Artificial Intelligence Methods in Computer-Based Instructional Design

The Minnesota Adaptive Instructional System

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Abstract. Design of computer-based instruction (CBI) is presented from a management systems perspective using methods of artificial intelligence (AI). Instructional design variables taken from a programmatic research effort based on the Minnesota Adaptive Instructional System (MAIS) are reviewed. AI concepts are an integral component of the MAIS. Instruction is iteratively adjusted for each learner according to at-the-moment learning needs. Following a brief introduction to AI methods appropriate for intelligent CBI, the six design variables of the MAIS are reviewed. A unique feature of the MAIS is the extensive collection of empirical research findings that support the application capabilities of the design variables.

For the past decade educational researchers have gradually moved from a behavioral learning theory base for the improvement of learning to a cognitive science base (Glaser, 1984; Newell, 1980; Scandura, 1984). This move has had a direct effect on the field of instructional development in terms of how we go about designing individualized systems of instruction. Recently, Gagne and Dick (1983), reviewed the research literature in instructional psychology and showed that current instructional theories have a definite cognitive science approach to learning. Concurrent with this transition period in learning and instructional theories, has been the movement in computer science research to the use of Artificial Intelligence (AI) methods in hardware and software designs (Feigenbaum, 1977). The assumption in AI designs is that the system will acquire not only an increase in the accumulation of knowledge but, with experience, improve decision making (Nilsson, 1971).

The purpose of this article is to review a programmatic educational research effort that has joined the methods of artificial intelligence to the development of a cognitive science-based instructional design system. This particular instructional system applies AI methods to the design of computer-based management systems that adapt the learning environment to individual differences and needs. The article will briefly review educational applications of AI, then present the empirically-based design variables for developing a management system for computer-based instruction (CBI).

AI Application

The formal study of AI in computer science can be traced to the early 1960s (Feigenbaum & Feldman, 1963). The focus was on the design of computer programs that would enhance decision making, as well as storing and retrieving information. Early attempts in cognitive science to simulate the brain with computer models piqued interest in how to simulate decision making by experts (Amarel, 1969). The application of AI in education came through cognitive science research on problem solving (Tennyson, 1982).

Although there are many forms of AI application (see Amarel, 1983), the two forms most widely used in education have been tree structure and heuristic models. Application of tree structures is readily seen in formal designs of "expert systems" in health sciences and industry. An expert system is basically an information retrieval system based on an expert analysis of a domain of information. The expert system structure of a given domain usually resembles a taxonomic form of closely networked concepts connected by subject matter attributes.

The other AI form which seems to lend itself directly to educational applications in CBI is the heuristic method (Lenat, 1982), built around direct connections to a cognitive science base of learning (Polya, 1945). A heuristic is a "rule of thumb" search strategy composed of variables that can be manipulated to provide increasingly better decisions as more knowledge is acquired. The method differs dramatically from the tree structure methodology of AI programming in that it is usually written as a conditional probability statement code. Also, a heuristic may be thought of as a higher order rule statement rather than a depository of domain-specific information or content.

Cognitive science theory suggests that higher order problem solving rules are more flexible than conditional rules which are useful under only specific and limited situations (Sternberg, 1981). In research dealing with CBI design variables at the University of Minnesota, we have focused on a heuristic approach for the instructional management system strategy variables because it allows for the growth of the system as we investigate simultaneously learning variables, instructional variables, and conditions. The heuristic approach makes it possible to increase the adaptability of the management system as we test additional design strategy variables that are linked to the improvement of learning. The next section of the article reviews those instructional design variables that allow for the development of adaptive CBI.

Minnesota Adaptive Instructional System

My first effort at designing an adaptive instructional model focused on the recognition of error patterns in concept learning (Tennyson, 1975). The error pattern recognition strategy attempted to adjust the sequence of examples according to identified errors of overgeneralization, undergeneralization, and misconception (Woolley & Tennyson, 1971). This early attempt at response-sensitive sequencing of instruction has led to a broader description of a CBI management system that individualizes the instruction to learner differences rather than merely making it self-instructional. The basic structure of the Minnesota Adaptive Instructional System (MAIS) was proposed around Bayes' conditional probability method (Tennyson & Rothen, 1977). Bayesian statistics have been widely applied in testing (e.g., Novick & Lewis, 1977) and economics because the formula's parameters can be manipulated while using current data to predict future needs.

Other basic fundamentals of the MAIS include (a) iterative updating of the decision making parameters, (b) use of a variety of variables concurrently to form a diagnosis of learning needs (e.g., performance data on prerequisite knowledge, on-task learning progress data, individual differences data), (c) flexibility that would easily allow the addition, modification, and deletion of heuristics, and (d) transportability to any hardware and/or software system as well as subject matter. In summary, the goal of the MAIS research program was to develop an intelligent adaptive management system for CBI that would enhance decision making to improve learning. Additionally, my colleagues and I set about to test the variables of the system using rigorous, experimental methods. We sought to design an empirically based theory rather than a model-based system. A review of the specific research studies supporting our design variables in presented in Tennyson, Christensen, and Park (1984).

The following presentation of the instructional design variables will be structured around two main sections. The first section concerns the Bayesian component of the MAIS and the learning theory and instructional theory upon which the MAIS is founded. The second section concerns the six main instructional design variables of the MAIS: amount of instruction, sequence of instruction, display time, advisement, refreshment of prerequisite information, and individual differences.

Theoretical Structure

The learning theory of the MAIS is philosophically grounded in cognitive psychology (Tennyson & Breuer, 1984). The theory views learning of information in reference to acquisition of conceptual and procedural knowledge around a schema theory of memory storage and retrieval (Tennyson & Cocchiarella, in press). Acquisition of conceptual knowledge is primarily a function of exposure to information through expository experiences. Information encoded from the expository experiences provides initially sufficient conceptual knowledge for development of a schema to solve problems, thus developing procedural knowledge. As the learner experiences additional problem solving situations, the conceptual knowledge of the schema is further formed and the procedural knowledge and the connections in the memory to other existing knowledge structures are further developed (Anderson, 1980; Scandura, 1977, 1984). As the knowledge base grows in the long-term memory around conditional problem solving, more creative higher order problem solving experiences become increasingly possible (Dorner & Reither, 1979).

An important construct of the MAIS, although not directly part of the management strategy, is how the structure of the information to be learned is organized for instruction. Typically, content analysis methods follow a taxonomic approach such that the relationships of concepts in a content area are based on critical attributes. A taxonomic structure of content seems to be the way individuals store information and the way they retrieve it when asked to recall relationships between concepts (Rosch, 1978). However, the taxonomic structure of information fails to provide the conditions necessary to use the knowledge to solve problems (Mandler, 1979). A taxonomic presentation seems to allow for the foundation of conceptual knowledge but not procedural knowledge. An alternative approach to the taxonomic method of content analysis is a schematic analysis (van der Waerden, 1973).

Bayesian Conditional Probability

The Bayesian component of the MAIS provides the basic data structure on which several instructional decisions are made. Mathematically, Bayes' theory of conditional probability uses a set of parameters that allow increasingly better predictions as more data are acquired. Since the parameters of the statistic are continuously adjustable, it is possible to have almost infinite predictions according to individual learner differences. Complete reviews of the Bayesian theory are given in Rothen and Tennyson (1978) and in Tennyson and Rothen (1979).

The parameters of the Bayesian statistic include a criterion level, an error ratio, and a performance value. The calculation of these parameters produces a matrix of beta weights that provide the data source for decision making in several of the design variables. Values for each of the parameters is determined according to both individual learner differences and program considerations.

The criterion level establishes the rate of performance desired at the conclusion of the instruction. It is not the same as a criterion level usually associated with testing (e.g., on a behavioral objective). Testing at the conclusion of instruction assumes that learning has occurred and that the measurement is a true assessment of what has been learned. A criterion level in instruction must assume and, therefore, account for errors in learning during the entire learning process. Bayes theory is excellent in this regard because it weights early errors progressively less and less as the learner advances in learning. Unlike a percentage statistic between correct and incorrect solutions, the Bayesian procedure is able to increase its power of predictability rapidly as the learner acquires sufficient procedural knowledge to solve problems correctly.

The goal was to develop an intelligent adaptive management system for CBI that would enhance decision making to improve learning.

The error ratio parameter, technically termed a loss ratio, determines the balance between falsely advancing a learner who has not actually learned to criterion, as contrasted to falsely retaining a learner who has in fact reached the criterion. This parameter value can be adjusted to the specific learning situation and/or individual differences. A higher error ratio value would require more evidence of correct solutions than a lower value. Using the heuristic method, the error ratio value can be adjusted as the MAIS accumulates experiences.

The third parameter, performance value, assesses performance by comparing the number of correct solutions to the number of problems presented. We have found that by varying the number of problems through simulations of data runs, that a maximum number of problems for learning concepts is 14. We have also found that a minimum of four solutions per concept or rule is necessary before predicting mastery at any given criterion level.

Instructional Theory

The main instructional focus of the MAIS is to increase the amount of interrogatory learning experiences in reference to expository experiences. Most formal instruction uses a learning experiences ratio of 70 percent expository to 30 percent interrogatory. In the MAIS, we attempt to reverse that ratio by minimizing the expository experiences in favor of the interrogatory, while continuously monitoring that ratio to insure sufficient formation of conceptual knowledge. In practice, that means each learner's ratio of expository experiences to interrogatory experiences varies individually.

Design Variables for CBI

A constant criticism of computer-based instruction is the failure to provide real-time individualized instruction. The best CBI has to offer is self-instructional lessons that make minimal use of a computer's capabilities (Breuer, 1981). Typically, the methods of "older" media are simply transferred to the design of computer-based lessons (L'Allier, 1984). Program designs usually follow branching methodologies that set arbitrary and static sequences of objectives, that allow for only a finite set of decisions to account for learning problems. The goal of the MAIS research program, in direct contrast to the conventional approach to CBI design, was to define a set of design strategies that would (1) allow for continuous adapting of instruction to individual learner needs, (2) provide an almost infinite means of presenting information, and (3) would respond intelligently to learner needs progressively better during instruction.

The MAIS is currently composed of six design variables that focus on the improvement of learning through intelligent management of the instruction. The six design variables are: amount of instruction, sequence of instruction, display time, advisement of learning progress, refreshment of prerequisite knowledge, and adjustments of instruction to individual differences. MAIS does not deal directly with specific display characteristics, such as use of color, graphics, and display layout. These variables are important elements of instructional design and we use them in the design of CBI.

The learning theory of the MAIS is philosophically grounded in cognitive psychology.

Amount of Instruction

Determining the amount of information to provide a learner is a primary function of an instructional system. Because of differences in background knowledge, prerequisite knowledge, prior knowledge, and aptitude, each learner requires a different amount of instruction to learn a given domain of information. For example, in our research findings (Tennyson & Rothen, 1977), we have shown that if learners receive more instruction on a concept than is necessary, performance actually deteriorates. And, of course, if insufficient information is provided, then the level of learning is limited.

Basically, a minimum presentation of expository information is provided initially. Our learning theory states that learners will attempt to solve problems first with existing knowledge, and when faced with the awareness that additional knowledge is necessary, proceed to acquire additional information. Thus, the amount of instruction is determined when the learner attempts to problem solve. A minimum amount of expository information is used to establish a working schema that problem solving with interrogatory instruction can elaborate.

It is during interrogatory instruction that a given schema is learned and connections with existing knowledge occur. The expository instruction that precedes interrogation consists of a statement of the problem area or context, the label and definition of relevant concepts or rules, and a best example, all of which initializes the schema. Exposure to problem solving experiences begins immediately after the expository instruction. Once in the interrogatory section of instruction, the amount of instruction is determined by the three parameters of the Bayesian method.

By adapting the amount of instruction to individual learning progress, an increasingly intelligent decision is made rather than setting an arbitrary amount of instruction. And, because the heuristic nature of the decision for amount of instruction includes adjustments to individual differences as well as content conditions, these adjustments can be increasingly refined from experience data. Closely associated with amount of instruction is the sequencing of the information.

Sequence of Instruction

Early attempts to provide response-sensitive sequencing of instruction followed decision algorithms based on mathematical or statistical probabilities (e.g., Atkinson, 1976; Hansen, Rakow & Ross, 1976). These procedures were limited because they are based on a system artificially independent from learning theory (Tennyson & Park, 1984). In contrast, we designed and tested a procedure directly connected to a theory of learning (Park & Tennyson, 1980). The response-sensitive sequence design variable of the MAIS uses a heuristic that adjusts the flow of information continuously according to learning needs at each given moment.

Sequence decisions are made during the interrogatory section of the CBI lesson based on assessment of each learner's response to a problem. For correct solutions, it is assumed that the learner understands the concept or rule, and needs additional problem solving to learn procedures. Additional problems are presented until mastery is reached.

If a learner either fails to provide an answer or provides an incorrect solution, a response-sensitive decision is made. In either case, it is assumed during initial learning that learners need to focus on conceptual understanding; therefore, the instruction is narrowed to only one concept or rule, even though a given lesson may have several coordinate concepts or rules. In this case, the next problem would be presented from the same concept or rule class used initially. Conceptual understanding implies the ability to generalize within a given domain of information; therefore, the instructional sequence strategy focuses the learner on the conditions of problem solving within a given concept or rule.

Assessment of mastery occurs after a minimum number of responses are made; this initial period ranges from 4 to 6 problem solutions. At this point, the amount of instruction is determined iteratively, and the sequence rule focuses on discrimination decision making as well as correct solution behavior. For incorrect solutions, the sequence decision is to present the next problem example from the same concept or rule class the learner incorrectly solved. The purpose is to focus on the decision process of selecting the appropriate concept or rule, not simply on producing a correct solution. Theoretically, the assumption implies conceptual understanding, with the need being to learn procedures.

Display Time Interval

One of the most overlooked design variables in CBI development is the means for controlling the allocation of learning time. Unfortunately, many developers of CBI materials have a misconception about learning time. Most approaches to CBI design are direct violations of good pedagogy (Walberg & Tsai, 1984). Many CBI developers assume that learners have unlimited time to learn and that learners can make good use of their time in learning new information. The idea that the computer was a patient tutor has led many developers to assume that worrying about time is not necessary. This represents a continuing use of programmed instruction (PI) approaches to CBI design as well as a misunderstanding of the mastery learning concept of sufficient learning time.

From a practical point, no learning situation is infinite in time. All learners have real constraints on time allocations. Quality instruction makes it possible to have efficient learning environments so that as much as possible can be learned within the time available for instruction. This is especially true for slow learners.

Likewise, understanding the learning process more fully indicates an instructional need to attend more directly to the monitoring of learning time. First, empirical findings on learning show that the initial period of learning is the most active time for acquisition of information. That initial period is approximately 20 minutes for secondary school age students. For younger learners the average time is probably shorter while for adults a longer period may be expected. Regardless of the length of that initial period, the learning environment needs to be immediately active.

The transition from expository to interrogatory instruction will not be the same for each learner. Learners with insufficient conceptual understanding of a concept or rule will be unable to understand the problem situation or to propose a solution. We investigated a design variable that permitted individual transition between expository and interrogatory instruction by sensing a lack of conceptual understanding (Tennyson & Park, 1984). This was done by monitoring the display time interval so that if the program sensed a no-response situation, it would interrupt. In our first test of the display time interval, each interrogatory example was normed and when time expired without a response, the correct solution was provided. This allowed the learner an opportunity to receive more conceptual knowledge without the fear of forcing responses and possibly encoding incorrect knowledge.

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To allow this design variable to exhibit intelligence, we have further adjusted the information presented and options to the learner when time expires (Tennyson & Park, in press). The presentation of other information is discussed below in the refreshment of existing knowledge section. Additional options include student control over the decision to resist the timer and adjusting the normed times to individual differences (Tennyson, Park, & Christensen, in press).

Advisement

An early recognized failure of learner-controlled CBI systems was the finding that learners were not good at decision making in reference to how much and what kind of instruction they needed. To effectively deal with these two problems, we introduced the concept of advising the learners continuously of their needs and progress in learning (Tennyson, 1981). Conventional CBI lessons, unlike a workbook, are not good in visually helping the student see the entire amount of instruction prior to and/or during instruction. The learner in most CBI situations is without a means for judging where they are in acquiring the information from a specific CBI lesson. For example, with a workbook, the learner can see how many pages need to be done; they can see lines being filled in or problems being answered. They can actually see their progress in finishing the work. One assumption in a schematic organization of information is that prerequisite knowledge can be readily recalled so that appropriate connections between existing knowledge and the information to be learned can be made. Typically, refreshing prerequisite knowledge is done in a review prior to instruction—if it is done at all.

Prior refreshment of prerequisite knowledge seems to contribute minimally to learning from a cognitive science view. First, the information recalled in a review is not kept in working memory once instruction begins. And, secondly, the presentation reviews the prerequisite knowledge without benefit of the connections to the new information.

Recently, we have investigated a means for refreshing specific prerequisite knowledge at that point in the instruction where the learner needs help in making connections with new knowledge (Tennyson, Welsh, Christensen, & Hajovy, in press). This instructional design variable, embedded refreshment, presents the specific prerequisite information only if the learner is unable to solve an interrogatory problem. Operationally, the embedded refreshment helps the learner recall the prerequisite knowledge, retrieving it for use in working memory simultaneously with the acquisition of the new information. Embedded refreshment offers help in both recalling prerequisite knowledge by placing it in working memory and by making the connections between the existing knowledge and the new knowledge to be learned.

Implied in embedded refreshment is the assumption that prerequisite knowledge is in long-term memory and that recalling it helps in learning new information. It is not a means by which the learner can at that point learn the prerequisite information. We have two associated design variables to assess and assist the learner in reestablishing a mastery level use of the prerequisite knowledge.

The first variable is a pretest that evaluates the learner's current mastery level of the prerequisite information. Thus, a learner would not even begin instruction until mastery was assessed. This system of testing actually presents instruction if the learner is assessed not to have the defined mastery level. The second variable is a procedure where the MAIS senses that the learner needs more than just the embedded refreshment of specific prerequisite knowledge. At that point, the learner is provided with remedial refreshment that temporarily removes the learner from the main program. The remedial refreshment provides additional instruction in the form of interrogatory practice. Again, we assume that refreshment is used to retrieve from long-term memory appropriate prerequisite knowledge for use in working memory. Remedial refreshment is provided for only specific situations and not for initial encoding.

Individual Differences

One of the first hopes of computer technology applications in education was the individualization of instruction according to individual learner differences. However, this hope is yet to come about because of two factors. The first is that attempts to identify the interactive effects of individual difference variables with instructional variables has been elusive. Too often experimental designs have approached the interactive effect with one possible individual factor crossed with one instructional design variable. For example, testing a learning style variable (e.g., field independent vs. field dependent) with a concept teaching strategy (e.g., best example vs. definition). When significant findings are reported, they usually appear to be situation specific and not generalizable. In our research, we view the study of individual differences from a multiple regression approach so that the contribution of a number of individual differences variables to interactions can be observed.

A second factor is the microcomputer and its limited memory capacity which moved instructional design away from management systems that could account for individual differences. Before microcomputers, there was much work on computer-managed instruction (CMI) (Tennyson & Park, 1984); but mostly for data storage and retrieval. The microcomputer revolution interrupted the serious study of using large amounts of data for instructional decision making.

For CBI, the value of individual differences can be appreciated from a curricular level. For CBI to be intelligent, it needs to accumulate information over time. For the next several years, our goal is to investigate management of CBI over time at the curricular level. Individual differences variables that we feel need testing range from personality to cognitive to biopsychological. Basic research in each of these areas indicates a high potential for application (Farley, in press).

One of the most overlooked design variables in CBI development is the means for controlling the allocation of learning time.

Summary

The purpose of this article was to identify instructional design variables that contribute to the development of intelligent CBI. The variables reviewed were part of a program of research that has brought together theories and research from the fields of learning, instruction, and educational technology. This interdisciplinary approach has allowed for the development of an adaptive instructional system that exhibits intelligence in instructional decision making.

An integral philosophy of the MAIS is that intelligence assumes a continuing advancement in decision making as knowledge is acquired. To implement this philosophy, the computer science method of heuristic programming has been used. Even as new variables are investigated we can continuously improve earlier variables with experience. At the present time, the MAIS operates at the instructional level of management; adapting instruction only after the learner enters the program and the program starts acquiring information. Future research will focus on the curricular level so that adaptation can begin before instruction begins and continuously interact between the curriculum and instruction levels.

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