(HAS R2 RESISTANCE)
(RESISTANCE BETWEEN R2-PORT1 R2-PORT2 IS R2R)

(ISA T TRIODE)
(HAS T T-PLATE)
(HAS T T-CATHODE)
(HAS T T-GRID)
(ISA T-PLATE ANODE)
(ISA T-PLATE PLATE)
(ISA T-CATHODE CATHODE)
(ISA T-GRID GRID)
(HAS T RESISTANCE)
(RESISTANCE BETWEEN T-PLATE T-CATHODE IS TR)

(ISA INP TERMINAL)
(LABEL INP INPUT)

(ISA OUT TERMINAL)
(LABEL OUT OUTPUT)

(CONNECTION HOT-PORT R1-PORT1)(CONNECTION R1-PORT1 HOT-PORT)
(CONNECTION R1-PORT2 T-PLATE)(CONNECTION T-PLATE R1-PORT2)
(CONNECTION T-PLATE OUT)(CONNECTION OUT T-PLATE)
(CONNECTION INP T-GRID)(CONNECTION T-GRID INP)
(CONNECTION COLD-PORT GND)(CONNECTION GND COLD-PORT)
(CONNECTION T-CATHODE R2-PORT1)(CONNECTION R2-PORT1 T-CATHODE)
(CONNECTION R2-PORT2 GND)(CONNECTION GND R2-PORT2)
```

Examples of each type of production rule will be given. Table 3 shows the production rule used to recognize the presence of a cathode-biased amplifier in a circuit. The production system used is the PPS system (see Covrigaru and Kieras 1987). In this notation, the *clauses* following the `IF` must all be present in the production system data base in order for the rule to fire, whereupon the actions listed after the `THEN` are taken. PPS has no built-in conflict resolution or refractoriness mechanism; each rule must contain condition clauses to ensure that it fires only at the right times. The condition of this sample rule is fairly elaborate; it consists mainly of a description of the components and their connection pattern that make up the structure of a cathode-biased amplifier. This can be seen by comparing the contents of the rule condition with Table 2. In the PPS notation, an item preceded by a question mark in a clause, as in `(ISA ?T TRIODE)`, represents a variable that is assigned a value when the condition is matched. If this rule finds matches in a target circuit a particular triode and two resistors which are connected as required, then it adds to working memory a proposition (in shorthand) that there is a cathode-biased

Table 3
Sample schema instantiation rule.

```
(RecognizeCathodeBiasAmplifier
IF (
    (GOAL PREPROCESS CIRCUIT)
    (STRATEGY RECOGNIZE SCHEMAS)
    (ISA ?T TRIODE)
    (HAS ?T ?T-PLATE)
    (ISA ?T-PLATE PLATE)
    (ISA ?T-CATHODE CATHODE)
    (HAS ?T ?T-CATHODE)
    (ISA ?T-GRID GRID)
    (HAS ?T ?T-GRID)
    (CONNECTION ?R1-PORT2 ?T-PLATE)
    (HAS ?R1 ?R1-PORT1)
    (ISA ?R1 RESISTOR)
    (CONNECTION ?T-CATHODE ?R2-PORT1)
    (HAS ?R2 ?R2-PORT1)
    (ISA ?R2 RESISTOR)
    (HAS ?R1 ?R1-PORT2)
    (HAS ?R2 ?R2-PORT2)
    (CONNECTION ?R2-PORT2 GND)
    (CONNECTION ?HOT-PORT ?R1-PORT1)
    (ISA ?HOT-PORT VOLTAGE-SOURCE)
    (NOT (SCHEMA CATHODE-BIAS-AMPLIFIER ?T ?T-GRID ?T-PLATE))
)
THEN (
    (ADDDB (NOTE CIRCUIT PREPROCESSED))
    (ADDDB (COMMENT CATHODE-BIAS-AMPLIFIER AT ?T ?R1 ?R2))
    (ADDDB (SCHEMA CATHODE-BIAS-AMPLIFIER ?T ?T-GRID ?T-PLATE))
;?T used as label for schema instantiation
    (ADDDB (SCHEMA PORT ?T ?T-GRID))   ;input
    (ADDDB (SCHEMA PORT ?T ?T-PLATE))  ;output
    (ADDDB (SCHEMA PORT ?T ?R1-PORT1)) ;power
    (ADDDB (SCHEMA PART ?T ?R1-PORT2))
    (ADDDB (SCHEMA PART ?T ?T-CATHODE))
    (ADDDB (SCHEMA PART ?T ?R2-PORT1))
))
```

amplifier based on the triode, and assigns the grid and plate of the triode as the input and output *ports* of the schematic subcircuit. It also describes various parts of the schematic subcircuit as being parts of the schema instantiation. Thus, if given the two-stage amplifier circuit shown in Figure 18, the rule will fire and deposit in working memory propositions showing the presence of a cathode-biased amplifier schema based on T1, and another based on T2. The negated clauses (using NOT) in the condition prevent the rule from firing more than once for each instantiation.

Table 4 is an example of the rules for doing voltage analysis. In these circuits, a very simple electrical theory suffices; the model does not need to do a full qualitative simulation of circuit behavior; it is only necessary to determine the polarities and relative magnitudes of voltages relative to the common *ground.* Since these circuits all have single voltage sources, all resistances appear in a chain between the voltage source and the common ground. Thus, this rule simply notices that if there is a resistor connected to a point at which there is a voltage, then the voltage at the other side of the resistor is of the same polarity, but of lesser magnitude than that at the first side.

Table 4
Sample voltage analysis rule.

```
(PropagateVoltageResistance
IF (
(GOAL PROPAGATE VOLTAGE)
(VOLTAGE AT ?P1 IS ?POLARITY ?RELATION ?MAGNITUDE)
(RESISTANCE BETWEEN ?P1 ?P2 IS ?RV)
(DIFFERENT ?P1 GND)
(DIFFERENT ?P2 GND)
(NOT (CONNECTION ?P1 GND))
(NOT (CONNECTION ?P2 GND))
(NOT (VOLTAGE AT ?P2 IS ?POLARITY LESS-THAN ?P1))
)
THEN (
(ADDDB (NOTE VOLTAGE PROPAGATED))
(ADDDB (VOLTAGE AT ?P2 IS ?POLARITY LESS-THAN ?P1))
))
```

Table 5 shows an example of the rules for propagating a change through a circuit. This simple rule merely says that if the voltage at one point has changed, and that point is connected to another point, then the voltage at that other point also changes, and in the same direction. Note that if the points are marked as being part of a schema instantiation, then this rule can not apply. Thus, unlike the AI system, in this model the first principle rules in the domain theory are not allowed to reason about events inside instantiated schemas. Table 6 shows a propagation rule for an individual component, the triode vacuum tube. The clauses in the condition of this rule recognize the presence of a triode and the event in working memory that the voltage on the grid of the triode has increased. The rule adds to working memory the information that the resistance between the plate and cathode of the triode has decreased.

Table 5
Sample basic change propagation rule.

```
(PropagateVoltageChangeConnection
IF (
(GOAL PROPAGATE CHANGE INFER)
(WM CHANGE ?DIRECTION VOLTAGE ?P1)
(CONNECTION ?P1 ?P2)
(DIFFERENT ?P1 GND)
(DIFFERENT ?P2 GND)
(NOT (CONNECTION ?P1 GND))
(NOT (CONNECTION ?P2 GND))
(NOT (WM CHANGE ??? VOLTAGE ?P2))
(NOT (VOLTAGE AT ?P2 IS ??? FIXED ???))
(NOT (WM CHANGE HELD-CONSTANT VOLTAGE ?P2))
(NOT (SCHEMA PART ??? ?P1))     ;hands off internal schema parts
(NOT (SCHEMA PART ??? ?P2))
)
THEN (
(ADDDB (NOTE CHANGE PROPAGATED))
(ADDDB (WM CHANGE ?DIRECTION VOLTAGE ?P2))
))
```

Table 6
Sample change propagation rule for a component.

```
(TriodeGridVoltageChangeIncrease
IF (
(GOAL PROPAGATE CHANGE INFER)
(ISA ?T TRIODE)
(HAS ?T ?T-PLATE)
(HAS ?T ?T-CATHODE)
(HAS ?T ?T-GRID)
(ISA ?T-PLATE PLATE)
(ISA ?T-CATHODE CATHODE)
(ISA ?T-GRID GRID)
(WM CHANGE INCREASE VOLTAGE ?T-GRID)
(NOT (WM CHANGE DECREASE RESISTANCE BETWEEN ?T-PLATE ?T-CATHODE))
(NOT (SCHEMA PORT ??? ?T-GRID))   ;apply only if ?T not schematized
)
THEN (
(ADDDB (NOTE CHANGE PROPAGATED))
(ADDDB (WM CHANGE DECREASE RESISTANCE BETWEEN ?T-PLATE ?T-CATHODE))
))
```

Table 7 shows the schema behavior rule for a cathode-biased amplifier, which would have been earlier recognized by the rule shown in Table 3. This rule is remarkably simple; if the cathode-biased amplifier has been instantiated with designated input and output ports, and the voltage at the input port has increased, then this rule simply adds to working memory the proposition that the voltage at the output port has decreased. The inference that this change is larger than the input change is not relevant in these materials, and so is not included.

Table 7
Sample behavior rule for a schema.

```
(CathodeBiasAmplifierInpIncrease
IF (
(GOAL PROPAGATE CHANGE INFER)
(SCHEMA CATHODE-BIAS-AMPLIFIER ?SCHEMA ?INP ?OUT)
(WM CHANGE INCREASE VOLTAGE ?INP)
(NOT (WM CHANGE DECREASE VOLTAGE ?OUT))
)
THEN (
(ADDDB (NOTE CHANGE PROPAGATED))
(ADDDB (WM CHANGE DECREASE VOLTAGE ?OUT))
))
```

Finally, Table 8 provides an example from the terminating model of how the answer to the question is determined. If the query stored in working memory is a query about how a quantity at a particular point in the circuit has changed, and in working memory is a proposition that quantity at that point in the circuit has changed in a certain direction, then this rule designates the proposition as being the answer to the question.

Table 8
Sample answer generation rule.

```
(PropagateChangeAnswerQueryIncreaseOrDecrease
IF (
(GOAL PROCESS INPUT)
(STEP PROPAGATE CHANGE ANSWER)
(STRATEGY FINAL ANSWER)
(WM QUERY CHANGE HOW ?QUANTITY ?P1)
(WM CHANGE ?DIRECTION ?QUANTITY ?P1)
(NOT (WM CHANGE HELD-CONSTANT ?QUANTITY ?P1))
)
THEN (
(ADDDB (COMMENT ANSWER IS ?QUANTITY ?P1 ?DIRECTION))
))
```

Comparison of the Model with Question-Answering Time Data

The processing time predictions of exhaustive and terminating models were compared by regression analysis to the mean times averaged over subjects taken to answer the *individual questions*. The average times included only times from the correctly answered questions. In addition, the questions whose accuracy was not above one-third (chance level) were also dropped from the comparison, giving $N = 19$. This subset of data is still quite noisy; although the questions are simple, the latencies are very long and variable as is usually the case with problem-solving latencies. Using ipsatized data in the comparisons did not result in substantially cleaner results, suggesting that most of the noise in the data is within-subject.

The predictor variable is the number of production system cycles required to answer the question starting from when the input is accepted and the propagation of the change begins, and stopping when the question answer is determined. These numbers were obtained by simply running the model on each combination of circuit and question, and calculating how many cycles were required until the answer was determined. A regression was then computed for each model using the number of cycles as the predictor variable, and the observed mean question-answering times as the predicted variable (see Kieras, 1984). Clearly the regression slope should be positive, in that more cycles should correspond to more time, and r^2 gives a measure of the goodness of fit.

An important result of the comparison is that the terminating model fails completely to account for the data. Figure 31 shows the relationship between the number of cycles required by the terminating model and the question answering time. Although this model is intuitively appealing, it clearly accounts for essentially none of the variance ($r^2 = .02$). While the utter failure of the model is discouraging, it does demonstrate rather clearly that the comparison of these models to the data is a valid exercise; a perfectly reasonable model can be disconfirmed, so one that accounts for a substantial part of the variance can be taken seriously.

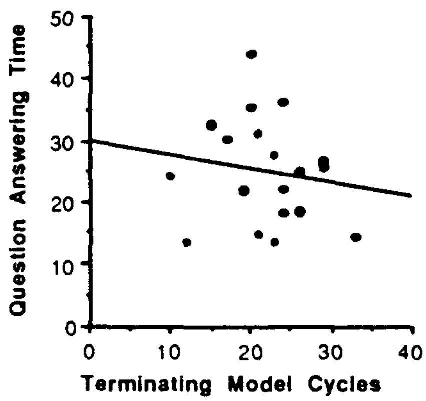


Figure 31. Scatter plot of cycles versus question-answering time for the terminating model.

Figure 32 shows the relationship between the number of exhaustive model cycles and the question answering time. The regression equation is:

$$Time\ (sec) = 5.38 + 0.63 * Cycles$$

This model accounts for a significant portion of the variance ($r^2 = .34, p < .01$). Accounting for 34% of the variance is impressive, considering that the data are quite noisy. The regression coefficient for the number of cycles is approximately 0.6 sec. There is reason to believe that production rules should take on the order of 50-100 msec per cycle to apply in the context of simple procedural tasks (see Card, Moran, and Newell, 1983, Ch. 2; Bovair, Kieras, and Polson 1990). The fact that these rules take more time suggests that there might be some inaccuracy about how the task is represented. For example, the propagation rules in the model can immediately apply to all points in the circuit, but perhaps subjects "trace" through the circuit and allow the rules to apply to only one point in the circuit at a time. The result would be that the propagation rules would appear to fire much more slowly. Resolving this issue would require more detailed study of how people answer questions about electrical circuits.

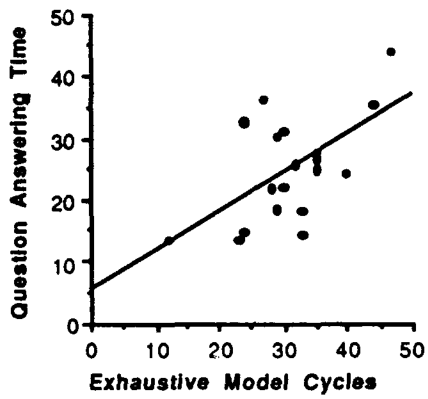


Figure 32. Scatter plot of cycles and question-answering time for the exhaustive model.

Figure 33 shows the predicted and observed times for the individual questions in each circuit, shown in the order in which they appeared in the experiment within each condition; the Irrelevant group questions appear first on the horizontal axis followed by the questions in the Relevant group. What this figure shows is that the model's predicted values track the observed values fairly well, but with some definite mispredictions. Given the noisiness of the data, it is probably not worthwhile to pursue the nature of the mispredictions in more detail. But the model does capture the effect of schema availability; notice that the times to the Irrelevant group questions tend to be longer than those for the Relevant group, and the model shows the same pattern. However, the effect of schema availability is fairly mild, both in the case of the data, and the number of cycles required by the model.

In the terminating model, the changes are propagated until quiescence; this strategy will tend to reduce the benefits of having the schema rules. How the rules would apply to the schematic subcircuits also suggests that the benefits would be relatively small. For example, in a simple triode amplifier circuit, the first-principle reasoning would be that if the voltage on the grid changes, then by the triode rule, the resistance of the triode changes, and by the voltage divider rule, the result is a change in the voltage on the triode plate. Thus when using first principles, going from a change in the voltage on the triode grid to a change in the voltage on the triode plate takes only two rules. The schema rule for the amplifier circuit would make the same inference in one rule instead of two. This is a relatively small change in the amount of inference required, so perhaps only mild benefits of schema knowledge should be expected for these materials and this task.

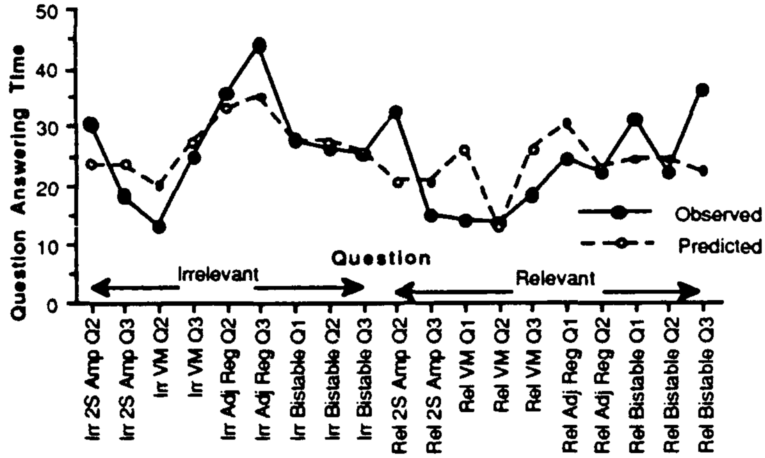


Figure 33. Predicted and observed times for each question in both conditions.

General Discussion

Summary of Results

The basic question addressed by this work is whether schemas and their explanations are involved in how practical electronics material is learned. The AI system and the question-answering model shows that in principle, schemas can be learned from these explanations and then used in further learning and answering questions about this kind of material, and thereby suggest that the schematic structure of textbook material is important. The experimental work shows that learning schemas from explanations can be effective in the classroom training of technical content. In the course of one or two hours, subjects were able to learn circuit schemas, and then enjoyed some benefit from applying them to understanding explanations and answering questions about more complex circuits. The comparison of the models with the data shows that the magnitude of the benefits of schemas for human learners can be predicted to some extent by the models, which suggests that the schema mechanisms used in the AI system and in the question-answering model are plausible as psychological models.

Difficulties of Experimentation in this Domain

The experimental work reported here shows that learning circuit schemas is beneficial in later learning, but the effect is fairly small, and it is susceptible to the specific task strategies that subjects adopt in dealing with the experimental paradigm. Several problems made it difficult to get definitive data on this phenomenon. The type of experiment attempted here involves collecting problem-solving latencies, which are highly variable, under conditions that severely limit the sample size: (1) There are relatively few realistic circuits at a reasonable level of complexity. (2) It is hard to get a large number of subjects willing and able to tackle these surprisingly difficult materials. (3) There are only a small number of distinct schema-relevant questions about an individual circuit. For example, in the two-stage amplifier circuit, all of the questions that are relevant to the schema-based understanding consist simply of what happens to the output of either the first or second stage when the input changes. Thus it is not possible to ask a large number of questions about each circuit. Clearly, if subjects were asked many questions about the same circuit, their question-answering strategies would change altogether, as they simply memorized the answers to the few possible questions.

Thus, although the electronics domain appears to be a clear-cut and relatively simple domain to explore either from the AI or the cognitive modeling perspective, it seems to be a very difficult one for collecting human data on complex learning processes.

The Need for Cognitive Analysis of Large-Scale Training Materials

This research focussed on the properties of realistic training materials in a technical domain. While this research used only a very small subset of the materials, it encompassed a relatively large set of concepts which were also relatively complex. The large scale of the complete set of training materials for this domain must be appreciated. In the electronics series used here (Van Valkenburgh, Nooger, & Neville, Inc., 1955) there are about 600 pages, and a similar quantity in a prerequisite series on basic electricity. The U.S. Navy considered this to be the amount of knowledge that should be taught to trainees to qualify them for basic electronics technician jobs. However, when the learning of electricity or electronics has been studied under laboratory constraints, the researchers typically use only a fragment that corresponds to a single page, or a few pages at most, of this corpus. The result is that we have no understanding from a cognitive science point of view of how such a mass of material is structured or learned.

The building-blocks approach is one important property of these materials, but the dominant property is that most of the content is the design rationale and principles for electronic circuits — how they work, and why they are configured the way they are. For example, a key topic is that vacuum tubes and transistors must have their "bias" set by additional components to place their operating characteristics in a desired range, for example, to produce a linear response function. Considerable space is spent explaining this issue mathematically, with heavy use of graphs, and formulas are supplied and illustrated for calculating the proper component values.

What is odd about this emphasis on design rationale is that these materials are not intended to prepare students for electronics engineering and circuit design, but for electronics maintenance, in which the trainee's future task is to diagnose and correct malfunctions in the equipment. As argued elsewhere (Bond & Towne, 1979; Kieras, 1988), understanding of fundamental quantitative principles and design rationale does not seem to be important in troubleshooting tasks. In contrast, electronics troubleshooting must be learned by apprenticeship or haphazardly; there is very little published material that presents general concepts of electronics troubleshooting. But despite this misdirection, the practical electronics materials studied here contain a fairly standard presentation of the complete domain theory of practical electronics, which many thousands of people have mastered.

These materials would be an ideal place to attempt a large-scale analysis of training materials. For example, a large semantic net could be constructed to show how each concept was related to the other concepts. The kinds of pedagogical techniques used to present each concept could be listed. There are many techniques used in these materials, and it would be valuable to know whether there is any pattern to their usage. For example, specific circuits are presented with diagram graphics and textual explanations, as was studied here. Some concepts (e.g., amplification) were introduced with several pages of relation to everyday life (e.g., amplifying the size of the catch in a fish story), and with analogies (e.g., amplification as regulating the flow of water from a tank). Illustrations of the actual physical appearance of components abound, corresponding to these materials teaching about actual components and devices, rather than the idealized ones presented in non-practical treatments. Cartoons are used to show causal sequences with a kind of animation. Static cartoons and humor often seem to be used to reinforce specific concepts and excite interest. There are many mathematical arguments, presented both graphically and algebraically. Finally, much information was just presented explicitly in text. Thus, trying to determine why each concept was presented the way it was, and whether the presentation was effective in theory, would yield many insights and hypotheses about technical training.

If cognitive science is to contribute toward improving instruction in real domains, such as technical ones, it will be necessary to complement the traditional detailed analysis of fragments of the domain with analysis of the domain in the large. By analyzing the structure and content of such complete materials from a cognitive-theoretic point of view, we will be able to ensure that our future detailed research is addressing the key properties of the materials and the domain.

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