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# A study of computer-assisted learning with artificial intelligence games.

Howard A. Peelle

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**FIVE COLLEGE  
DEPOSITORY**

A STUDY OF COMPUTER-ASSISTED LEARNING  
WITH ARTIFICIAL INTELLIGENCE GAMES

A Dissertation Presented

By

HOWARD A. PEELLE

Submitted to the Graduate School of the  
University of Massachusetts in  
partial fulfillment of the requirements for the degree of  
DOCTOR OF EDUCATION

July, 1971

A STUDY OF COMPUTER-ASSISTED LEARNING

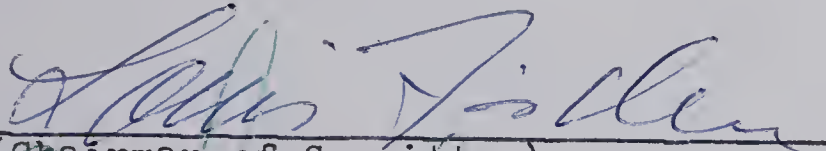
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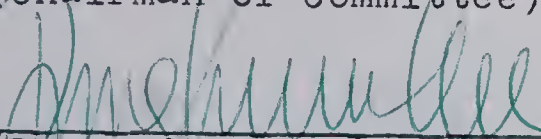
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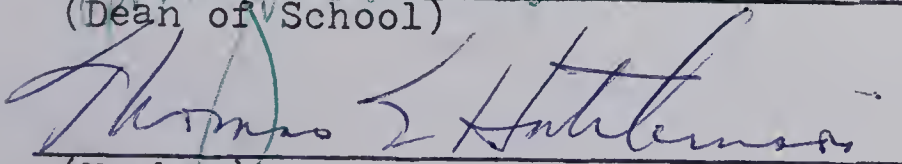
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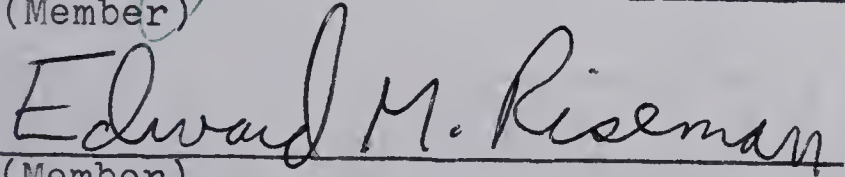
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July, 1971



A STUDY OF COMPUTER-ASSISTED LEARNING  
WITH ARTIFICIAL INTELLIGENCE GAMES

July, 1971

Howard A. Peelle, B.S., Swarthmore College

Ed.D., University of Massachusetts

Using two intellectual games implemented on an interactive computer system, learning patterns of elementary school 5th and 6th grade children are examined. Computer-assisted instructional games, LAST-ONE-LOSES and EVEN-WINS (both variants of NIM), are programmed (in APL) to exhibit artificial intelligence characteristics. Subjects first select the level of their machine opponent's game-playing ability and then compete with programs which are either "learning" or "static" (non-learning). Machine learning is programmed algorithmically to adapt to an optimal strategy by progressive steps; the effect resembles some human learning patterns. Additionally, some subjects play with an "executive option"; that is, after any game, they may adjust the level of the program's expertise by typing PLAY EASIER or PLAY HARDER. Comprehensive performance data gathered on-line reflect differences in effectiveness of the programs. Although statistically significant differences were not found in variables identified to measure learning, results bear consideration for subsequent hypothesis generation.

DEDICATION

To my wife, Carolyn, for her unwavering support of this investigation and of this investigator; and to my daughter, Juliet, who was conceived about the same time as this dissertation.

ACKNOWLEDGEMENTS

The investigator wishes to acknowledge the assistance, cooperation, and encouragements of the following persons: Mr. Michael Greenebaum, Principal of Mark's Meadow Elementary School, for his overall support of this study and his interest in computer-assistance instruction for children; Mr. John Byron and Mrs. Linda Streeter, teachers at Mark's Meadow School, for their daily cheerful assistance in recruiting and scheduling subjects for testing; Miss Andrea Wright, Director of Hampshire College's Early Identification Program for her provision of subjects for this study; and Dr. Conrad Wogrin, Director of the University Computing Center, University of Massachusetts, for his generous provision of computer resources and research grants.

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## CHAPTER I

### THE CHALLENGE

Computer technology purports to make an unprecedented impact on education; in fact, computers are already being used in schools. The question, indeed, the profound challenge facing us all, is no longer whether or not to utilize the computer as an educational resource, but how to use this tool-- the most versatile and powerful tool mankind has ever known.

The urgent need for research directed at exploring creative and effective applications of computers in education becomes apparent when some causes of the current crises in American education are cited:

- a) pervading societal racism, alienation, and impersonalization
- b) pressure for increased centralization of knowledge and efficiency of information distribution
- c) conflicting demands for greater specialization and greater adaptability to a rapidly changing economy, coupled with needs for retraining and more general education (1)
- d) pressure for reform in school curriculum, staffing, and organization

- e) shortage of well-qualified teachers
- f) antiquated teacher-training methods and facilities
- g) rapidly expanding student populations
- h) demands for more student-initiated activities and 'freedom to learn'<sup>1</sup>
- i) pressure for alternatives to compulsory schooling<sup>2</sup>

At the same time, advanced technology offers great promise for present-day education to meet some of the pressing needs with vast new capabilities, including:

- a) mammoth information storage and retrieval capacity
- b) high computing speed, accuracy, and endurance
- c) centralized communications functions
- e) multi-media systems

Although the growth of computer usage in all fields during the last two decades has surpassed nearly all expectations, only four years ago there were those who believed that this technology was in an embryonic stage (2). Today, progress is reported somewhat differently in two basic areas of computer applications in education:

- 1) Educational Data Processing (EDP)
- 2) Computer-Assisted Instruction (CAI)

The data processing power of computers is well

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<sup>1</sup>See Carl Rogers' Freedom to Learn, 1969.

<sup>2</sup>See De-Schooling Society, by Ivan Illich (Director, Centro Intercultural de Documatacion, Cuernavaca, Mexico), 1971. Also, Compulsory Mis-Education, by Paul Goodman, 1962 and The Under-Achieving School, by John Holt, 1970.



demonstrated and acknowledged by many in the hierarchy of public educational systems. Computer support for educational innovations--such as flexible scheduling--as well as for the traditional administrative functions--such as student record-keeping--is now generally accepted as the rule rather than an exception. In fact, many large-scale operations in education (the nation's biggest industry) are just not feasible without computers. As Louis Bright (3), Associate Commissioner for Research, U.S. Office of Education, has stated:

Computers have already altered both the techniques and concepts of school administration at elementary-secondary and higher levels of education.

Other indications confirm that this area has clearly taken hold: large professional associations such as AEDS (Association for Educational Data Systems) now meet regularly to share information and experience; a bevy of private management consulting firms including Educational Coordinates at Stanford and The Diebold Group in New York have appeared on the scene; and at a major conference at Stanford University on the role of computers in education, there was unanimous expression of need for a clearinghouse, but no emphasis for further research (4).

In addition to performing administrative functions, computers are also a subject of and a vehicle for learning.

In the second basic area of computer applications,

Computer-Assisted Instruction,<sup>1</sup> dire need for research was stressed as recently as last year in a consensus result of seminars with leading scientists and educators discussing policy developments on utilization of computers in education. Margolin and Misch (5) reported:

It is felt that there is a basic need to know more before we proceed too far. It is recommended that R & D into the process and dynamics of CAI and of education should be accepted as a primary need at this time.

That computer-assisted instruction holds potential for contributing to education has been the opinion of many pioneers in the field. Patrick Suppes (6), Director of the Institute for Mathematical Studies in the Social Sciences at Stanford University, advocated individualizing instruction for the masses:

Perhaps the most important aspect of computerized instructional devices is that the kind of individualized instruction once possible only for a few members of the aristocracy can be made available to all students at all levels of abilities.

Lawrence Stolurow (7), once Director of Harvard University's Computer-Assisted Instruction Laboratory, saw the computer as a boon to the behavioral sciences, particularly in the psychology of teaching:

. . . the use of a computer for instruction is a significant development . . . because of its immediate contribution to the clarification of teaching as a set of dynamic processes.

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<sup>1</sup>"Computer-Assisted Instruction" or "Computer-Aided Instruction" (abbreviated CAI) is a method relying on a computer to present prespecified material in any of a variety of modes and styles to a number of students individually for the purpose of learning.

Hopeful of an emerging theory of instruction because of the highly controlled conditions offered by CAI are people like Richard Atkinson (8) who is conducting research in an initial reading CAI program.<sup>1</sup> He stated:

It is my hope that prospects for CAI, both as a tool for research and a mode of instruction, will act as a catalyst for a rapid evolution of new concepts in learning theory as well as a corresponding theory of instruction.

Other researchers and developers of CAI systems, notably Bitzer, Seidel, Grubb and Adams, and Glaser,<sup>2</sup> laud the management functions computer operations afford. Among the qualities of "computer-managed instruction" (or "computer-mediated instruction") are: simultaneous service of large numbers of users by a single computer ("time-sharing"), rapid information retrieval, continuous monitoring of student performance, broad selection of instructional materials, sequential testing, and 'instant' evaluation.

Directors of computer installations across the country seldom agree about future directions for CAI, and industry is generally over-cautious in speculations, but both sectors seem to agree on one forecast--computers are coming! Sylvia

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<sup>1</sup>Developed at Stanford University and field tested at Brentwood School, East Palo Alto, California.

<sup>2</sup>Donald Bitzer directs the PLATO system at the University of Illinois; Robert J. Seidel conducts research at the Human Resources Research Office, George Washington University; Ralph Grubb and E.N. Adams are with IBM in San Jose and Yorktown Heights, respectively; Robert Glaser is of Learning Research and Development Center, University of Pittsburgh.



Charp (9), Director of Instructional Systems Center, Philadelphia (supported by the Board of Education), said with certainty:

Computers, without doubt, will play an increasingly prominent role in education during the last third of the Twentieth Century.

In 1967 IBM discovered that their decision to purchase an educational publishing firm<sup>1</sup> reflected a trend in the business world. IBM's Marketing Research and Forecasting Department reported (10):

Many large electronic firms are acquiring or merging with educational publishing companies or developing in-house educational capabilities . . . . Publishers are interested in publishing CAI courses . . . .

Predictions by eminent authorities in technological fields indicate that not only will the computer play an important role in education of the future, but that it will play a major role in bringing about changes. Management systems technocrat John Diebold (11) wrote in his book, Man And The Computer:

Technological developments give promise that, in the course of the next decade, highly effective educational systems can be created that would alter totally the future processes of education . . . . Such improvements, particularly in the man-machine interface, are making possible increasingly easy, natural communications between students and machine systems, so that we can begin to think in terms of computer-based systems playing a vital role in the educational process.

Oettinger (12), Director of Harvard University's Computing

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<sup>1</sup>Science Research Associates, Inc. (Chicago, Illinois) became a wholly owned subsidiary of IBM in 1964, and the Computer-Related Instructional Systems Center was established in 1967.

Center, compromised his reputation for pessimism (with regard to CAI) in Run, Computer, Run when he said:

More subtle qualities, however, make computers capable of profoundly affecting science and education by stretching human reason and intuition, such as telescopes or microscopes extend human vision. I suspect that the ultimate effects of this stretching will be as far-reaching as the effects of the invention of writing.

Computer-assisted instruction has already been utilized at many levels of education--from elementary schools to post-graduate courses to adult education--in a potpourri of subject areas including foreign languages, mathematics, natural sciences, social sciences (primarily for statistical work), reading and spelling, computer science, operations research and management systems, business and job training. Typical modes of instruction via CAI are drill and practice, tutorial, and simulation--all with a large degree of computer control--and "inquiry," "dialogue," problem-solving, laboratory, and "ad-lib," with the learner in control most of the time.

Unfortunately, developments in computer-assisted instruction over the last five years have proved mostly disappointing. While prospects for widespread CAI appear exciting and hopeful, problems are still extremely challenging and sometimes foreboding. Costs remain prohibitively high; marketed hardware is generally not tailored for educational purposes; software support often lacks compatibility or is not available; most CAI-integrated learning

systems are designed with a myopic view of students' creative pursuits; quality of curricular materials developed to date is dubious at best; and training programs in computer usage are few and often threatening.

Furthermore, teachers are overburdened and frequently resist innovations; school administrators are generally technologically uninformed; parents and community personnel are not involved; and, while many students happily take interest in computers, their choices are subverted by entrenched certification procedures ("the system"). Finally, there is conspicuous absence of cooperation between major factions-- professional educators, industry, computer scientists, governmental agencies, and laymen. This communications failure has compounded problems and severely limited the range of possible styles and uses of CAI.

In the face of these (and other) problems, this investigator raises positive questions: "What is the potential of CAI? How can computers serve to enhance learning experiences for increasing numbers of students? How can CAI complement human instruction?" This optimism, however, is no longer couched in the context of a novel technology. Rather, this study seeks to revitalize CAI by introducing new techniques drawn from the highly specialized, somewhat clandestine research area of artificial intelligence.



Artificial intelligence (AI)<sup>1</sup> offers computer-assisted instruction a quality heretofore weak or altogether lacking: sensitive and "intelligent" interaction with a machine. Specifically, application of certain AI techniques could further some or all of the following goals:

- 1) facilitate information retrieval
- 2) finely discriminate patterns
- 3) approach natural language conversation
- 4) adapt and change as a result of 'experience'

In the instructional setting these goals could be translated into advantages for the learner. One could control the computer's behavior more easily, receive greater variation in responses, and generally engage the machine less as a task-master and more as an intellectual partner in an educational pursuit.

It is the opinion of this investigator, then, that the prospect of achieving these advantages warrants exploring AI in CAI.

Of the existant modes of CAI, one is particularly attractive for the purpose of testing AI techniques--that is, gaming. A game provides a limited, specifiabile problem area with well-defined, not-too-complex rules, and is ideally suited for tree structure modelling. AI techniques for searching trees (for best moves) can be readily carried

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<sup>1</sup>"Artificial Intelligence" (abbreviated AI) is behavior by a machine that we call intelligent behavior when we observe it in human beings.

out in a game context, whether by algorithmic procedures or by pattern-recognizing heuristics.<sup>1</sup> In previous research efforts, automated games have proved to be excellent vehicles for experimentation with some AI techniques--usually to demonstrate machine learning. (See Chapter II, RELATED RESEARCH.)

Gaming offers opportunities often not possible in real life. While conducive to full emotional and intellectual involvement, games permit players to repeatedly test solutions (or strategies) for problems (or situations) which are in reality either too risky, too expensive, or irreversible. Mathematical models of physical, economic, political or other systems can be used to simulate the future.<sup>2</sup> In a

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<sup>1</sup>Differences in the two procedures--algorithmic and heuristic--are often illustrated by machine learning in the two games Tic Tac Toe and checkers (or chess). In the trivial game of Tic Tac Toe a computer program can be instructed by a set procedure, or "algorithm," to explore all possible outcomes of a given move (an "exhaustive search"). In the complex game of checkers, however, to examine every possible move sequence (approximately  $10^{40}$  choices) would take over sextillion centuries using the fastest of present day computers (capable of executing about 300 million moves per second) for the computer to 'decide' its first move. This game requires a heuristic approach--resembling a human checker player's approach. A heuristic is a method or trick used to improve the efficiency of a system, such as recognizing winning strategies in a game.

<sup>2</sup>e.g. "The World Game," a simulation game of earth resources allocation based on Buckminster Fuller's ideas, World Resources Inventory, Carbondale, Illinois.

e.g. "Dangerous Parallel," a classroom simulation of international decision-making, Parker Brothers.



benign environment, mistakes can be made, their probable consequences scrutinized, and, as Seymour Papert has pointed out, "the errors may be turned into positive advantage,"<sup>1</sup> all at no risk to society.

Game-playing is generally regarded as a natural, enjoyable activity for persons of all ages in all cultures. Views that "all the world's a stage, and all the men and women merely players,"<sup>2</sup> and "that life is a game and man is homo ludens--the playing animal"<sup>3</sup> have held credibility over the ages. Using Haney's (13) words, "whether man is viewed as a child of God, a prisoner of fate, a reasoning animal, a political animal, a playing animal--or some combination of all of these--seems to depend on how the viewer handles the question of uncertainty in human existence." In any case, age-old pastimes like chess, checkers, and Go, which rely on uncertainty,<sup>4</sup> are woven into cultural fabrics.

Gaming theorists have been trying for years with little agreement to define the essential features of educational games. That games stimulate active participatory learning

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<sup>1</sup>Conversation with Seymour Papert, Director, Artificial Intelligence Laboratory, M.I.T., April 12, 1971.

<sup>2</sup>"As You Like It," Shakespeare.

<sup>3</sup>See Homoludens: A Study of Play in Culture by John Huizinga, 1950.

<sup>4</sup>The game of Tic Tac Toe illustrates that when uncertainty disappears (as it does for the player who discovers that he can predict outcomes of his moves), so does interest in the game.

is a common tenet. Clark Abt (14) cites evidence that in properly constructed and supervised gaming situations, students appear to learn more quickly and more fully, retaining what they have learned better and longer (15). In his new book, Serious Games, Abt aptly describes the value of games designed with specific educational goals as enabling children (and adults) to learn abstract concepts that are required to function in a world becoming increasingly complex.<sup>1</sup> Furthermore, because of the need for new educational tools, he forecasts increasingly widespread use of serious gaming in education and training at all levels. Games-makers like Allen, Gamson, Goodman, and Duke<sup>2</sup> readily admit that simulations simplify, caricature, and distort the real-world systems they represent, but quickly add that a simulation is economical, observable, controllable, reproducible, and changeable--hence useful to students who are willing to experiment (13).

Despite increased popularity of late, gaming and simulation remain virtually untapped modes of CAI. Execution of some educational games and simulations by computer offers appealing advantages, including:

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<sup>1</sup>Abt adds that in the technical society of the United States, its educational system is not responding to these increasing demands.

<sup>2</sup>University of Michigan professors who developed games like WFF 'N PROOF, QUERIES 'N THEORIES, SIMSOC (Simulated Society), COMMUNITY, and POLICY NEGOTIATIONS.

- 1) rapid execution of multiple consequences
  - 2) simultaneous usage by students learning at different rates
- and
- 3) accurate branching on complex conditions

While automated games represent viable vehicles for learning, little research has been conducted in their usage.

(See Chapter II, RELATED RESEARCH.)

Preliminary observations<sup>1</sup> of children playing intellectual games on a computer lent support to the notion that AI could appreciably complement CAI. Some children appeared deeply intrigued by playing against a computer program which was 'learning'<sup>2</sup> concurrent with their own learning. Presently, however, there exists no documentation of children's patterns of learning while interacting with artificial intelligence programs. To generate hypotheses for study in the new area of AI in CAI without empirical data would be merely speculative.

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<sup>1</sup>During Mark's Meadow Elementary School's "Learning Fair," November 1970 - April 1971, by this investigator.

<sup>2</sup>In this instance the computer was programmed to exhibit artificial intelligence by progressively improving its performance; that is, (basically) the more often it loses, the faster it learns to make winning moves. (See Appendix A for details.)



In summary, the need for this research is seen from the following:

- 1) Although computer-assisted instruction (CAI) has great potential for meeting some of the pressing needs of education, major problems remain to be overcome.
- 2) Humanistic (complementary) applications of computers in education, particularly using games and simulations, are few. (Refer to Chapter II, RELATED RESEARCH.)
- 3) Of the research conducted in artificial intelligence (AI), little has been directed at studying AI implemented in computer-assisted instruction curriculum, which is in dire need of revitalization. (Refer to Chapter II, RELATED RESEARCH.)
- 4) Certain artificial intelligence techniques offer advantages in the teaching-learning setting.
- 5) Presently there exists no empirical data on the efficacy of AI in CAI on which to base hypotheses for further studies.

The problem area this investigation addresses is usage of computers in the learning process. Since the computer is, as Allan Ellis<sup>1</sup> said, "an anything machine," a multitude of philosophical ramifications surround its actual and anticipated usage. Given all that the prospects for behavioral control portend, it is crucial to be on guard against abuses and misuses of this (or any) technology. Questions of whether computers will be integrated into a salvaged educational system of tomorrow or used as an instrument of salvation or serve to provoke radical changes toward a de-schooled society remain to be answered.

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<sup>1</sup>Harvard University, Cambridge, Massachusetts.

Within the above-mentioned problem area, particular aspects have been identified for exploration in this investigation. Specifically, the problem of this investigation is to demonstrate differences in learning when children play intellectual games on a computer capable of exhibiting 'artificial intelligence.' Factors which contribute to such differences will be scrutinized, and hypotheses deemed reasonable for further investigation will be generated.

This is an exploratory study, dedicated to gathering preliminary data on children's usage of automated learning systems. It is the first and necessary step in research aimed toward the development of a 'comprehensive psychological operating system' for CAI.<sup>1</sup> It is toward the eventual goal of a discerning, sensitive response system that this study commits itself.

In order to accomplish the foregoing, this investigator has conceptualized two sub-problems, hereafter called main hypotheses. These hypotheses were derived from pilot testing conducted earlier by this investigator,<sup>2</sup> from discussions with university faculty and students in education, computer science and psychology, and from theoretical notions on concepts of learning via computer systems.

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<sup>1</sup>Proposed joint research project, Professor E. Rise-man, Department of Computer Science, UMASS and H.A. Peelle, School of Education, UMASS.

<sup>2</sup>Use of computer games by approximately 100 elementary school children, grades K through 6 from Mark's Meadow Elementary School, November 1970 - April 1971.

The main conceptual hypotheses are:

1. Children playing an intellectual game on a computer learn more effectively when the computer program is "learning" concurrent with their learning than do children using a computer program which plays with a static strategy. (The mode hypothesis)
2. Children playing an intellectual game on a computer learn more effectively when an "executive" computer program permits them the "option" after any game to adjust the level of difficulty exhibited by the computer than do children using a computer program having no option. (The control hypothesis)

While to 'learn more effectively' certainly connotes a complex set of diverse descriptors, variables identified for the purpose of measuring learning in this study are the following:

- 1) "Winningness"
- 2) "Attentiveness"
- 3) "Intolerance"
- 4) "Decision-speed"
- 5) "Understanding"
- 6) "Generalizability"

(See Chapter III, METHODS AND PROCEDURES for operational definitions.)

In order to research the problem of this investigation, twelve experimental hypotheses were identified. (See Chapter III, METHODS AND PROCEDURES.) Testing of hypotheses was conducted and results described and discussed. (See Chapter IV, RESULTS AND DISCUSSION.)



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## CHAPTER II

### RELATED RESEARCH

In this chapter no attempt is made to review comprehensively literature in both fields of AI (artificial intelligence) and CAI (computer-assisted instruction).<sup>1</sup> Rather, it is intended here to examine pertinent research and overlapping developments emerging from each of these fields toward a common ground.

In general, developments and research in Computer-Assisted Instruction have yet to make a significant impact in education. Although the plethora of materials now in circulation on CAI-- its projects, prospects, and problems-- would seem to imply a long history and an abundance of research results in this area, the case is quite the contrary.

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<sup>1</sup>The reader is referred to Machine Intelligence Series, edited by Donald Michie (1) and to ENTELEK Corporation's Computer-Assisted Instruction: A Survey of the Literature, edited by Albert Hickey (2) for sources of review. Also, for descriptions of selected developments in the two fields, respectively, see Computers And Thought, edited by Feigenbaum and Feldman (3) and Computer-Assisted Instruction: A Book of Readings, edited by Atkinson and Wilson (4).

CAI is a field in its infancy.<sup>1</sup> As Long (8) confirms, early uses of computers in teaching did not differ radically from the more sophisticated experiments carried out in 1969! Even in the last five years, relatively few of the possibilities of CAI have actually been developed, and few of the new or old applications have been used more than experimentally (9).

In general, research in Artificial Intelligence is seen to lack an education orientation. In the area of AI, concentrated research has been ongoing since early 1950's (when the term was first coined), but results rarely filter through to the general public,<sup>2</sup> much less to educational circles. The latest thinking, major breakthroughs, and problems encountered in AI are most often disseminated in

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<sup>1</sup> According to Miller (5), in 1958 Nancy Anderson and Gustave Rath (6) were perhaps the first researchers to experiment with computers in instruction, using an IBM 650 computer to teach binary arithmetic. Other early experimentation was carried out at Systems Development Corporation and Bolt, Beranek and Newman. Significant development efforts did not occur until around 1961, when the Coordinated Science Laboratory of the University of Illinois produced the PLATO system (Programmed Logic for Automatic Teaching Operations) under the direction of Donald Bitzer. 1966 saw an upsurge of CAI activity (with magnanimous federal fundings), and news of Patrick Suppes' (7) pioneering work teaching arithmetic and reading skills to elementary school children on an IBM 1500 system reached readers of a popular magazine.

<sup>2</sup> except occasionally under undesirable circumstances, the most recent case of which involved LIFE article "Shaky, The First Electronic Person" by Brad Darrach, November 20, 1970. Reactions to journalistic distortions were promptly forthcoming from those currently conducting controversial research in AI. See, for example, Marvin Minsky's (10) rebuttal.



technical journals by authors from universities and from government-supported research companies.

Examination of work performed in the field of AI which points to application in CAI and examination of work in CAI which begins to employ AI techniques together give indications of the prospective marriage of AI and CAI.<sup>1</sup>

In what appears to be a vanguard effort in the area of AI in CAI, Jaime Carbonell (11) demonstrated 'mixed-initiative dialogue'<sup>2</sup> between a student of geography and a computer. Although the actual AI techniques employed differ from those used in this investigation, his work does explicitly use AI for "new and more powerful" CAI. Using an information network<sup>3</sup>, Carbonell's program (SCHOLAR) can generate text, questions and corresponding answers, as well as answer questions formulated by the student. Proudly, Carbonell claims that:

SCHOLAR can prompt the student, indicate when it does not understand him, detect misspellings, and answer

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<sup>1</sup>The research reported herein is, to this investigator's knowledge, one of the first documentations of use of artificial intelligence per se in a computer-assisted instruction simulation-gaming context.

<sup>2</sup>By 'mixed-initiative dialogue' he means that questions and answers are possible from both sides.

<sup>3</sup>An information or 'semantic' network (first introduced by Quillian (12)) is an array of facts, concepts, and procedures arranged in a multi-level tree structure. Each unit of information in the network (a branch of the tree) points to a list of other units, which in turn point to their respective lists, and so on, hence 'defining' a word or event.

the student's question using acceptable English. SCHOLAR can also generate questions and evaluate the student's answers, deciding when these are correct, wrong, or only approximately or partially correct, and then take some conditional actions.

Because of its direct relevance to this investigation, a sample of on-line interaction with SCHOLAR is reprinted here in Fig. II-1 (with permission from the publisher).

The aspect of Carbonell's work which has central bearing on this investigation is adaptability during man-machine discourse. As the AI-CAI games used in this research are pre-programmed to adapt progressively to an optimal strategy, so SCHOLAR can (by keeping track of descriptive content from its information network) change its procedures according to time and relevancy considerations without specific and detailed directions. The difference between this capability and classical tutorial design<sup>1</sup> would surely impress an author/teacher who would no longer need to enter into a CAI program all anticipated answers along with questions and text.

Although using subject matter different from that of this investigation (mathematics) and a mode of CAI different from simulation-gaming, nevertheless Carbonell's achievement demonstrates feasibility of use of AI in CAI. No results of field testing were mentioned, however.

Before discussing related research any further, it is appropriate to point out that each field--AI and CAI--is

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<sup>1</sup>Conventionally, in CAI tutorials, the data base consists of specific 'frames' of learning material.



REPHRASE YOUR STATEMENT. I CAN'T UNDERSTAND IT.

\*INCORRECT\*

VERY GOOD.

THE AREA OF PARAGUAY IS APPROX 157000 SQUARE MILES.

THE LANGUAGE IN BRAZIL IS FRENCH.  
RIGHT OR WRONG?

\*WRONG\*

YOU ARE CORRECT.

THE LANGUAGE IN BRAZIL IS PORTUGUESE.  
IS IT TRUE THAT THE CAPITAL IN BRAZIL IS BRAZILIA?

\*YES\*

THAT'S FINE.

APPROX WHAT IS THE POPULATION IN BRAZIL?

\*60000000\*

APPROXIMATELY TRUE, BUT A MORE EXACT VALUE IS 700000000.

WHAT IS BRAZIL?

\*TELL ME SOMETHING ABOUT PERU.\*

WAIT A MINUTE, I'M CHECKING MY FILES.

LET'S PROCEED NOW.

PERU IS A COUNTRY.  
IT IS IN SOUTH AMERICA.  
THE POPULATION IS APPROX 70000000 PEOPLE.  
THE CAPITAL IS LIMA.

NOW ANSWER THE QUESTION YOU DIDN'T ANSWER BEFORE.

\*Q/A\*

DO YOU WANT TO CHANGE THE GENERAL MODE OF THE INTERACTION  
TO Q/A?

PLEASE ANSWER Y OR N.

\*Y\*

OK, MR. JONES. LET'S GO AHEAD.

\*PLEASE, TELL ME MORE ABOUT PERU.\*

THE AREA OF PERU IS APPROX 480000. SQUARE MILES.  
THE LANGUAGE IS SPANISH.

\*800300\*

YOUR ANSWER IS INCORRECT.  
THE CORRECT ANSWER IS: 214000.

THE POPULATION IN CHILE IS APPROX 6500000. PEOPLE.  
TRUE OR FALSE?

\*TRUE\*

YOU ARE CORRECT.

USE ONE OF THE FOLLOWING:

- SUCRE
- FRENCH
- ARGENTINA
- SPANISH

TO ANSWER THE QUESTION:

WHAT IS THE LANGUAGE IN CHILE?

\* YOU ARE TAKING TOO MUCH TIME...\*

\*SPANISH\*

YOU SHOULD HAVE WRITTEN "SPANISH".

VERY GOOD,

THE CAPITAL IN CHILE IS SANTIAGO,  
CORRECT OR INCORRECT?

\*CORRECT\*

THAT'S RIGHT.

APPROX WHAT IS THE AREA OF BRAZIL?

\*2500000 SQUARE MILES\*

WRONG.

PLEASE INDICATE IF THE FOLLOWING STATEMENT IS CORRECT  
OR INCORRECT:

THE AREA OF PARAGUAY IS APPROX 47432 SQUARE MILES.

\*WHAT IS THE AREA OF BRAZIL?\*

THE AREA OF BRAZIL IS APPROX 3600000 SQUARE MILES.

NOW ANSWER THE QUESTION YOU DIDN'T ANSWER BEFORE.

\*FALSE\*

\*SCHOLAR\*

HELLO, MY NAME IS SCHOLAR. I WILL HELP YOU IN REVIEWING  
THE GEOGRAPHY OF SOUTH AMERICA. THIS IS ABC REGIONAL  
HIGH SCHOOL. TODAY IS 04/29/70.

IF YOU HAVE CAREFULLY STUDIED YOUR INSTRUCTIONS, WE  
MAY BEGIN THE REVIEW NOW.

WHEN YOU ARE READY TO START, TYPE READY --- REMEMBER  
TO TERMINATE WITH AN ASTERISK \* FOLLOWED BY A CARRIAGE  
RETURN.

\*READY\*

PLEASE TYPE YOUR NAME --- MR., MISS, OR MRS. FOLLOWED  
BY FIRST NAME, MIDDLE NAME OR MIDDLE INITIAL, AND LAST  
NAME.

\*MR. JAMES R. JONES/S/6/65\*

NAME OF YOUR INSTRUCTOR, PLEASE:

\*MR. BROWN\*

LET'S BEGIN OUR DISCUSSION NOW, MR. JONES.

WHAT IS CHILE?

\*A COUNTRY\*

THAT'S FINE.

SELECT AN ALTERNATIVE FROM THE LIST:

- 214000.
- 800300.
- 49883.
- 63690.

FOR THE QUESTION:

APPROX WHAT IS THE AREA OF CHILE?

Figure II - 1 A protocol of student conversation with program SCHOLAR (J. Carbonell)

interdisciplinary and embraces a variety of activities.<sup>1</sup>

Both terms 'artificial intelligence' and 'computer-assisted instruction' are subject to broad interpretations; therefore, one would not expect uniform agreement on what is 'AI in CAI.'

It can be presumed that most research in AI was not pursued with intentional applications to education in mind. One has to stretch to imagine what Minsky (13) meant in 1961 when he said that "we can work toward programming what will be, in effect, 'thinking aids'." In any event, Minsky's later treatise, Semantic Information Processing (14), is a major foundation block. If certain progress in areas of AI like design of question-answering systems<sup>2</sup> is considered potentially applicable to CAI, then that progress is legitimate groundwork for AI in CAI.

To the extent that progress in CAI systems and curriculum development was spurred on by challenges of artificial intelligence problems, research in AI leading to such progress has helped justify CAI on performance bases. Hagamen (17) attempted applications of artificial intelligence, natural language analysis, and interactive graphics in a CAI approach to medical education in hopes of

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<sup>1</sup>AI is the generic name for specialized areas such as robotics, cybernetics and bionics and includes topics of machine learning, pattern recognition, automatic theorem-proving, simulation of cognitive processes, question-answering systems and natural language translation.

CAI draws liberally from fields of psychology, statistics, education, and computer science.

<sup>2</sup>Research in question-answering systems, notably by Quillian (12), Wexler (15), and Simmons (16), was aimed primarily at solving problems in natural language processing.



"a truly two-way, free-format discussion where each student is treated as an individual." And as a rationale for using AI in CAI he argued:

Since we can formally present only a small fraction of the problems our students may some day have to deal with, we are concerned not only with presenting factual information, but even more with developing their power to reason and handle new problems.

Hagamen's program gave the learner of anatomy a choice: "DO YOU WANT TO BEGIN BY ASKING QUESTIONS? (SQ) OR DO YOU WANT ME TO INITIATE THE DISCUSSION? (CP)."

Apparently he was seeking the kind of interactive capability Carbonell's SCHOLAR performs automatically; that is, the ability to discern the mode of learning preferred by the student at any time and to adapt accordingly. But, frustrated by the system (IBM 1500) and the language (COURSEWRITER II) which were not designed to further the 'interdisciplinary' capacities he sought, Hagamen concluded that CAI could justify itself on a performance basis only if "a really interdisciplinary phase of research and development is undertaken now."

Lawrence Stolurow (18), an early leader in the design and implementation of CAI systems, alluded to the use of AI when he exhorted re-examination of concepts and approaches to instruction:

We need greater flexibility. With a CAI system this can be provided by different approaches, such as artificial intelligence.

Also, John Starkweather (19) proposed a computer



language (PILOT)<sup>1</sup> for a variety of conversational programming needs in admonition against monolithic CAI. His concern, too, was for users' options to change curriculum. Believing that education will become less fact-transmission and more focused on inquiry and problem-solving, he propounded greater control for the student. While Starkweather saw the need for CAI systems which "can analyze and respond to relatively unconstrained input from the student," he stopped short of deploying more powerful heuristic techniques from AI, as are now available due to developments by Slagle (20) and Nilsson (21).

In these examples, the overall relation to the current investigation is seen in the salient need for two AI capabilities in CAI:

- 1) more sensitive adaptability (by the machine)
- 2) greater control (by the student)

These are the two general factors to be studied in this investigation using games.

A survey of research in AI using games reveals that a game is a desirable (and natural) vehicle for experimenting with artificial intelligence techniques--particularly in machine learning. It is understandable why authors such as Donald Fink (22) got a lot of literary mileage from publicity of games exhibiting artificial intelligence. In

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<sup>1</sup>PILOT has been tried in teaching electrical engineering and elementary arithmetic, for simulating a patient in a medical interview, and for conversational introduction to university course offerings.

the first chapter of his Computers And The Human Mind, he introduced the topic of "Minds and Machines" with an account of Samuel's checker-playing program (23) defeating a former checkers state champion.<sup>1</sup>

Representative of early explorations in AI, Joseph Weizenbaum (24) developed a computer program to play GOMOKU (five-in-a-row) without using an exhaustive look-ahead algorithm. More recently, AI pattern recognition techniques have been used by Koffman (25) for rapid machine learning of forcing states in a class of games including HEX, Qubic, GOMOKU, and Bridge-It. These works differ from 'classical' learning programs like Samuel's checker player in that only patterns discovered by the machine to be strategic in a game are stored and used.

In "Some New Approaches to Machine Learning" by Nicholas Findler (26), again the game of GOMOKU is used to explore different models of learning. In his learning of "type 1" the machine adjusts program parameters in 'educating' OWL (Old Wise Logician). This heuristic process of optimization differs from the algorithmic adaptive learning mechanism used in the learning games of this investigation (See Appendix A).

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<sup>1</sup>It should be noted that while several researchers have admitted that their programs can consistently defeat their minds in a game, they quickly insist that the computer could never out-think them in planning the grand strategy of the program itself. Other computer scientists ('positivists' like Newell, Shaw and Simon) prefer to ask why a computer cannot write its own program using its own higher abstractions.



A second program, NIP (Novice-In-Playing), plays against OWL and learns first by imitation ("type 2") and then by inductively generalizing patterns encountered ("type 3"). Other models probe qualitatively new kinds of learning by generating their own strategies. Findler claims rudiments of creative discovery are manifest here. Following this line of research is extremely interesting (especially to this investigator) but is beyond the specified goals of this investigation.

Of the studies in AI using games, only a few suggest applications in an educational setting. Samuels hinted at values of such games beyond pure AI research:

The ability to have the program play against human opponents adds spice to the study and demonstrates for those who do not believe that machines can learn (22).

H.D. Block (27) appears to be the first to mention using learning games with children (as try-out subjects). It was from scrutinizing this work that this investigator first began to ponder relationships between human learning and machine learning. Specifically, what would be reactions of human learners to learning machines 'tuned-up' to varying levels of playing ability? Block analyzed two games: LAST-ONE-LOSES and EVEN-WINS. The same games--both variants of the ancient intellectual game of NIM--are employed in this study. Although the language (APL) and the computer system (CDC 3600) in which the games were programmed are different from Block's, the basic property of the machine-executable versions of the games is identical. They possess the

capacity to change automatically during game-playing.

(See Appendix A for details.)

Another learning game entitled "HEXAPAWN: A Game You Win to Lose," distributed through IBM's Editorial Promotions Department, bears properties similar to the games used in this study. In Hexapawn, moves which led to a loss are marked off on an auxiliary playing board (with all possible different move sequences enumerated). Like LAST-ONE-LOSES and EVEN-WINS, after several games a player may find that the 'board' begins to play better.

Although neither Samuel nor Block nor IBM make the explicit connection between their games and CAI, it is clear that these works were seeds of synthesis for this new area under investigation: AI in CAI.

Despite the high potential value of games and simulations in CAI, little formal research has been conducted in their usage. Richard Wing's (28) research in games for instruction in social science is one outstanding exception. He reported differences (in some cases statistically significant differences) in the direction favoring learning by 6th grade children interacting with computerized games over children receiving normal classroom instruction in the same subject. One particularly successful game called "The Sumerian Game"<sup>1</sup> was used for publicity by IBM, the company on whose machines the game was implemented.

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<sup>1</sup>The computer program is a model of an economic system: the ancient kingdom of Sumer, circa 3500 B.C. The child plays the role of King and is asked to make decisions regarding allocation of resources (grain, soldiers, etc.).



Similarities in work by Wing and this investigation are two: he used CAI games on an interactive computer, and he tested them with elementary school children. None of his games overtly exhibit AI capabilities; that is, none have adaptive characteristics, other than pseudo-random generation of 'events.'

The topic of computerized games is found in a variety of sources--from secondary school mathematics texts to articles in technical journals--perhaps the single most comprehensive of which is Donald Spencer's book, Game Playing With Computers (29).

Finally, shifts in emphasis by key persons in each of the two fields, respectively, point to the eventual introduction of AI in CAI. Patrick Suppes (7), often looked up to as a father of CAI, must have had his imagination piqued by possibilities of AI in 1966 when he said:

One can predict that in a few more years millions of school children will have access to what Philip of Macedon's son Alexander enjoyed as a royal prerogative: the personal services of a tutor as well-informed and responsive as Aristotle.

Later (1968), Suppes (30) toned down to a more realistic stance:

Just as books freed serious students from the tyranny of overly simple methods of oral recitation, so computers can free students from the drudgery of doing exactly similar tasks unadjusted and untailored to their individual needs.

Duncan Hansen (31), whose development work in CAI began with tutorials in college level physics, is now conducting research in computer-control of psychological

dimensions:

. . . we would suggest that computer-based approaches to testing may allow for an acceptable and feasible way of controlling test anxiety. The conception is to adjust the item difficulty level for each examinee in order to minimize the extreme anxiety reactions found when examinees are working on impossible test items.

Concurrently, researchers in AI are expressing greater concern for education. Most notably, Marvin Minsky (10) said recently:

. . . such goals as understanding the mind, getting a theory of education, exploring the stars, or repairing our own planet, make such (AI) research important.

and

AI research will be an important shot-in-the-arm for the current depressed quality of educational theory.

A colleague of his at M.I.T., Seymour Papert, who directs the Artificial Intelligence Laboratory there, has clearly shifted his interests toward education (and kids). Accordingly, the latest major conference on AI on April 11, 1970, which drew several hundred persons from all over the country, was entitled "Teaching Children Thinking." Papert is now deeply involved in experimenting with radical techniques to influence education in a variety of ways--particularly using programming as a conceptual framework for teaching (the unteachable) mathematics (32).

In summary, when research in the area of overlap between AI and CAI is reviewed, it is found to be sparse, particularly in field testing AI-CAI games with 'live' subjects. Related studies in both fields of AI and CAI indicate a prospective marriage--AI in CAI.



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## CHAPTER III

### METHODS AND PROCEDURES

Described in this chapter are the general methods and procedures employed in this investigation with regard to setting, subjects, the instructional system, research design, testing, and data analysis.

This study was designed to investigate the effects on children's learning by game-playing computer-assisted instructional programs with artificial intelligence components. Specifically, this study treats the following main hypotheses:

1. Children playing an intellectual game on a computer learn more effectively when the computer program is "learning" concurrent with their learning than do children using a computer program which plays with a static strategy. (The mode hypothesis)
2. Children playing an intellectual game on a computer learn more effectively when an "executive" computer program permits them the "option" after any game to adjust the level of difficulty exhibited by the computer than do children using a computer program having no option. (The control hypothesis)

#### SETTING

This study was conducted in two different locations: School of Education at University of Massachusetts, Amherst, Massachusetts and Hampshire College, South Amherst, Mass.

At the School of Education, two testing settings were utilized: semi-private faculty office space and unenclosed space in a corner of the Children's Library. Each was within three minutes walking distance from Mark's Meadow Elementary School. At Hampshire College, the testing setting utilized was a private office adjacent to the Natural Sciences Laboratory on the third floor of the Library Center.

### SUBJECTS

Subjects participating in this study were drawn from two sources: Mark's Meadow Elementary School and Hampshire College's Early Identification Program. A total of forty-nine different subjects from both sources were utilized in generating data for the study--42 subjects played the game of LAST-ONE-LOSES and 41 subjects played the game EVEN-WINS. All were children between the ages of ten and twelve, both male and female, currently attending school in 5th or 6th grade. Most (39) of the subjects were from Mark's Meadow.

Mark's Meadow Elementary School is a public school in Amherst, Massachusetts serving approximately 300 children in grades K through 6. Students live in nearby locale and are generally of moderately affluent parentage--a large percentage of whom are university personnel. Affiliated with the University of Massachusetts, the school is physically contiguous to the School of Education and serves as a laboratory school for experimental programs.



Hampshire College has identified approximately thirty 'high-potential' children, ages ten to twelve, from low-income families in inner-city Holyoke, Massachusetts to participate in its Early Identification Program. Now in its second year since inception, the program plans to provide special tutoring for these children through the time of their admission to college. Selected staff, faculty, and students from the college organize and carry out instructional sessions with the children who are transported to the college for tutoring on Saturdays and one 'special' week in February plus six weeks (live-in) during the summer.

All subjects who participated in this study were self-selected; that is, students from Mark's Meadow 5th and 6th grades (with permissions from their teachers) volunteered to play games on the computer, and Early Identification Program children scheduled for mathematics and/or computer programming class voluntarily missed a class in order to play computer games.

#### THE INSTRUCTIONAL SYSTEM

The instructional system supporting this study utilized computer equipment (hardware), system programming (software), and instructional materials (curriculum).

##### 1. Hardware

This study was actualized through the use of the Control Data Corporation 3600 time-sharing computer ("UMASS")



resident at the University Computing Center, Amherst, Massachusetts. This was the only computer involved in the investigation, although several pieces of communications equipment were employed. As input-output devices, seven Datel telecommunications terminals (Time-Sharing Terminals, Inc.) were available for use in the study--two at the School of Education and five at Hampshire College--although typically only one terminal was in usage at any one time. The terminals consisted of a conventional typewriter keyboard with an APL type-ball and type font. Additionally, a total of seven acoustic couplers (Ominitec, Inc.) and seven ordinary telephones (New England Telephone Co.) were available to make on-line connections between the computer and terminals.

## 2. Software

The central processing unit of the CDC 3600 time-sharing computer is monitored by a second, smaller computer--a PDP-8 (Digital Equipment Corp.). The translator for this machine is a composite of compilers and interpreters. The interpreter on which this study depended was designed to process APL (A Programming Language) and was implemented under the direction of James Burrills, University Computing Center, University of Massachusetts.

APL is a multi-purpose programming language conceived by Kenneth Iverson (1) of IBM Corporation. Its interactive capability and rich set of function symbols make it well-suited for programming in computer-assisted instruction. (2), (3), (4)

### 3. Curriculum

The materials of instruction employed in this study consist of two intellectual games programmed by the investigator for interactive use on a computer: "LAST-ONE-LOSES" and "EVEN-WINS". Both games are variants of the ancient intellectual game of NIM, which is documented in many secondary mathematics texts<sup>1</sup>.

LAST-ONE-LOSES is a game of taking away boxes (or any distinct items) between two players. The game begins with some number of boxes (which may be determined by a random roll of two dice). One player goes first and takes 1 or 2 or 3 boxes away; the other player then moves, likewise removing 1, 2, or 3 boxes. The players alternate moves in this manner until there is one box left. Whoever takes the last box loses (hence the name "LAST-ONE-LOSES").

EVEN-WINS is a similar game of taking away boxes, played with two opponents. The game begins with a randomly determined odd number of boxes. One player goes first and takes 1 or 2 boxes; then the other player moves, taking 1 or 2 boxes. The players alternate in this manner until there are no boxes left. Whoever has an even number of boxes in his possession at the end of the game wins (hence the name "EVEN-WINS").

In this study each game is designed with a 'learning' capability; that is, the computer-opponent automatically and

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<sup>1</sup>e.g. Beck, et al, Excursions Into Mathematics, 1969

progressively improves its performance. LAST-ONE-LOSES usually requires about 10 to 15 games to be played before the machine arrives at an optimal strategy. There are nine losing configurations which must be expulsed. A more subtle game, EVEN-WINS generally requires the machine to play 15 or 20 games before adapting to an optimal strategy. Another artificial intelligence component is built into the games: an "executive option". The option to direct the computer to PLAY EASIER or PLAY HARDER gives the player control over the level of difficulty exhibited by the machine. (See Appendix A for details of LAST-ONE-LOSES and EVEN-WINS)

#### RESEARCH DESIGN

In order to circumscribe and confine the problem, it was necessary to delimit the investigation in certain ways. The delimitations of the study are as follows:

- 1) Subjects for the study will be restricted to the age range of ten through twelve and will be classified as elementary school 5th or 6th graders. No attempt will be made to generalize study results beyond the age range stated.
- 2) Subjects for the study were selected "ad hoc", but not randomly, from the population they represent. No attempt will be made to generalize study results to the larger population.
- 3) No formal precautions were taken to ensure that subjects participated in the study under the same conditions (primarily timing). No attempt will be made to generalize study results to any condition or setting of learning.

In conducting the research reported herein, five basic assumptions were made. The assumptions are:



- 1) The effects of the artificial intelligence components in the computer-assisted instructional games are noticed by the subjects (when the effects are in force).
- 2) The games are both interesting and challenging for the selected age range of subjects, and, more importantly, the general level of difficulty is neither over their heads nor patently easy. That is, it is expected that a significant percentage of subjects will come to understand the mathematical principles underlying the game during the learning session at the computer and that a significant portion will not.
- 3) Variations in the learning environments and in the investigator's influence will not affect study results.
- 4) Typing ability will neither add to nor subtract from subjects' ability to utilize computer-assisted instructional games. Specifically, it is expected that facility in entering a response--typing a single numeral--will become normalized before actual game-playing begins and that, hence, scores on variables measuring response latency will not include typing ability factors.
- 5) Neither computer hardware nor reliability of the computer system will bias results of the study.

In a two-by-two factorial design, subjects are randomly<sup>1</sup> assigned artificial intelligence computer-assisted instruction game-playing programs in one of four groups:

- I. LEARN and Executive Option
- II. STATIC and Executive Option
- III. LEARN and No Option
- IV. STATIC and No Option

Total numbers of subjects in each group are shown in Table III-1 for both games.

---

<sup>1</sup>Using a machine-executed random number generator

TABLE III-1

## TWO-BY-TWO FACTORIAL DESIGN

	LEARN	STATIC	
	(I)	(II)	Totals
Executive Option	LOL 13	LOL 8	21
	EW 12	EW 13	25
	(III)	(IV)	
No Option	LOL 12	LOL 9	21
	EW 9	EW 7	16
Totals	LOL 25	LOL 17	42
	EW 21	EW 20	41

TOTALS

LOL = LAST-ONE-LOSES

EW = EVEN-WINS

Data are gathered on six sets of variables identified for the purpose of measuring learning in this study. The variables are:

1. "Winningness" (X1)
  - X1.1 Percentage of winning moves made out of total possible winning moves
  - X1.2 Average rate of learning: slope of learning curve of net cumulative frequencies of winning moves plotted against total possible winning moves (See Appendix C for sample learning curves)
2. "Attentiveness" (X2)
  - X2.1 Total number of games played
  - X2.2 Total connect time (seconds on-line with computer)
  - X2.3 Total CPU time (seconds using central processing unit)
  - X2.4 Ratio of total game-playing time to average response time ("the itchy-pants factor")
3. "Intolerance" (X3)
  - X3.1 Percentage of infractions of rules and mistyped responses to total moves
4. "Decision-Speed" (X4)
  - X4.1 Average response time (seconds delay in making a move)
  - X4.2 Average rate of change of response time
5. "Understanding" (X5)
  - X5.1 Score on Strategy Understanding Test with same rules as during game-playing (See Appendix F)
6. "Generalizability" (X6)
  - X6.1 Score on Strategy Understanding Test with altered (but similar) rules (See Appendix F)



In order to research the problem of this study, twelve hypotheses were subjected to experimental investigation. The experimental hypotheses are:

Of a sample of children voluntarily playing an intellectual game on a computer, children playing against a computer program (LEARN) which is 'learning' concurrent with their learning,

- 1) win more often (as measured by variable X1)
- 2) play longer (as measured by variable X2)
- 3) make fewer errors of intolerance (as measured by variable X3)
- 4) respond faster (as measured by variable X4)
- 5) better understand the principles of the game (as measured by variable X5)
- 6) more successfully generalize their understanding of the game (as measured by variable X6)

than do children playing against a computer program exhibiting a constant level of playing ability (STATIC).

And, of a sample of children voluntarily playing an intellectual game on a computer, children playing with an "executive option" to adjust the level of difficulty exhibited by the computer,

- 7) win more often (as measured by variable X1)
- 8) play longer (as measured by variable X2)
- 9) make fewer errors of intolerance (as measured by variable X3)
- 10) respond faster (as measured by variable X4)
- 11) better understand the principles of the game (as measured by variable X5)
- 12) more successfully generalize their understanding of the game (as measured by variable X6)

than do children playing with no option to adjust the computer's level of difficulty.

Each subject plays individually against one of the four computer game-playing programs in a single session. The machine opponent, LEARN or STATIC, is selected without informing the subject or the investigator. Since there is no external way of telling which program is interacting with the subject (unless many games are scrutinized), the investigator intends to remain a neutral factor in the learning setting. Additionally, computer outputs—particularly the questions "DO YOU WANT THE COMPUTER TO PLAY EASIER OR HARDER?" and "DID THE COMPUTER PLAY EASIER OR HARDER?" for programs with "executive option" and no option, respectively, were designed to be highly similar in order to reduce possibilities of the Hawthorne effect. (See Appendix A for sample print-outs of games)

#### TESTING PROCEDURES

Subjects participating in this study were scheduled to play 'computer games' one at a time on an informal and impromptu basis. An outline of the steps followed in testing (for a typical subject) follows:

1. Subject is excused from regular classroom activity (with permission and by previous arrangement with his teacher) and is escorted by the investigator to the computer terminal area.
  - a) Mark's Meadow children: During 'integrated day' (open) classroom or free period, children walk approximately thirty yards in about three minutes through hallways within a single building to the investigator's office where a Datel terminal is located.

- b) Early Identification Program children: During remedial mathematics sessions on Saturdays, children brought by bus from Holyoke to Hampshire College walk less than one minute within the Natural Sciences Laboratory to an enclosed office equipped with a Datel terminal.
2. The individual subject is instructed to sign-on the computer (with as-needed help), request APL language, load workspace GAME1 or GAME2, and type HELLO.
  3. Program HELLO 'greet' the subject, gives basic directions, explains rules of the game, and randomly assigns one of four game-playing programs.
  4. Subject plays the game for as long as he wishes (within a reasonable limit of about one hour). LAST-ONE-LOSES is the first game to be played; upon subsequent visit, he plays EVEN-WINS. During game-playing, the program automatically collects data on the subject's performance.
  5. When the subject voluntarily indicates that he is finished playing, the investigator types QUIT and then )SAVE.
  6. The investigator administers the Strategy Understanding Test (both forms) and collects the tests within ten minutes.
  7. Subject is thanked and is personally escorted back to his previous activity.

#### DATA ANALYSIS PROCEDURES

Performance data for all subjects for both games are analyzed for each of the twelve hypotheses of this study. Tools for gathering data on each of the six sets of variables identified to measure learning in this study are built into the game-playing programs. (See Appendix B for documentation of computer sub-routines START, TALLY, and QUIT which accomplish data accumulation.)



Data are stored into computer memory following a playing session by the command )SAVE and are retrievable in a form conducive to statistical manipulation. (Appendix C contains synthesized data for all subjects.)

The principal statistical procedures used in hypotheses testing are two-way analysis of variance (5),(6) and t test (7). (Tools for performing statistical reduction and analysis of raw data are found in Appendix D.) Two-way analyses of variance (ANOVA) for unequal N's are executed by computer and examined for significance. (Results of 57 ANOVAs are shown in Appendix E.)

Actual steps followed in generating, transferring, reducing, and statistically analyzing data are listed below from the perspective of data from a single subject:

1. Data are generated in a workspace (containing game-playing programs plus data from previous subjects).

Note: Computer system restraints<sup>1</sup> necessitated using several different workspaces for generating and storing data. Specifically, for each game separate workspaces were used: GAME1, AGAME, GAME1A, GAME1B, GAME1C, GAME1D for LAST-ONE-LOSES; GAME2A, GAME2B, GAME2C for EVEN-WINS.

2. All APL game-playing and data-collection functions and variables are periodically copied into a new workspace. A sample procedure follows:

```
)CLEAR
)COPY GAME2B ADAPT ADJUST AMOVE ARE ASSIGN EW HELLO
)COPY GAME2B LIT MMOVE QUIT REMIND RESPONSE RULES
)COPY GAME2B START TALLY ROLL CON CPU DI1 DI2 FACE
)COPY GAME2B EVM ODM LEARN NAMES OPTION RESPONSES
)SAVE GAME2C
```

---

<sup>1</sup>The primary restraint was the symbol table, which holds a maximum of 1600 units for variable and function names.

3. Data from previous subjects are copied into a workspace containing only performance data (no game-playing programs). A sample procedure follows:

```
)LOAD DATA2
)COPY GAME2B N13 N14 N15 N16 N17 N18 N19 N20 N21
)COPY GAME2B M13 M14 M15 M16 M17 M18 M19 M20 M21
)COPY GAME2B T13 T14 T15 T16 T17 T18 T19 T20 T21
)ERASE CON CPU LEARN NAMES OPTION
)COPY GAME2B CON CPU LEARN NAMES OPTION
)SAVE DATA2
```

Note: Extra workspaces for storing data were necessary because of limited size<sup>1</sup> of a single workspace: DATA1, DATA1A, DATA1B, D1 were used for LAST-ONE-LOSES; DATA2 for EVEN-WINS.

4. APL functions are applied to raw data, reducing them to a single variable with 42 values (one per subject in LAST-ONE-LOSES). A sample procedure follows:

```
)CLEAR
)COPY DATA1 F11
)COPY DATA1 N01 N02 N03 N04 N05 N06 N07 N08 N09 N10
)COPY DATA1 N11 N12 N13 N14 N15 M01 M02 M03 M04 M05
)COPY DATA1 M06 M07 M08 M09 M10 M11 M12 M13 M14 M15
V11 ← (F11 01), (F11 02), (F11 03), (F11 04), F11 05
V11 ← V11, (F11 06), (F11 07), (F11 08), (F11 09), F11 10
V11 ← V11, (F11 11), (F11 12), (F11 13), (F11 14), F11 15
)COPY DATA1A N16 N17 N18 N19 N20 N21
)COPY DATA1A M16 M17 M18 M19 M20 M21
V11 ← V11, (F11 16), (F11 17), (F11 18), (F11 19), F11 20
V11 ← V11, F11 21
)COPY DATA1B N22 N23 N24 N25 N26 N27 N28 N29 N30 N31
)COPY DATA1B M22 M23 M24 M25 M26 M27 M28 M29 M30 M31
V11 ← V11, (F11 22), (F11 23), (F11 24), (F11 25), F11 26
V11 ← V11, (F11 27), (F11 28), (F11 29), (F11 30), F11 31
)COPY DATA1C N32 N33 N34 N35 N36 N37 N38 N39 N40 N41
)COPY DATA1C M32 M33 M34 M35 M36 M37 M38 M39 M40
)COPY DATA1C M41 M42
V11 ← V11, (F11 32), (F11 33), (F11 34), (F11 35), F11 36
V11 ← V11, (F11 37), (F11 38), (F11 39), (F11 40), F11 41
V11 ← V11, F11 42
```

ρV11

42

```
)SAVE
```

Note: This procedure is repeated eleven times, once for each of the eleven sub-variables.

<sup>1</sup>A clear workspace in APL on "UMASS" system holds a maximum of approximately 32,000 words.

5. Variables are copied into a workspace for statistical analysis. An abbreviated procedure is shown here:

```
)LOAD ANOVA1
)COPY CONTINU V11 V12 V21 V22 V23 V24 V31 V41 V42
)COPY CONTINU V51 V61
)SAVE ANOVA1
```

Note: Functions for performing two-way analysis of variance for data from LAST-ONE-LOSES have been written and stored in workspace ANOVA1.

6. Two-way analysis of variance with examination of interaction effects is executed for each variable for all subjects for both games. A sample procedure is shown here:

ANOVA2X2

ENTER RAW SCORES FOR CELL 1

□: (LEARN ^ OPTION)/V11

ENTER RAW SCORES FOR CELL 2

□: ((~ LEARN) ^ OPTION)/V11

ENTER RAW SCORES FOR CELL 3

□: (LEARN ^ ~OPTION)/V11

ENTER RAW SCORES FOR CELL 4

□: ((~ LEARN) ^ ~OPTION)/V11

COLUMN VARIANCE NOT SIGNIFICANT AT .05 LEVEL  
 ROW VARIANCE NOT SIGNIFICANT AT .05 LEVEL  
 INTERACTION EFFECT NOT SIGNIFICANT AT .05 LEVEL

MEANS:

68.74	84.5	74.74
74.5	71.88	73.38
71.5	77.82	74.06

SOURCE	D.F.	MEAN SQUARES	F
COL VAR.	1	403.37	0.96
ROW VAR.	1	19.61	0.05
INTERACTION	1	862.3	2.05
ERROR	38	421.62	



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## CHAPTER IV

### RESULTS AND DISCUSSION

This investigation was designed to study learning by children interacting with computer-assisted instructional programs which exhibit artificial intelligence characteristics. Two main hypotheses were conceptualized in order to consider relationships in variables identified to measure learning.

Specifically, the main conceptual hypotheses were:

1. Children playing an intellectual game on a computer learn more effectively when the computer program is "learning" concurrent with their learning than do children using a computer program which plays with a static strategy. (The mode hypothesis)
2. Children playing an intellectual game on a computer learn more effectively when an "executive" computer program permits them the "option" after any game to adjust the level of difficulty exhibited by the computer than do children using a computer program having no option. (The control hypothesis)

In this chapter results of hypotheses testing are described and discussed.

The present investigation identified twelve experimental hypotheses (repeated from Chapter I, THE CHALLENGE):

Of a sample of children voluntarily playing an intellectual game on a computer, children playing against a computer program (LEARN) which is 'learning' concurrent with their learning,

- 1) win more often (as measured by variable X1)
- 2) play longer (as measured by variable X2)
- 3) make fewer errors of intolerance (as measured by variable X3)
- 4) respond faster (as measured by variable X4)
- 5) better understand the principles of the game (as measured by variable X5)
- 6) more successfully generalize their understanding of the game (as measured by variable X6)

than do children playing against a computer program exhibiting a constant level of playing ability (STATIC).

And, of a sample of children voluntarily playing an intellectual game on a computer, children playing with an "executive option" to adjust the level of difficulty exhibited by the computer,

- 7) win more often (as measured by variable X1)
- 8) play longer (as measured by variable X2)
- 9) make fewer errors of intolerance (as measured by variable X3)
- 10) respond faster (as measured by variable X4)
- 11) better understand the principles of the game (as measured by variable X5)
- 12) more successfully generalize their understanding of the game (as measured by variable X6)

than do children playing with no option to adjust the computer's level of difficulty.

In order to study these hypotheses, data were gathered on each of the following variables identified to measure learning:



1. "Winningness" (X1)
  - Percentage of winning moves (X1.1)
  - Average rate of learning (X1.2)
2. "Attentiveness" (X2)
  - Total number of games played (X2.1)
  - Total connect time (X2.2)
  - Total CPU time (X2.3)
  - Ratio of total time to average response time (X2.4)
3. "Intolerance" (X3)
  - Percentage errors of intolerance (X3.1)
4. "Decision-Speed" (X4)
  - Average response time (X4.1)
  - Average rate of change of response time (X4.2)
5. "Understanding" (X5)
  - Score on Strategy Understanding Test (X5.1)
6. "Generalizability" (X6)
  - Score on Strategy Understanding Test with altered rules (X6.1)

(See Chapter III, METHODS AND PROCEDURES for precise definitions of these variables.)

Although testing of experimental hypotheses was important to the study itself in determining existence of relationships to learning, the major contribution of this research is dependent on the ability of this investigator and others to utilize the results in generating hypotheses for further study. The lack of predecessor studies or

theoretical models makes statements of new hypotheses with foundations in empirical data more plausible; and, studies with larger sample sizes are more justifiable because of results and experience engendered in this investigation. (See Chapter V, CONCLUSIONS AND RECOMMENDATIONS)

Results of hypotheses testing are now reported and discussed (in pairs):

"Winningness"

Hypotheses 1 and 7 will be considered jointly.

The first experimental hypothesis is concerned with the relationship between the "winningness" variable (X1) and the mode of AI-CAI game-playing programs (LEARN/STATIC) for each of two games (LAST-ONE-LOSES and EVEN-WINS). The hypothesis specifically asserts that the mean of scores on variable X1 by subjects using program LEARN will be higher than the mean of scores on variable X1 by subjects using program STATIC. The null hypothesis asserts no significant difference between the two group means.

The seventh experimental hypothesis is concerned with the relationship between the "winningness" variable (X1) and control of AI-CAI game-playing programs ("executive option"/no option) for each of two games (LAST-ONE-LOSES and EVEN-WINS). Specifically, the hypothesis asserts that the mean of scores on variable X1 by subjects using a program with an "executive option" will be higher than the mean of scores on variable X1 by subjects using a program

with no option. The null hypothesis asserts no significant difference between the two group means.

Before conducting specific comparisons between groups, analyses of variance were carried out in order to look for overall effects of the experimental factors. Results of two-way analysis of variance are reported for each sub-variable for both games in Table IV-1.

For hypothesis 1 concerning the mode factor, computed F ratios for both sub-variables were insufficient for either game to reject the null hypotheses of no significant differences between group means. That the means for both games for both sub-variables were moderately higher for subjects using STATIC is possibly explained by (unwanted) "intimidation" effects. It is conceivable that a subject encountering a game-playing opponent (LEARN) which improves noticeably and rapidly would be discouraged from improving further himself because "the computer will win anyway". Additionally, program STATIC may have encouraged (an unexpected) confidence in subjects. Finding that they could indeed win, after early uncommitted exploration of the game and the computer, they may have set out with fervor to do something they seldom get a chance to do in an educational setting: win.

For hypothesis 7 concerning the control factor, three of four computed F ratios were insufficient to reject the null hypotheses of no significant differences between group means. For sub-variable X1.1 (percentage winning moves to possible



TABLE IV - 1

Two-way Analysis of Variance Results for Variable X1  
 "Winningness"

LAST-ONE-LOSES

## MEANS FOR X1.1

(Percentage Winning Moves)

	LEARN	STATIC
Executive Option	68.74	84.50
No Option	74.50	71.88

## COMPUTED VALUES FOR X1.1

(Percentage Winning Moves)

Source of Variation	df	Mean Squares	F
Mode Factor	1	403.37	0.96
Control Factor	1	19.61	0.05
Interaction	1	862.30	2.05
Error	38	421.62	

TABLE IV - 1--Continued

LAST-ONE-LOSES

## MEANS FOR X1.2

(Average Rate of Learning)

	LEARN	STATIC
Executive Option	0.43	0.70
No Option	0.35	0.41

## COMPUTED VALUES FOR X1.2

(Average Rate of Learning)

Source of Variation	df	Mean Squares	F
Mode Factor	1	0.19	1.06
Control Factor	1	0.22	1.22
Interaction	1	0.17	0.94
Error	34	0.18	

TABLE IV - 1--Continued

EVEN-WINS

## MEANS FOR X1.1

(Percentage Winning Moves)

	LEARN	STATIC
Executive Option	70.24	76.58
No Option	84.44	83.34

## COMPUTED VALUES FOR X1.1

(Percentage Winning Moves)

Source of Variation	df	Mean Squares	F
Mode Factor	1	70.38	0.39
Control Factor	1	1060.38	5.86
Interaction	1	185.12	1.02
Error	37	180.97	



TABLE IV - 1--Continued

EVEN-WINS

## MEANS FOR X1.2

(Average Rate of Learning)

	LEARN	STATIC
Executive Option	0.41	0.60
No Option	0.63	0.73

## COMPUTED VALUES FOR X1.2

(Average Rate of Learning)

Source of Variation	df	Mean Squares	F
Mode Factor	1	0.21	2.33
Control Factor	1	0.24	2.67
Interaction	1	0.06	0.67
Error	35	0.09	

winning moves) two-way analysis of variance found a significant difference in means for EVEN-WINS--but opposite in direction to that predicted by the hypothesis. That is, subjects using no option were found to have significantly higher "winningness" (as measured by sub-variable X1.1) than subjects using "executive option". Since this is counter to the intuition of the investigator, it is difficult to explain. One possible interpretation of the results is that, in exploring the upper ranges of the computer's playing abilities, subjects using "executive option" encountered more situations in which finding a winning strategy was difficult; whereas subjects with no option to adjust the level of difficulty exhibited by the computer encountered more instances in which they could win easily and repeatedly because they could depend on the machine not to change.

Means of sub-variable X1.2 (average rate of learning) for EVEN-WINS also differed (but not significantly) in the direction favoring no option; whereas means of both sub-variables X1.1 and X1.2 were slightly greater for subjects using "executive option" in LAST-ONE-LOSES. This may reflect a difference in the basic character of the two games more than differences due to the control factor.

In the absence of significant F ratios in directions predicted by the hypotheses, results of t tests--which may be regarded as suspicious--are not recorded here.

Statistical data for variable X1 are found in Appendix C. Shown are means, medians, ranges, and standard deviations

for the two sub-variables for both games for all subjects tested.

In summary, results did not support the first or seventh hypothesis that "winningness" is related to mode and control factors of AI-CAI game-playing programs.

#### "Attentiveness"

Hypotheses 2 and 8 will be considered jointly.

The second experimental hypothesis is concerned with the relationship between the "attentiveness" variable (X2) and the mode of AI-CAI game-playing programs (LEARN/STATIC) for each of two games (LAST-ONE-LOSES and EVEN-WINS). The hypothesis specifically asserts that the mean of scores on variable X2 by subjects using program LEARN will be higher than the mean of scores on variable X2 by subjects using program STATIC. The null hypothesis asserts no significant difference between the group means.

The eighth experimental hypothesis is concerned with the relationship between the "attentiveness" variable (X2) and control of AI-CAI game-playing programs ("executive option"/no option) for each of two games (LAST-ONE-LOSES and EVEN-WINS). Specifically, the hypothesis asserts that the mean of scores on variable X2 by subjects using a program with an "executive option" will be higher than the mean of scores on variable X2 by subjects using a program with no option. The null hypothesis asserts no significant difference between the group means.



Before conducting specific comparisons between groups, analyses of variance were carried out in order to look for overall effects of the experimental factors. Results of two-way analysis of variance are reported for each sub-variable for both games in Table IV-2.

For hypothesis 2 concerning the mode factor, computed F ratios for the four sub-variables were insufficient for either game to reject the null hypotheses of no significant differences between group means. In LAST-ONE-LOSES sub-variable X2.1 (the only sub-variable of X2 for which data were preserved for that game) yielded a distinctly (but not significantly) larger mean of total games played by subjects using LEARN in contrast to subjects using STATIC. Perhaps interest in the behavior of LEARN held subjects' attention. In EVEN-WINS reasons related to "intimidation" (discussed earlier) may have been responsible for a higher mean on variable X2.1 for subjects using STATIC. That is, possibly those subjects felt freer to play more games when their computer program was easily beatable (although it provided no better competition). Here, perhaps just winning was reinforcing. As for results of no systematic relationships in data on sub-variables X2.2 and X2.3 and X2.4, an explanation is proposed: variability in style and intensity of game-playing (whether on a computer or not) can be greater from individual to individual than variance produced by different effects. A high within-cells variance (error variance) on these three sub-variables

TABLE IV - 2

Two-way Analysis of Variance Results for Variable X  
"Attentiveness"

LAST-ONE-LOSES

## MEANS FOR X2.1

(Number of Games Played)

	LEARN	STATIC
Executive Option	21.46	20.25
No Option	30.17	25.33

## COMPUTED VALUES FOR X2.1

(Number of Games Played)

Source of Variance	df	Mean Squares	F
Mode Factor	1	73.70	0.42
Control Factor	1	528.60	3.00
Interaction	1	53.71	0.30
Error	38	176.43	

TABLE IV - 2 -- Continued

EVEN-WINS

## MEANS FOR X2.1

(Number of Games Played)

	LEARN	STATIC
Executive Option	14.75	14.69
No Option	15.89	24.00

## COMPUTED VALUES FOR X2.1

(Number of Games Played)

Source of Variance	df	Mean Squares	F
Mode Factor	1	75.34	0.87
Control Factor	1	217.12	2.52
Interaction	1	183.73	2.13
Error	37	86.21	



TABLE IV - 2 -- Continued

EVEN-WINS

## MEANS FOR X2.2

(Seconds Connect Time)

	LEARN	STATIC
Executive Option	1972.67	1973.69
No Option	2073.11	2529.14

## COMPUTED VALUES FOR X2.2

(Seconds Connect Time)

Source of Variance	df	Mean Squares	F
Mode Factor	1	237877.81	0.22
Control Factor	1	874686.15	0.80
Interaction	1	580990.75	0.53
Error	37	1089012.19	

TABLE IV - 2 -- Continued

EVEN-WINS

MEANS FOR X2.3  
(Seconds CPU Time)

	LEARN	STATIC
Executive Option	21.33	18.31
No Option	14.67	25.14

COMPUTED VALUES FOR X2.3  
(Seconds CPU Time)

Source of Variation	df	Mean Squares	F
Mode Factor	1	50.66	0.35
Control Factor	1	2.54	0.02
Interaction	1	438.61	3.04
Error	37	144.28	

TABLE IV - 2 -- Continued

EVEN-WINS

## MEANS FOR X2.4

(Ratio Total Time to Average Response Time)

	LEARN	STATIC
Executive Option	1.05	1.14
No Option	1.22	0.81

## COMPUTED VALUES FOR X2.4

(Ratio Total Time to Average Response Time)

Source of Variance	df	Mean Squares	F
Mode Factor	1	0.10	0.21
Control Factor	1	0.03	0.06
Interaction	1	0.61	1.27
Error	37	0.48	



supports this contention. Additional reasons for homogeneity on variable X2.4 are offered under discussion of hypotheses 4 and 10.

For hypothesis 8 concerning the control factor, computed F ratios for the four sub-variables were insufficient for either game to reject the null hypotheses of no significant differences between group means. Means for "no option" subjects on sub-variable X2.1 (total games played) were clearly (and nearly significantly) higher than for subjects using "executive option" for both games. This result, while contrary to that predicted by the hypothesis, is possibly explained by need for more games played by subjects lacking the power to explore (by controlling the computer's game-playing ability) their interests efficiently.

In the absence of significant F ratios, results of t tests--which may be regarded as suspicious--are not recorded here.

Statistical data for variable X2 are found in Appendix C. Shown are means, medians, ranges, and standard deviations for the four sub-variables for both games for all subjects tested.

In summary, results did not support the second or eighth hypotheses that "attentiveness" is related to mode and control factors of AI-CAI game-playing programs.

"Intolerance"

Hypotheses 3 and 9 will be considered jointly.

The third experimental hypothesis is concerned with the relationship between the "intolerance" variable (X3) and the mode of AI-CAI game-playing programs (LEARN/STATIC) for each of two games (LAST-ONE-LOSES and EVEN-WINS). The hypothesis specifically asserts that the mean of scores on variable X3 by subjects using program LEARN will be lower than the mean of scores on variable X3 by subjects using program STATIC. The null hypothesis asserts no significant difference between the two group means.

The ninth experimental hypothesis is concerned with the relationship between the "attentiveness" variable (X3) and control of AI-CAI game-playing programs ("executive option"/no option) for each of two games (LAST-ONE-LOSES and EVEN-WINS). Specifically, the hypothesis asserts that the mean of scores on variable X3 by subjects using a program with an "executive option" will be lower than the mean of scores on variable X3 by subjects using a program with no option. The null hypothesis asserts no significant difference between the two group means.

Before conducting specific comparisons between groups, analyses of variance were carried out in order to look for overall effects of the experimental factors. Results of two-way analysis of variance for both games are reported in Table IV-3.

TABLE IV - 3

Two-way Analysis of Variance Results for Variable X3  
"Intolerance"

LAST-ONE-LOSES

## MEANS FOR X3.1

(Percentage Errors of Intolerance)

	LEARN	STATIC
Executive Option	10.05	3.61
No Option	6.89	0.54

## COMPUTED VALUES FOR X3.1

(Percentage Errors of Intolerance)

Source of Variance	df	Mean Squares	F
Mode Factor	1	433.31	1.76
Control Factor	1	123.09	0.50
Interaction	1	21.13	0.09
Error	38	246.27	



TABLE IV - 3 -- Continued

EVEN-WINS

## MEANS FOR X3.1

(Percentage Errors of Intolerance)

	LEARN	STATIC
Executive Option	5.76	9.63
No Option	13.84	7.31

## COMPUTED VALUES FOR X3.1

(Percentage Errors of Intolerance)

Source of Variance	df	Mean Squares	F
Mode Factor	1	1.66	0.01
Control Factor	1	100.42	0.41
Interaction	1	260.05	1.07
Error	37	243.39	

For hypothesis 3 concerning the mode factor, computed F ratios for variable X3 were insufficient for either game to reject the null hypotheses of no significant difference between group means. That the means for subjects using LEARN were greater (but not significantly greater) for both games in percentage errors of intolerance than for STATIC subjects may not seem so surprising when possible intrusion of effects of anxiety are considered. It is conceivable that subjects who noticed that their computer program was becoming more competitive, themselves became more anxious to make the right move; and, consequently, for some of those subjects, frustration and anxiety stimulated more typing errors, breaking of the rules, etc.

For hypothesis 9 concerning the control factor, computed F ratios for variable X3 were insufficient for either game to reject the null hypotheses of no significant difference between group means. Differences in means showed contradictory results for the two games on variable X3. In LAST-ONE-LOSES subjects using "executive option" made more (but not significantly more) errors of intolerance on the average than subjects using no option. A multitude of possible factors could contribute to an explanation of this phenomenon; for example, excitement generated due to the control granted subjects using "executive option" might have encouraged exploration of other facets of the computer's game-playing capacities, only some of which were proper entries (tolerable by the machine). Additionally,

subjects with no option may have been considerably more careful about entering their responses knowing that they had no overt control over the computer. In EVEN-WINS subjects using "executive option" made fewer (but not significantly fewer) errors than subjects with no option--the difference of means being in the direction supporting the hypothesis. Again, differing outcomes for the two games suggests further examination.

In the absence of significant F ratios, results of t tests are not recorded here.

Statistical data for variable X3 are found in Appendix C. Shown are means, medians, ranges, and standard deviations for both games for all subjects tested.

In summary, results did not support the third or ninth hypotheses that "intolerance" is related to mode and control factors of AI-CAI game-playing programs.

#### "Decision-Speed"

Hypotheses 4 and 10 will be considered jointly.

The fourth experimental hypothesis is concerned with the relationship between the "decision-speed" variable (X4) and the mode of AI-CAI game-playing programs (LEARN/STATIC) for each of two games (LAST-ONE-LOSES and EVEN-WINS). The hypothesis specifically asserts that the mean of scores on variable X4 by subjects using program LEARN will be lower than the mean of scores on variable X4 by subjects using program STATIC. The null hypothesis asserts no significant difference between the group means.



The tenth experimental hypothesis is concerned with the relationship between the "decision-speed" variable (X4) and control of AI-CAI game-playing programs ("executive option"/no option) for each of two games (LAST-ONE-LOSES and EVEN-WINS). Specifically, the hypothesis asserts that the mean of scores on variable X4 by subjects using a program with an "executive option" will be lower than the mean of scores on variable X4 by subjects using a program with no option. The null hypothesis asserts no significant difference between the group means.

Before conducting specific comparisons between groups, analyses of variance were carried out in order to look for overall effects of the experimental factors. Results of two-way analysis of variance for **each** sub-variable for both games are reported in Table IV-4.

For hypothesis 4 concerning the mode factor, computed F ratios for both sub-variables were insufficient for either game to reject the null hypotheses of no significant differences between group means. Differences in means, however, showed results contrary to the hypothesis. That subjects using STATIC would make moves faster on the average (less response time for sub-variable X4.1) and increase their rate of move-making faster (have smaller slope of response time curve for sub-variable X4.2) than subjects using LEARN could be explained by postulating a general build-up of confidence during game-playing by those subjects. Subjects using STATIC may have

TABLE IV - 4

Two-way Analysis of Variance Results for Variable X4  
 "Decision-Speed"

LAST-ONE-LOSES

## MEANS FOR X4.1

(Seconds Average Response Time)

	LEARN	STATIC
Executive Option	16.21	13.50
No Option	15.07	13.91

## COMPUTED VALUES FOR X4.1

(Seconds Average Response Time)

Source of Variance	df	Mean Squares	F
Mode Factor	1	33.94	4.01
Control Factor	1	3.57	0.42
Interaction	1	4.88	0.58
Error	35	8.46	

TABLE IV - 4 -- Continued

LAST-ONE-LOSES

## MEANS FOR X4.2

(Average Rate of Change of Response Time)

	LEARN	STATIC
Executive Option	0.17	-0.11
No Option	0.21	0.00

## COMPUTED VALUES FOR X4.2

(Average Rate of Change of Response Time)

Source of Variance	df	Mean Squares	F
Mode Factor	1	0.54	0.75
Control Factor	1	0.04	0.06
Interaction	1	0.02	0.03
Error	35	0.72	



TABLE IV - 4 -- Continued

EVEN-WINS

## MEANS FOR X4.1

(Seconds Average Response Time)

	LEARN	STATIC
Executive Option	18.22	18.08
No Option	17.37	14.26

## COMPUTED VALUES FOR X4.1

(Seconds Average Response Time)

Source of Variance	df	Mean Squares	F
Mode Factor	1	12.78	1.41
Control Factor	1	44.75	4.95
Interaction	1	25.42	2.81
Error	37	9.04	

TABLE IV - 4 -- Continued

EVEN-WINS

## MEANS FOR X4.2

(Average Rate of Change of Response Time)

	LEARN	STATIC
Executive Option	-0.10	0.38
No Option	1.03	-0.17

## COMPUTED VALUES FOR X4.2

(Average Rate of Change of Response Time)

Source of Variance	df	Mean Squares	F
Mode Factor	1	0.41	0.23
Control Factor	1	1.23	0.69
Interaction	1	6.77	3.82
Error	37	1.77	

encountered game situations which they had seen before and knew that they could win (but not necessarily by the optimal strategy) because the computer demonstrated a constant level of strategic expertise. In other words, a subject could feel confident in making a move more rapidly without much thought because he could count on the computer to make a 'dumb' move (random move) later on.

It is noted here that the results of testing on variable X4 are questionable in light of two discoveries made during the investigation (much to the chagrin of the investigator). First, data on response times recorded by a computer command executed within an APL function contained total time for printing and cycle time accumulated during other users' CPU time. It was expected that only accumulated open keyboard time would be tallied. Second, many unanticipated distractions--such as ten-minute trips to the bathroom, conversations with friends and needs for fixing crumpled paper at the terminal--may have distorted data on timing.

For hypothesis 10, concerning the control factor, computed F ratios for both sub-variables were insufficient for LAST-ONE-LOSES to reject the null hypotheses of no significant differences between group means. A significant difference in means at the .05 level was found for one of the sub-variables (X4.1, average response time) for EVEN-WINS. But the difference in means was opposite to that predicted by the hypothesis. A possible explanation for this unexpected outcome lies in the degree to which the control factor lures the



subjects into deeper involvement with making a given move, thereby lengthening their response times. Mean rates of increase of response times (sub-variable X4.2) were lower (but positive) for subjects using "executive option" for both games. The fact that means were not negative<sup>1</sup> defeats the intent of the hypothesis, although the difference in the means was in the direction predicted by the hypothesis. Mean response times (X4.1), however, were higher for "executive option" subjects for both games (significantly higher for EVEN-WINS). An alternative explanation is found in possible accruing "boredom" of subjects using both versions of control programs, but greater boredom on the part of subjects with no option to change the level of difficulty of the computer's **game-playing**. That boredom was present and did increase during game-playing for all subjects is supported by overall positive slopes of response time curves for both games: 0.1 for LAST-ONE-LOSES and 0.29 for EVEN-WINS. Generally, departure from expected results on this variable is confirmed by extremely high error variance in both games and distorted data (discussed above).

In the absence of significant F ratios in directions predicted by hypotheses, results of t tests are not recorded here.

Statistical data for variable X4 are found in Appendix C. Shown are means, medians, ranges, and standard deviations for the two sub-variables for both games for all subjects tested.

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<sup>1</sup>A negative slope of response time curve indicates a decrease in response times with time, or an increase in speed of decision-making.

In summary, results did not support the fourth or tenth hypotheses that "decision-speed" is related to mode and control factors of AI-CAI game-playing programs.

### "Understanding"

Hypotheses 5 and 11 will be considered jointly.

The fifth experimental hypothesis is concerned with the relationship between the "understanding" variable (X5) and the mode of AI-CAI game-playing programs (LEARN/STATIC) for each of two games (LAST-ONE-LOSES and EVEN-WINS). The hypothesis specifically asserts that the mean of scores on variable X5 by subjects using program LEARN will be higher than the mean of scores on variable X5 by subjects using program STATIC. The null hypothesis asserts no significant difference between the two group means.

The eleventh experimental hypothesis is concerned with the relationship between the "understanding" variable (X5) and control of AI-CAI game-playing programs ("executive option" /no option) for each of two games (LAST-ONE-LOSES and EVEN-WINS). Specifically, the hypothesis asserts that the mean of scores on variable X5 by subjects using a program with an "executive option" will be higher than the mean of scores on variable X5 by subjects using a program with no option. The null hypothesis asserts no significant difference between the two group means.

Before conducting specific comparisons between groups, analyses of variance were carried out in order to look for

overall effects of the experimental factors. Results of two-way analysis of variance are reported for both games in Table IV-5.

For hypothesis 5 concerning the mode factor, computed F ratios for variable X5 were insufficient for either game to reject the null hypotheses of no significant differences between means. However, analysis of variance found an F ratio of 5.21, significant at the .05 level, indicating interaction effects operating between the two factors for LAST-ONE-LOSES. No interaction effect was found for EVEN-WINS.

For hypothesis 11 concerning the control factor, computed F ratios for variable X5 were insufficient for either game to reject null hypotheses of no significant differences between group means. The game of LAST-ONE-LOSES did show a moderately higher (but not significantly higher) mean of post-test scores (X5) for "executive option" subjects than for subjects with no option. This result is consistent with assumptions underlying the hypothesis; namely, subjects capable of controlling the computer's level of playing ability were better able to understand the principles of the game. It is further noted that the mean of STATIC/"executive option" subjects on this variable was greatly different from those on all other cells: 13.00 vs. 9.67, 10.08, 8.11. Results for EVEN-WINS showed no systematic differences in means.

A plausible explanation for lack of appearance of significant differences in both hypotheses 5 and 11 is cued



TABLE IV - 5

Two-way Analysis of Variance Results for Variable X5  
 "Understanding"

LAST-ONE-LOSES

## MEANS FOR X5.1

(Score on Strategy Understanding Test)

	LEARN	STATIC
Executive Option	9.67	13.00
No Option	10.08	8.11

## COMPUTED VALUES FOR X5.1

(Score on Strategy Understanding Test)

Source of Variance	df	Mean Squares	F
Mode Factor	1	1.35	0.10
Control Factor	1	27.38	2.10
Interaction	1	67.78	5.21
Error	36	13.01	



TABLE IV - 5 -- Continued

EVEN-WINS

## MEANS FOR X5.1

(Score on Strategy Understanding Test)

	LEARN	STATIC
Executive Option	7.08	7.08
No Option	7.88	7.86

## COMPUTED VALUES FOR X5.1

(Score on Strategy Understanding Test)

Source of Variance	df	Mean Squares	F
Mode Factor	1	0.01	0.00
Control Factor	1	5.66	0.58
Interaction	1	0.01	0.00
Error	35	9.70	

by the interaction effect discovered in LAST-ONE-LOSES. It is conceivable that the effect of "executive option" overshadowed the mode factor. That is, it may have made little difference to subjects using "executive option" whether or not their program was learning--or possibly even the effect of LEARN served to distract subjects from the relatively more complex task of using "executive option". In other words, subjects who can control the machine's level of game-playing ability can explore better strategies at a rate of their own choosing, and, hence, for them there is no need for the machine to be learning if that control is present. This interaction between the two factors (mode and control) may have had a major influence in causing the difference in means on variable X5 ("understanding") for subjects using "executive option": 9.67 for LEARN, 13.00 for STATIC.

For subjects without control (no option), the effect of LEARN may have provided an example of improved strategy for them to view. The interaction between the two factors again may have had a major influence in causing the difference in means on variable X5 for subjects using no option: 10.08 for LEARN, 8.11 for STATIC. It is further noted that subjects deprived of any interesting effects--STATIC and no option--produced the lowest mean (8.11). This may then be explained by the fact that the optimal strategy was never revealed to them; that is, the machine contributed nothing to their learning.

No interaction effect was discovered in data for EVEN-WINS. This is understandable if this game was too difficult for the subjects to understand. The optimal strategy, in that case, would not be understood or used. Comparative differences in the two games, LAST-ONE-LOSES and EVEN-WINS, will be discussed later in greater depth.

In the absence of significant F ratios for either of the two main factors, results of t tests are not recorded here.

Statistical data for variable X5 are found in Appendix C. Shown are means, medians, ranges, and standard deviations for both games for all subjects tested.

In summary, results did not support the fifth or eleventh hypotheses that "understanding" is related to mode and control factors of AI-CAI game-playing programs.

#### "Generalizability"

Hypotheses 6 and 12 will be considered jointly.

The sixth experimental hypothesis is concerned with the relationship between the "generalizability" variable (X6) and the mode of AI-CAI game-playing programs (LEARN/STATIC) for each of two games (LAST-ONE-LOSES and EVEN-WINS). The hypothesis specifically asserts that the mean of scores on variable X6 by subjects using program LEARN will be higher than the mean of scores on variable X6 by subjects using program STATIC. The null hypothesis asserts no significant difference between the two group means.



The twelfth experimental hypothesis is concerned with the relationship between the "generalizability" variable (X6) and control of AI-CAI game-playing programs ("executive option"/no option) for each of two games (LAST-ONE-LOSES and EVE-WINS). Specifically, the hypothesis asserts that the mean of scores on variable X6 by subjects using a program with an "executive option" will be higher than the mean of scores on variable X6 by subjects using a program with no option. The null hypothesis asserts no significant difference between the two group means.

Before conducting specific comparisons between groups, analyses of variance were carried out in order to look for overall effects of the experimental factors. Results of two-way analysis of variance for both games are reported in Table IV-6.

For hypothesis 6 concerning the mode factor, computed F ratios for variable X6 were insufficient for either game to reject the null hypotheses of no significant differences between group means. Differences in means were in different directions for the two games. For LAST-ONE-LOSES the mean of LEARN subjects' scores on X6 was slightly higher (but not significantly higher) than the mean for STATIC subjects. Again, as in the cases of hypotheses 5 and 11, interaction effects between the two main factors may offer a possible interpretation of these results. That subjects with "executive option"



TABLE IV - 6

Two-way Analysis of Variance Results for Variable X6  
 "Generalization"

LAST-ONE-LOSES

## MEANS FOR X6.1

(Score on altered Strategy Understanding Test)

	LEARN	STATIC
Executive Option	7.58	7.57
No Option	8.42	7.11

## COMPUTED VALUES FOR X6.1

(Score on altered Strategy Understanding Test)

Source of Variance	df	Mean Squares	F
Mode Factor	1	4.54	0.33
Control Factor	1	0.77	0.06
Interaction	1	4.23	0.31
Error	36	13.73	

TABLE IV - 6 -- Continued

EVEN-WINS

## MEANS FOR X6.1

(Score on altered Strategy Understanding Test)

	LEARN	STATIC
Executive Option	6.58	6.58
No Option	4.63	5.71

## COMPUTED VALUES FOR X6.1

(Score on altered Strategy Understanding Test)

Source of Variance	df	Mean Squares	F
Mode Factor	1	2.09	0.51
Control Factor	1	19.41	4.75
Interaction	1	2.34	0.57
Error	35	4.09	

produced nearly equivalent mean scores (7.58 for LEARN, 7.57 for STATIC) supports the contention that the control factor (when it was in effect) overshadowed the "learning" effect; in other words, there is no need for the computer to display learning when one can command the computer to play at a superior level at any time. In this way, use of the "executive option" alone offers a subject opportunities for seeing the optimal strategy. That for subjects with no option the mean scores of LEARN were higher than the mean scores of STATIC (8.42 and 7.11, respectively) and had the greatest spread of all four means support the contention that subjects without control found LEARN's display of improved strategy useful for their learning. Additionally, it is understandable that subjects deprived of any interesting effects--STATIC and no option--produced the lowest mean (7.11). This may be explained by the fact that the optimal strategy is never revealed to them by the machine.

For EVEN-WINS, LEARN subjects generated a mean lower (but not significantly lower) than STATIC subjects, which again suggests exploring differences in subjects' receptivity and understanding of the two games.

For hypothesis 12 concerning the control factor, the computed F ratio for variable X6 was insufficient to reject the null hypothesis for LAST-ONE-LOSES; and an F ratio of 4.75, significant at the .05 level, indicated a significant difference in group means for EVEN-WINS. Differences in means were found

to be in different directions for the two games. LAST-ONE-LOSES showed a small (and not statistically significant) difference in means, favoring subjects using no option. This puzzles the investigator. In EVEN-WINS, a significant difference between means favored subjects using the "executive option". This last result supports the hypothesis that the control factor is related to "generalizability". Referring to results on variable X1.1--that "no option" subjects showed significantly higher "winningness"--suggests a confirming interpretation. With no control over raising (or lowering) the level of the computer's game-playing ability, subjects encountered more game situations which were easy to win but fewer game situations in which a deeper understanding of winning strategy was required. Thus, "no option" subjects were not able to generalize their understanding of EVEN-WINS even though they were often winning.

Since results of analysis of variance found only one (of four) significant F ratios, results of t tests are not recorded here.

Statistical data for variable X6 are found in Appendix C. Shown are means, medians, ranges, and standard deviations for both games for all subjects tested.

In summary, results did not support the sixth or twelfth hypotheses that "generalizability" is related to mode and control factors of AI-CAI game-playing programs.



Casual inspection of the data indicated a recurring "games" effect for a number of the variables. Since two games with different rules and objectives were employed as vehicles for testing in this investigation, the possible impact of their differences on results is discussed here.

LAST-ONE-LOSES (described in detail in Appendix A) appeared to be an excellent choice of game for the purposes of this study because: 1) it is simple and easy to learn;<sup>1</sup> 2) a single game can be completed briefly;<sup>2</sup> 3) machine learning can be discerned within a reasonable period;<sup>3</sup> and 4) children at 5th and 6th grade level appear to clearly separate on their ability to understand and articulate the mathematical principles underlying the game.<sup>4</sup>

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<sup>1</sup>The average time between introduction of rules and (voluntary) beginning of play was on the order of 45 seconds.

<sup>2</sup>Average time to complete one game (with 12 boxes to start with) was on the order of one minute.

<sup>3</sup>Nine games are required for the computer to adapt from its starting state (random play) to an optimal strategy. During actual game-playing ten to fifteen games will usually suffice.

<sup>4</sup>Standard deviations of scores on the Strategy Understanding Test (variable X5) were generally higher for LAST-ONE-LOSES (3.37, 1.73, 4.36, 3.82) than for EVEN-WINS (2.97, 2.11, 4.02, 3.67). Standard deviations of scores on the Strategy Understanding Test with altered rules (variable X6) were all higher for LAST-ONE-LOSES (3.80, 4.47, 3.58, 3.06) than for EVEN-WINS (2.31, 2.19, 1.71, 1.25). Casual inspection of the test results revealed that subjects either discovered the correct pattern of the optimal strategy (scored high) or discovered little beyond minimal strategic move-making (scored low) in the game of LAST-ONE-LOSES.

EVEN-WINS (described in detail in Appendix A) possesses some similar characteristics: 1) rules of play are described simply and briefly;<sup>1</sup> 2) a complete game is played in short time;<sup>2</sup> and 3) machine learning can be discerned quickly.<sup>3</sup> But, it is a more subtle game, potentially more interesting and yet considerably more difficult to win.<sup>4</sup> In this game the optimal strategy is by no means obvious. (The reader is invited to try discovering how to win.) The computer program (LEARN) learns to play optimally more quickly than most human players, if, indeed, they learn it at all.<sup>5</sup>

Since the effects of factors operating in this investigation were contingent upon subjects noticing them (refer to list of assumptions, Chapter III METHODS AND PROCEDURES), the investigator conducted informal post-experiment interviews in order to judge more accurately their powers of observing. Results of casual interviews with all subjects following testing confirmed that the "learning" effect was often beyond their observing powers: 1) most did not notice that the computer was

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<sup>1</sup>The average time between introduction of rules and (voluntary) beginning of play was on the order of one minute.

<sup>2</sup>Average time to complete one game (with 9 boxes to start with) was approximately one and one-half minutes.

<sup>3</sup>Ten games are required for the computer to adapt from its starting state (random play) to an optimal strategy. During actual game-playing fifteen to twenty games will usually suffice.

<sup>4</sup>Because of the additional parameter of parity.

<sup>5</sup>From H.D. Block, "Learning In Some Simple Non-Biological Systems", American Scientist, Vol 53., No. 1, March 1965 p. 70

learning (when LEARN was in effect) and some imagined a learning effect (when STATIC was in effect); 2) some did not use the "executive option" at all even though they knew it was available at their discretion; 3) many did not understand the 'gist' of the game--particularly EVEN-WINS--after playing.

Hard data on number of games played (variable X2.1) for the two games suggests that subjects preferred attending to LAST-ONE-LOSES over EVEN-WINS. On the average subjects played more games of LAST-ONE-LOSES (25.7) than EVEN-WINS (16.5). (This popularity of LAST-ONE-LOSES is perhaps also due to the fact that it was the first game played.)

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In overall summary, for subjects selected to play AI-CAI games in this investigation, two-way analyses of variance did not find clear relationships between any variables identified to measure learning and mode or control factors. The four significant differences found in the total 57 ANOVA tests are nearly within the range which can be attributed to chance factors. If there are differences in learning produced by mode (LEARN/STATIC) or control ("executive option"/no option) in AI-CAI games, they were not pronounced enough to show up in the small sample used in this study.

Of the alternative explanations offered in interpretations of the results, possible interaction between the two factors (mode and control) was predominant. Contended was



that the control factor (when it was operating) overshadowed the "learning" effect; that is, subjects have no need to witness automatic learning when they can control the level of sophistication of the computer's game-playing strategy. This interpretation is supported by two significant outcomes of the ANOVA tests: interaction effect significant at the .05 level on the "understanding" variable (X5) for LAST-ONE-LOSES, and control effect significant at the .05 level on the "generalizability" variable (X6) for EVEN-WINS.

Inspection of the data indicated a "games" effect for a number of the variables. LAST-ONE-LOSES appeared to be the more appropriate game for use in testing in this study. For that game, the cell for which data seemed most supporting of learning variables was STATIC/"executive option". Of the eight total comparisons of means, five were the single-most pronounced (in the direction of maximum learning as measured by the six sets of variables) for subjects with STATIC and "executive option" AI-CAI programs. This result is considerably more than the two expected by chance alone. Similar results for EVEN-WINS may have been obscured by the difficulty of the game; that is, presentation of the optimal strategy by the computer may have been to no avail because it was not understood by subjects.

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This discussion now focuses on several post-experiment reflections, their evaluation and implications for future research.



First, reflection on assessed attitudes of subjects toward the AI-CAI games is revealing. Impromptu comments by subjects and responses to casual questions from the investigator about the games were positive or neutral in every case. It was immediately apparent that some children were significantly intrigued by a game which could 'improve itself' automatically while they were playing with it. Undoubtedly some of these observant children were impressed by sheer novelty of the idea that a machine could 'learn'; others may have wanted to take advantage of opportunities to watch the computer's moves in order to do well themselves when placed in a competitive situation; still others may simply have been fascinated by strategic procedures; and perhaps some were attracted by the appeal of learning. Informal evaluations by the investigator, several colleagues, plus subjects' teachers whole-heartedly supported the belief that the children found the games appealing.<sup>1</sup>

Secondly, a look at general learning patterns of users of the AI-CAI games is revealing. The mean rates of learning (sub-variable X1.2) for all subjects were positive<sup>2</sup> for both games: 0.47 for LAST-ONE-LOSES, 0.57 for EVEN-WINS. Learning gains, as indicated by slopes of individual learning curves

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<sup>1</sup>Once the 'word' got around that the computer games were fun, children were so anxious to 'be next' to play that often several were competing simultaneously.

<sup>2</sup>A positive rate of learning indicates that subjects learned (to win) faster as they played.

(see Appendix C) occurred in 63 per-cent of subjects for the two games; that is, 68 per-cent of the 42 subjects playing LAST-ONE-LOSES had a positive rate of learning, and 58 per-cent of the 41 subjects playing EVEN-WINS had a positive rate of learning. Confirming this hard data are informal evaluations by the investigator, several colleagues visiting the testing setting, and the subjects themselves. Participation in an event in which one's partner is also learning often comprises substantial motivation for learning.<sup>1</sup> To be sure, when one human being engages another in a game, there are often psychological, social, emotional, and sometimes even political or economic overtones. But what is the motivation for playing when a machine is involved? It is conjectured here in this investigation that, once the effects of novelty wear off, continuing competition with a machine must be mostly for purposes of learning.<sup>2</sup> Changes in motivation and/or attitude which occur when one's partner is progressing too quickly or too slowly may be dealt with by machine through use of an "executive option".

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<sup>1</sup>A striking parallel exists in Carl Rogers' work in psychotherapy. He praises the value of a "helping relationship" in which the counselor is involved with and experiences feelings of the patient. (See, for example, On Becoming A Person, by Carl Rogers, Houghton Mifflin, 1961)

<sup>2</sup>An alternative conjecture puts forth that the goal is being victorious over one (the machine) who is supposed to be 'so smart'.

The positive attitudes and learning gains observed in this investigation suggest that the use of AI-CAI games might be extended beyond this study. (It is not appropriate, however, to generalize any results reported herein beyond this investigation.) The prospect of promoting use of AI-CAI games is supported by two recent decisions: 1) School of Education and Department of Computer Science faculty have collaborated to offer a new course in the coming fall, 1971 semester at the University of Massachusetts. This course, entitled "AI in CAI", Seminar in Education 705, will permit a highly specialized research team to pursue research in this new field (perhaps using results of this investigation as a springboard); 2) Mark's Meadow Elementary School will open a Learning Resources Area in the fall, 1971 which will include two computer terminals for use by children.

Thirdly, and finally, the prospective marriage of AI and CAI may mark the beginning of developments of new theories and practices in education. Implications of the use of artificial intelligence in education are far-reaching--from models in teacher-training to applications in learning theory. For example, the myth of 'teacher as expert' may be exposed and more effectively dealt with when machines are capable of acting both as a 'partner' in an intellectual pursuit and as an 'infinitely patient' mentor. Most likely with grateful relief, then, many classroom teachers may relinquish the redundancy and tedium of the information storage and retrieval function



(for one) in favor of concentrating on those elements of teaching which are uniquely human and humanizing.

Learning theorists may soon consider mechanical learning systems as a proving ground for their conjectures. Utilizing carefully monitored instruction by computer, theorists (and educators) may gain information about children who are unduly discouraged from learning by encountering a far too proficient opponent (or partner) and about children who are easily bored by play (or teaching) at a level far below their ability. One analog would compare learning with heuristic techniques themselves; that is, some persons learn "breadth-first", some explore learning materials "depth-first", and others combine the two techniques.

In summary, it is my hope to stimulate further thinking in this new area: AI in CAI. Dissemination and further discussion of these research results may serve to dissolve some of the myths, assuage some of the fears, and point to more positive and humanizing directions for computer usage.



## CHAPTER V

### CONCLUSIONS AND RECOMMENDATIONS

This study was designed to explore differences in learning by children using artificial intelligence game-playing computer-assisted instruction programs. Based on the experimental results of this study, the investigator offers the following conclusions and recommendations.

#### Conclusions

In this investigation concerned with artificial intelligence aspects of computer-assisted instructional games, twelve experimental hypotheses have been examined for six sets of variables used to measure learning in each of two games. Six hypotheses were concerned with the mode factor of AI-CAI games (LEARN/STATIC); of these six, none received experimental support for either game. Therefore, on the basis of this research, the investigator concludes that no systematic relationship between mode of AI-CAI games and learning was found.

Six hypotheses were concerned with the control factor of AI-CAI games ("executive option"/no option); in one game (LAST-ONE-LOSES) none of eight sub-variables received experi-

mental support, and three of eleven sub-variables produced significant differences in means at the .05 level of confidence in the second game (EVEN-WINS). (Two of the three significant differences were in directions counter to that predicted by the hypotheses.) Therefore, on the basis of this research, the investigator concludes that no consistent relationship between control of AI-CAI games and learning variables was found.

Interaction effects between the two factors--mode and control--were also studied. Two-way analysis of variance for a total of nineteen sub-variables disclosed one interaction effect significant at the .05 level of confidence for one game. Therefore, on the basis of this research, the investigator is led to conclude that no interaction function was found to be operating on the two factors under study.

A total of four significant differences in means were found in outcomes of 57 analyses of variance tests. These four fall near to the range expected by chance. Therefore, results of t tests--which may be regarded as suspicious--are not reported.

In summary, on the basis of this research, the investigator concludes that if there are differences in learning due to mode and control factors in AI-CAI games, they were not large enough to show up for the small sample used in this investigation.

Interpretations

Of the alternative explanations offered in interpreting the results, one seemed most plausible: possible presence of interaction between the two factors under study. It is conceivable that the control factor (when it was operating) overshadowed the mode effect; that is, subjects using the "executive option" may have had little need for the computer's automatic learning capacity since they could fully control the level of sophistication of the computer's game-playing. By contrast, subjects with no option may have had little opportunity for learning since they could not command the computer to play with an improved strategy. For these subjects, the effect of machine "learning" may have provided an example of superior strategy for them to observe; however, "intimidation" effects may have thwarted their attention and their learning. In fact, data supported these contentions. The data revealed that subjects using program STATIC with "executive option" most frequently produced scores on variables in the direction of maximum learning.

Casual inspection of the data also indicated that a "games" effect may have been operating in this study. While results in LAST-ONE-LOSES--such as subjects deprived of both effects (STATIC/no option) producing means in the direction of minimum learning--were found, similar results were not apparent for EVEN-WINS. It was then conjectured that presentation of the optimal strategy by the computer was obscured because the game was too difficult to understand.



## Recommendations

From analysis of data collected during hypotheses testing and from experience gained while conducting this study, the investigator is compelled to make the following recommendations. Listed in three sections, the recommendations are: 1) suggestions for further data analysis, 2) practical suggestions for further research efforts, and 3) proposed designs for future research. Appendix H contains a list of related research topics.

### Suggestions for Further Data Analysis

Excessive data bulk and time constraints prevented the investigator from conducting further analysis of data gathered in the investigation. Using data now available, some suggestions for follow-up study are:

1. Correlations of learning variables with subjects' self ratings and selected starting levels of difficulty
2. Correlations of learning variables with frequency and timing of use of "executive option"; e.g.
  - a) discontinuities in learning curves
  - b. percentage errors of intolerance (variable X3)
3. Creation of refined learning sub-variables, such as (for "winningness"):
  - a. percentage winning moves/possible winning moves for each level of difficulty; e.g. for LAST-ONE-LOSES, 1-4 boxes (level 1), 5-8 boxes (level 2), 9-12 boxes (level 3), etc.
  - b. percentage winning moves/possible winning moves by period; e.g. 1st quarter, 2nd quarter, etc.
  - c. rate of change of learning curve (2nd derivative)
4. Correlations of learning variables with measures of aptitude: e.g. test scores, teacher ratings

### Practical Suggestions for Further Research

Experience gained while conducting this investigation has led this investigator to make some practical suggestions for improving research design and methodology which might be used in similar research efforts of this kind. Specifically, the suggestions are:

1. Select a larger sample

Larger sample sizes should be utilized in order to reduce the risk of making type II errors of inference.

2. Choose fewer variables and sub-variables

Fewer variables will reduce the number of tests for statistical significance and may simplify interpretation of results.

3. Choose different variables

Variables more closely related to learning by subjects will strengthen the meaning of results.

4. Tighten controls on testing procedures

Eliminating distractions in the testing setting may allow effects of learning to appear more clearly.

5. Consider different factorial designs

Controlling for a single factor may yield clearer results and avoid possible complications due to interaction effects.

6. Choose simple vehicles for testing

A game which is easy to learn, has brief rules, and can be completed in a short time should facilitate learning if it is to be an effective vehicle for testing.

7. Permit subjects a wide range for response discrimination

A wide range of possible choice (of moves in a game) reduces chance factors and may separate responses by subjects who are learning from those who are guessing.



Practical Suggestions for Further Research, continued

8. Accommodate research design to computer system constraints

Larger workspaces (in APL) and larger symbol tables (CDC 3600 systems programming) would permit greater magnitude of data collection and storage and would facilitate data manipulation.

Proposed Designs for Future Research

Pursuing research in the area of AI-CAI games is important because artificial intelligence techniques offer potential contributions to revitalizing computer-assisted instruction in American education. (See Chapter I, THE CHALLENGE)

Observations made by this investigator during testing procedures conducted in this investigation have suggested designs for continued research in the area of AI in CAI. Specifically, studies proposed for future research are outlined:

1. Studies of learning variables correlated with psychological measures, such as anxiety; e.g. Which data correlate with response times when the user has the computer in a forced-move sequence? when the computer has the user in a forced-move sequence?
2. Studies of learning effects due to different games; e.g. NIM, GOMOKU, TAC TIX, QUERIES 'N THEORIES, MEM What is learned? at what points? how fast?
3. Studies correlating use of "executive option" with measures of self-esteem; e.g. the ring-toss experiments<sup>1</sup>
4. Studies of use of "executive option" by subjects mismatched with the computer's playing ability

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<sup>1</sup> See The Achieving Society, by D.C. McClelland, 1961, Princeton, Van Nostrand



Proposed Designs for Future Research, continued

5. Studies contrasting learning patterns of radically different age groups
6. Studies testing subjects playing games in pairs; in groups
7. Studies of use of AI-CAI games with "low-achievers"
8. Studies correlating use of AI-CAI games with development of 'computer literacy'; e.g. Are children encouraged to learn computer programming by playing games on a computer?
9. Development of more sophisticated AI components in CAI games; e.g.
  - a. an option to alter level of computer's strategy mid-game
  - b. a running commentary on each individual player's progress (when requested)
  - c. a "HELP" option
  - d. a "TEACH" option (enabling a player to request a lesson after any given game)
10. Exploration of teaching techniques via AI-CAI games; e.g. Explain the optimal strategy at the onset or permit initial periods of unstructured play?

The investigator concludes this investigation having achieved his goals: 1) to make a foray into a new area of knowledge, and 2) to provide bases for further study in the problem area. Whereas little or nothing was known previously about the use of AI techniques in CAI games, now results of this research may be used to shed light on how to study the problem further and for subsequent hypothesis generation. It was the hope of this investigator to stimulate thinking and to encourage continued exploration in this new area: AI in CAI.

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APPENDICES

APPENDIX A  
DESIGN OF LEARNING GAMES

LAST-ONE-LOSES

LAST-ONE-LOSES--a variant of the ancient intellectual game of NIM--is a game played with two players (or opponents). The game involves taking away boxes (or any distinct items) from an initial pile of boxes (an arbitrary starting number). One player decides to move first and may take away a number of boxes--a whole number not less than one and not greater than the established maximum. (Here the maximum is 3 boxes.) The second player then moves, similarly taking 1, 2, or 3 boxes. The players alternate moves in this manner until there are no boxes left. Whoever took the last box(es) loses the game. Hence the name LAST-ONE-LOSES.

The optimal strategy for LAST-ONE-LOSES is, when it is one's move, to remove a number of boxes equal to the remainder after dividing one less than the number of boxes available by four. For example, if there are 7 boxes to choose from, the winning move is to take 2--the remainder of (7 minus 1) divided by 4. Then, with 5 boxes available, the other player must take 1 or 2 or 3. If 1 is his move (4 left), the winning move is to take 3, leaving the last 1; if 2 is his move (3 left), the winning move is to take 2, leaving the last 1; and if 3 is his move (2 left), taking 1 is the winning move, leaving the last 1. Once such a "forced-move sequence" has been initiated, optimal



move-making amounts to taking the number of boxes equal to the difference from 4 of the opponent's last move. When there are 1 or 5 or 9 or 13 or 1 plus any multiple of 4, there is no move guaranteeing a win. Hence, this game is also known as a modulus-4 game.

Learning the optimal strategy typically occurs in two stages for most human players: First, several "losing states" are recognized (after a period of play); 1 and 5 and perhaps 9 are soon found to be states which, when it is one's move, the opponent can win--that is, if he plays optimally and continues the forced-move sequence. Second, the modulus pattern of the losing states is discovered (here, modulus-4), and generalization to higher number losing states is then possible. (To generate new losing states, add 4 to previous losing state numbers.)

"Learning" by machine is accomplished by the following algorithm:

1. The starting number of boxes is generated by rolling two simulated dice (with faces 1,2,3,4,5,6) and adding 5 to the two resulting numbers.
2. The (human) player enters his move (if he elected to go first) and that number is subtracted from the total number of boxes available.
3. If the total number of boxes remaining is 1, the machine prints a message informing the player that he has won. If the number remaining is 0, the machine prints a message informing the player that he has lost. In either case the game ends. If, however, the number of boxes remaining is greater than 1, the machine makes its move.

4. The machine selects its move from a (3 by 4) matrix of possible moves. Each column of the matrix contains a 1, 2, and 3 (indicating a move of that number) or 0's (indicating no move of that number). At the onset of game-playing, the matrix appears as follows:

```

1 1 1 1
2 2 2 2
3 3 3 3

```

(A)(B)(C)(D)

These might be conceptualized as four cups, A, B, C, and D, each containing a 1, 2, and 3.

A column of the matrix is determined by the total number of boxes available according to the following rule:

```

0 1 2 3 4 5 6 7 8 9 10 11 12 etc.
A B C D A B C D A B C D A etc.

```

The machine's move, then, is simply a random selection from the numbers greater than 0 appearing in the column (cup) determined above. (If there are only zeros in the column, a random number from 1 to 3 becomes the move.)

5. If the total number of boxes remaining after the machine moves is 1, the machine prints a message informing the player that he has lost. If the number remaining is 0, the machine prints a message informing the player that he has won. If, however, the number is greater than 1, steps 2 thru 4 are repeated.
6. If the last move made by the machine led to a loss, it is replaced in the matrix (of cups) by a 0 in the proper row and column. If the last move came from a column with all 0's, the previous move in that game is considered instead. This process is repeated until the machine reaches the optimal strategy, encoded in the matrix:

```

0 0 1 0
0 0 0 2
3 0 0 0

```

See Appendix B for actual APL coding of these procedures.

Computer programs which enact the game-playing sequence in LAST-ONE-LOSES are described below for a typical game:

1. The player is greeted and is requested to enter his/her name and age. (Program HELLO)
2. Variables used for data gathering are initialized. (Program START)
3. One of four AI-CAI game-playing programs is assigned: LEARN/STATIC and "Executive option"/No option (Program ASSIGN)
4. The player is given the rules; he rates himself on a 1 to 9 scale; he designates the starting level of difficulty of the machine's game-player on a 1 to 9 scale. (Program LASTONELOSES)
5. A single game is played; (Program LOL)
  - Starting number of boxes is printed (Program ROLL)
  - Player decides to go first or second
  - Player and machine alternate moves (Programs MMOVE and PMOVE, respectively)
  - Game-playing data tallied (Program TALLY)
  - If machine loses, "learning" mechanism is called (Program ADAPT)
  - Appropriate response is printed for win or loss (Program RESPONSE)
  - Reminder to use "executive option" (if in force) is printed (Program REMIND)
  - Message to type LOL to play again is printed
6. Player may adjust level of difficulty of machine's game-player by typing PLAY EASIER or PLAY HARDER (Using programs TONEDN or TONEUP)
7. Another game is played (by repeating steps 5 and 6)

A sample of on-line interaction with the computer programs is included here.



SAMPLE GAMES

)LOAD GAME2C  
SAVED 06/21/71

HELLO  
WELCOME TO EVEN-WINS, A COMPUTER GAME.



|>°<|

I AM SOREZ, THE COMPUTER.  
AND WHO ARE YOU?

KING FARUK

HELLO, KING!  
WOULD YOU LIKE AN EXPLANATION OF THE RULES?

YES, PLEASE.

EVEN-WINS IS A GAME OF TAKING AWAY BOXES.  
THE GAME STARTS WITH SOME BOXES IN A ROW, LIKE THIS:

□ □ □ □ □ □ □ □ □ □

YOU AND THE COMPUTER TAKE TURNS TAKING BOXES AWAY UNTIL  
THERE IS NONE LEFT. THAT IS THE END OF THE GAME.  
WHOEVER HAS AN EVEN NUMBER OF BOXES WINS.

WHEN IT IS YOUR TURN, YOU MAY TAKE 1 OR 2 BOXES.  
THEN THE COMPUTER WILL GO AND TAKE 1 OR 2 BOXES.

AT THE START, YOU MAY DECIDE TO GO FIRST OR SECOND.

HOW GOOD A PLAYER ARE YOU?

BEGINNER	FAIR	MEDIUM	GOOD	EXPERT
		X		

AND HOW HARD DO YOU WANT THE COMPUTER TO PLAY?

EASIEST	EASY	MEDIUM	HARD	HARDEST
	X			

O.K.

TYPE EW WHEN YOU ARE READY TO PLAY.

)LOAD GAME1C  
SAVED 05/19/71

HELLO  
HELLO!

WELCOME TO A COMPUTER GAME

MY NAME IS SOREZ (THE COMPUTER)  
WHAT'S YOURS?

PLEASE TYPE YOUR FIRST NAME, A SPACE, THEN YOUR LAST NAME.

DONALD DUCK  
THANK YOU, DONALD DUCK  
DO I HAVE YOUR NAME RIGHT?  
TYPE YES OR NO

YES  
AND HOW OLD ARE YOU, DONALD?  
PLEASE TYPE THE NUMBER OF YEARS.

11

NOW I WILL INTRODUCE YOU TO THE GAME OF LAST-ONE-LOSES.

WOULD YOU LIKE AN EXPLANATION OF THE RULES?  
TYPE YES OR NO

YES

LAST-ONE-LOSES IS A GAME OF TAKING AWAY BOXES.  
THE GAME STARTS WITH SOME BOXES IN A ROW, LIKE THIS:

□ □ □ □ □ □ □ □ □ □

TO START, YOU DECIDE WHETHER TO GO FIRST OR SECOND.  
WHEN IT IS YOUR TURN, YOU MAY TAKE 1 OR 2 OR 3 BOXES.  
THEN THE COMPUTER WILL GO AND TAKE 1 OR 2 OR 3 BOXES.

YOU AND THE COMPUTER TAKE TURNS TAKING BOXES AWAY UNTIL  
THERE IS ONE LEFT. THAT IS THE END OF THE GAME.  
WHOEVER HAS TO TAKE THE LAST ONE LOSES.

NOW, BEFORE WE BEGIN THE GAME, PLEASE TELL ME  
HOW GOOD A PLAYER YOU THINK YOU ARE.

TYPE X UNDER A LINE BELOW.  
BEGINNER            FAIR            MEDIUM            GOOD            EXPERT  
                 |            |            |            |            |            |  
                 X

ALSO, PLEASE TELL ME  
HOW HARD YOU WANT THE COMPUTER TO PLAY

TYPE X UNDER A LINE BELOW.  
EASIEST            EASY            MEDIUM            HARD            HARDEST  
                 |            |            |            |            |            |  
                 X

THANK YOU.

TYPE LOL WHEN YOU ARE READY TO PLAY.

LOL  
TO START WITH THERE ARE 15  
□ □ □ □ □ □ □ □ □ □ □ □ □ □ □  
DO YOU WANT TO GO FIRST OR SECOND?  
TYPE F OR S

F  
YOUR MOVE.

3  
NOW THERE ARE 12  
□ □ □ □ □ □ □ □ □ □ □ □ □  
MY MOVE.  
I'LL TAKE 2  
NOW THERE ARE 10  
□ □ □ □ □ □ □ □ □ □  
YOUR MOVE.

1  
NOW THERE ARE 9  
□ □ □ □ □ □ □ □ □ □  
MY MOVE.  
I'LL TAKE 1  
NOW THERE ARE 8  
□ □ □ □ □ □ □ □ □ □  
YOUR MOVE.

3  
NOW THERE ARE 5  
□ □ □ □ □  
MY MOVE.  
I'LL TAKE 2  
NOW THERE ARE 3  
□ □ □  
YOUR MOVE.

2  
NOW THERE IS 1  
□  
RATFINK!!!, YOU WIN!

TYPE LOL TO PLAY AGAIN.

DID THE COMPUTER PLAY TOO HARD OR TOO EASY?  
TYPE TOO HARD -OR- TOO EASY -OR- OK

TOO EASY

O.K.  
TYPE LOL TO PLAY AGAIN.



LOL  
TO START WITH THERE ARE 11  
□ □ □ □ □ □ □ □ □ □  
FIRST OR SECOND?

FIRST  
YOUR MOVE.

3  
NOW THERE ARE 8  
□ □ □ □ □ □ □ □  
MY MOVE.  
I'LL TAKE 3  
NOW THERE ARE 5  
□ □ □ □ □  
YOUR MOVE.

2  
NOW THERE ARE 3  
□ □ □  
MY MOVE.  
I'LL TAKE 2  
NOW THERE IS 1  
□  
LAST ONE...YOU LOSE.

TYPE LOL TO PLAY AGAIN.

TOO HARD OR TOO EASY?  
TYPE TOO HARD -OR- TOO EASY -OR- OK  
TOO HARD

O.K.  
TYPE LOL TO PLAY AGAIN.

LOL  
TO START WITH THERE ARE 16  
□ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □  
FIRST OR SECOND?

FIRST  
YOUR MOVE.

3  
NOW THERE ARE 13  
□ □ □ □ □ □ □ □ □ □ □ □ □  
MY MOVE.  
I'LL TAKE 2  
NOW THERE ARE 11  
□ □ □ □ □ □ □ □ □ □ □  
YOUR MOVE.

2  
NOW THERE ARE 9  
□ □ □ □ □ □ □ □ □  
MY MOVE.  
I'LL TAKE 1  
NOW THERE ARE 8  
□ □ □ □ □ □ □ □  
YOUR MOVE.

*APPENDIX B*

*APL CODING*

```

▽HELLO[ ]▽
▽ HELLO;A;N;R;T
[1] 'HELLO!'
[2] ''
[3] 'WELCOME TO A COMPUTER GAME'
[4] ''
[5] 'MY NAME IS SOREZ (THE COMPUTER)'
[6] 'WHAT'S YOURS?'
[7] L2:'PLEASE TYPE YOUR FIRST NAME, A SPACE, THEN YOUR LAST NAME.'
[8] N←
[9] 'THANK YOU, ',N
[10] 'DO I HAVE YOUR NAME RIGHT?'
[11] 'TYPE YES OR NO'
[12] →L1×1'Y'∈
[13] 'OOPS. I'M SORRY.'
[14] 'LET'S TRY AGAIN.'
[15] →L2
[16] L1:→L5×1CONTIN N←20+N,20ρ' '
[17] NAMES←NAMES,[1]N
[18] LN←LIT(ρNAMES)[1]
[19] 'AND HOW OLD ARE YOU, ';(1+N1' ')↑N;'?'
[20] L4:'PLEASE TYPE THE NUMBER OF YEARS.'
[21] →L4×10=ρA←,
[22] →L4×10=ρA←(A≠' ')/A
[23] →L3×1^/A∈'0123456789'
[24] 'JUST TYPE ONE NUMBER. FOR EXAMPLE,'
[25] 'IF YOU ARE NEARLY 10 YEARS OLD, TYPE 10'
[26] →L4+1
[27] L3:AGES←AGES,[1↑,∈A
[28] ''
[29] A'BY THE WAY, IF YOU EVER NEED TO CORRECT A TYPING MISTAKE,'
[30] A'DO THIS:'
[31] A' 1. PUSH THE INT KEY (ON RIGHT OF KEYBOARD)'
[32] A' 2. BACKSPACE TO LEFTMOST PART OF YOUR MISTAKE'
[33] A' 3. CONTINUE TYPING FROM THERE'
[34] ''
[35] 'NOW I WILL INTRODUCE YOU TO THE GAME OF LAST-ONE-LOSES.'
[36] LASTONELOSES
[37] →0
[38] L5:'OH. YOU'VE PLAYED BEFORE, HAVEN'T YOU?'
[39] 'WELL, YOU MAY CONTINUE WHERE YOU LEFT OFF.'
[40] ''
[41] 'TYPE LOL TO PLAY AGAIN.'

```

▽

▽LIT[ ]▽

▽ Z←LIT N

```
[1] Z←'0123456789'[1+([N÷10),10|N]
```

▽

▽CONTIN[ ]▽

▽ Z←CONTIN N;V

```
[1] →2×Z←v/V←NAMES^.=N
```

```
[2] LN←LIT V11
```

```
[3] ∈'G←F21 N'
```

▽



```

    ∇LASTONELOSES[□]∇
  ∇ LASTONELOSES;X;I
[1]  START
[2]  ASSIGN
[3]  ''
[4]  'WOULD YOU LIKE AN EXPLANATION OF THE RULES?'
[5]  'TYPE YES OR NO'
[6]  →L1×1∧/'NO'∈□
[7]  ''
[8]  RULES
[9]  L1:''
[10] 'NOW, BEFORE WE BEGIN THE GAME, PLEASE TELL ME'
[11] 'HOW GOOD A PLAYER YOU THINK YOU ARE.'
[12] ''
[13] L3:'TYPE X UNDER A LINE BELOW.'
[14] 'BEGINNER      FAIR      MEDIUM      GOOD      EXPERT'
[15] '  |      |      |      |      |      |      |      |'
[16] →L3×1~'X'∈X←□,' '
[17] RATING←RATING,X←[0.5+(X1'X')÷5
[18] ((∈LN)≠ρRATING)/'HAP CHECK'
[19] 'ALSO, PLEASE TELL ME'
[20] 'HOW HARD YOU WANT THE COMPUTER TO PLAY'
[21] ''
[22] L4:'TYPE X UNDER A LINE BELOW.'
[23] 'EASIEST      EASY      MEDIUM      HARD      HARDEST'
[24] '  |      |      |      |      |      |      |      |'
[25] →L4×1~'X'∈X←□,' '
[26] DOD←DOD,X←[0.5+(X1'X')÷5
[27] ((∈LN)≠ρDOD)/'HAP CHECK'
[28] SETUP
[29] →L6×1~OPTION[∈LN]
[30] I←0
[31] L7:→L6×1X<I←I+1
[32] TONEUP
[33] →L7
[34] L6:'THANK YOU.'
[35] ''
[36] 'TYPE LOL WHEN YOU ARE READY TO PLAY.'
  ∇

```

```

    ∇START[□]∇
  ∇ START
[1]  G←0
[2]  CLOCK0←I20
[3]  ∈'T',LN,'←10'
[4]  ∈'N',LN,'←10'
[5]  ∈'M',LN,'←10'
[6]  ∈'E',LN,'←10'
[7]  ∈'TOOH',LN,'←10'
[8]  ∈'TOOE',LN,'←10'
  ∇

```

```

    ∇ASSIGN[□]∇
  ∇ ASSIGN
[1]  LEARN←LEARN,¯1+?2
[2]  OPTION←OPTION,¯1+?2
[3]  →0×1((∈LN)=ρLEARN)∧(∈LN)=ρOPTION
[4]  'HAP CHECK'
  ∇

```

```

    ▽RULES[ ]▽
  ▽ RULES
[1]  'LAST-ONE-LOSES IS A GAME OF TAKING AWAY BOXES.'
[2]  'THE GAME STARTS WITH SOME BOXES IN A ROW, LIKE THIS:'
[3]  ''
[4]  20ρ'□ '
[5]  ''
[6]  'TO START, YOU DECIDE WHETHER TO GO FIRST OR SECOND.'
[7]  'WHEN IT IS YOUR TURN, YOU MAY TAKE 1 OR 2 OR 3 BOXES.'
[8]  'THEN THE COMPUTER WILL GO AND TAKE 1 OR 2 OR 3 BOXES.'
[9]  ''
[10] 'YOU AND THE COMPUTER TAKE TURNS TAKING BOXES AWAY UNTIL'
[11] 'THERE IS ONE LEFT. THAT IS THE END OF THE GAME.'
[12] 'WHOEVER HAS TO TAKE THE LAST ONE LOSES.'
  ▽

    ▽SETUP[ ]▽
  ▽ SETUP
[1]  CUPS←Q4 3ρ13
  ▽

    ▽TUNEUP[ ]▽
  ▽ TUNEUP
[1]  TCUPS←CUPS←3 4ρ0 0 1 0 0 0 0 2 3 0 0 0
  ▽

    ▽LOL[ ]▽
  ▽ LOL;A
[1]  G←G+1
[2]  R←C+0
[3]  'TO START WITH THERE ARE';N←5+(ROLL DI)+ROLL DI
[4]  (2×N)ρ'□ '
[5]  L4:((G<5)/'DO YOU WANT TO GO '), 'FIRST OR SECOND?'
[6]  (G<3)/'TYPE F OR S'
[7]  →L4×1~v/'FS'cA←□
[8]  →L3×1v/'F'=A
[9]  L1:'MY MOVE.'
[10] 'I''LL TAKE';M←MMOVE
[11] 'NOW THERE ';ARE;N←N-M
[12] (2×N)ρ'□ '
[13] →WIN×1N=1
[14] →LOSE×1N=0
[15] L3:'YOUR MOVE.'
[16] P←PMOVE
[17] TALLY
[18] 'NOW THERE ';ARE;N←N-P
[19] (2×N)ρ'□ '
[20] →LOSE×1N=1
[21] →L1×1N>0
[22] WIN:'LAST ONE...YOU LOSE.'
[23] →L2
[24] LOSE:RESPONSE;', YOU WIN!'
[25] ''
[26] →L2×1~LEARN[εLN]
[27] ADAPT
[28] L2:''
[29] 'TYPE LOL TO PLAY AGAIN.'
[30] ''
[31] REMIND
  ▽

```

```

    ▽MMOVE[□]▽
    ▽ Z←MMOVE;CUP
[1]   Z←?3|N
[2]   →0×10=ρCUP←(CUP≠0)/CUP←,CUPS[;1+4|N]
[3]   C←1+4|N
[4]   Z←N|R←ROLL CUP
    ▽

```

```

    ▽ARE[□]▽
    ▽ Z←ARE
[1]   Z←,(2 3ρ'AREIS ')[1+N=1;]
    ▽

```

```

    ▽PMOVE[□]▽
    ▽ Z←PMOVE
[1]   T←I20
[2]   Z←,□
[3]   T←[0.5+0.001×(I20)-T
[4]   U←I23
[5]   →L1×11=ρZ
[6]   'PLEASE ENTER ONE AND ONLY ONE NUMBER'
[7]   ∈'E',LN,'←E',LN,',1+ρM',LN
[8]   →1
[9]   L1:→L2×1Z∈'123'
[10]  'PLEASE ENTER 1 2 OR 3'
[11]  ∈'E',LN,'←E',LN,',1+ρM',LN
[12]  →1
[13]  L2:→0×1N≥Z←∈Z
[14]  'NICE TRY, BUT THERE AREN'T THAT MANY'
[15]  'LEFT TO CHOOSE FROM. MOVE AGAIN PLEASE.'
[16]  ∈'E',LN,'←E',LN,',1+ρM',LN
[17]  →1
    ▽

```

```

    ▽ADAPT[□]▽
    ▽ ADAPT
[1]   →0×1(R=0)∨C=0
[2]   CUPS[R;C]←0
    ▽

```

```

    ▽RESPONSE[□]▽
    ▽ Z←RESPONSE
[1]   Z←RESPONSES[?(ρRESPONSES)[1];]
[2]   Z←(1+-(φZ=' ')10)+Z
    ▽

```

### RESPONSES

```

NICE PLAY OLD CHAP
*ε!.*.*?ε!.*?
RATFINK!!!
AAAAAAGGGGGHHHH..
OH NO....
AGAIN
GULP....
GOOD PLAY
NO COMMENT.....

```



```

    ∇TALLY[□]∇
  ∇ TALLY
[1]   €'T',LN,'←T',LN,',T'
[2]   €'N',LN,'←N',LN,',N'
[3]   €'M',LN,'←M',LN,',P'
  ∇

```

```

    ∇REMIND[□]∇
  ∇ REMIND
[1]   →L1×\OPTION[€LN]
[2]   ((G<5)/'DID THE COMPUTER PLAY '), 'TOO HARD OR TOO EASY?'
[3]   (G<8)/'TYPE TOO HARD -OR- TOO EASY -OR- OK'
[4]   →0
[5]   L1:((G<5)/'YOU MAY NOW TELL THE COMPUTER TO '), 'PLAY EASIER
[6]   (G<8)/'TYPE PLAY EASIER -OR- PLAY HARDER -OR- PLAY SAME
  ∇

```

```

    ∇ROLL[□]∇
  ∇ Z←ROLL X
[1]   Z←X[?ρX←,X]
  ∇

```

DI

1 2 3 4 5 6

```

    ∇PLAY[□]∇
  ∇ Z←PLAY X
[1]   Z←X
  ∇

```

```

    ∇HARDER[□]∇
  ∇ Z←HARDER
[1]   €'TOOE',LN,'←TOOE',LN,',G'
[2]   TONEUP
[3]   TONEUP
[4]   TONEUP
[5]   'O.K!'
[6]   Z←'TYPE LOL TO PLAY AGAIN.'
  ∇

```

```

    ∇EASIER[□]∇
  ∇ Z←EASIER
[1]   €'TOOH',LN,'←TOOH',LN,',G'
[2]   TONEDN
[3]   TONEDN
[4]   TONEDN
[5]   'O.K.'
[6]   Z←'TYPE LOL TO PLAY AGAIN.'
  ∇

```

```

    ∇SAME[□]∇
  ∇ Z←SAME
[1]   'O.K.'
[2]   Z←'TYPE LOL TO PLAY AGAIN.'
  ∇

```

```
    ∇TOO[□]∇
  ∇ Z←TOO X
[1] Z←X
  ∇
```

```
    ∇EASY[□]∇
  ∇ Z←EASY
[1] ε 'TOOE',LN,'←TOOE',LN,',G'
[2] 'O.K.'
[3] Z←'TYPE LOL TO PLAY AGAIN.'
  ∇
```

```
    ∇HARD[□]∇
  ∇ Z←HARD
[1] ε 'TOOH',LN,'←TOOH',LN,',G'
[2] 'O.K.'
[3] Z←'TYPE LOL TO PLAY AGAIN.'
  ∇
```

```
    ∇OK[□]∇
  ∇ Z←OK
[1] 'O.K.'
[2] Z←'TYPE LOL TO PLAY AGAIN.'
  ∇
```

```
    ∇TONEDN[□]∇
  ∇ TONEDN;V;C;R
[1] →0×10=+/V←+/[1]CUPS=0
[2] C←ROLL(V=[/V)/1ρV
[3] R←ROLL(0=,CUPS[;C])/13
[4] CUPS[R;C]←R
  ∇
```

```
    ∇TONEUP[□]∇
  ∇ TONEUP;C;R;L
[1] L←(CUPS≠0)∧TCUPS=0
[2] →0×10=ρC+(∇/[1]L)/14
[3] C←ROLL C
[4] R←ROLL(,L[;C])/13
[5] CUPS[R;C]←0
  ∇
```

CUPS

0	0	1	0
0	0	0	2
3	0	0	0

```

      ▽HELLO[□]▽
    ▽ HELLO;N
[1]  'WELCOME TO EVEN-WINS, A COMPUTER GAME.'
[2]  ''
[3]  FACE
[4]  ''
[5]  'I AM SOREZ, THE COMPUTER.'
[6]  'AND WHO ARE YOU?'
[7]  L1:N←□
[8]  →L2×10≠ρN
[9]  'TYPE YOUR NAME, PLEASE.'
[10] →L1
[11] L2:NAMES←NAMES,[1]N←10↑N,10ρ' '
[12] LN←LIT 1↑ρNAMES
[13] ASSIGN
[14] 'HELLO, ',((-1+N1' ')↑N),'!'
[15] 'WOULD YOU LIKE AN EXPLANATION OF THE RULES?'
[16] →L5×1'N'∈□,' '
[17] ''
[18] RULES
[19] ''
[20] L5:'HOW GOOD A PLAYER ARE YOU?'
[21] 'BEGINNER      FAIR      MEDIUM      GOOD      EXPERT'
[22] '  |      |      |      |      |      |      |'
[23] →L5×10=ρ,□
[24] L6:'AND HOW HARD DO YOU WANT THE COMPUTER TO PLAY?'
[25] ' EASIEST      EASY      MEDIUM      HARD      HARDEST'
[26] '  |      |      |      |      |      |      |'
[27] →L6×10=N←ρ,□
[28] →L7×1~OPTION[∈LN]
[29] ADJUST[0.5+N÷5]
[30] L7:'O.K.'
[31] 'TYPE EW WHEN YOU ARE READY TO PLAY.'
[32] START

```

▽

```

      ▽LIT[□]▽
    ▽ Z←LIT N
[1]  Z←'0123456789'[1+(LN÷10),10|N]

```

▽

FACE



|>◦<|

```

    ∇RULES[□]∇
  ∇ RULES
[1] 'EVEN-WINS IS A GAME OF TAKING AWAY BOXES.'
[2] 'THE GAME STARTS WITH SOME BOXES IN A ROW, LIKE THIS:'
[3] ''
[4] 20ρ'□ '
[5] ''
[6] 'YOU AND THE COMPUTER TAKE TURNS TAKING BOXES AWAY UNTIL'
[7] 'THERE IS NONE LEFT. THAT IS THE END OF THE GAME.'
[8] 'WHOEVER HAS AN EVEN NUMBER OF BOXES WINS.'
[9] ''
[10] 'WHEN IT IS YOUR TURN, YOU MAY TAKE 1 OR 2 BOXES.'
[11] 'THEN THE COMPUTER WILL GO AND TAKE 1 OR 2 BOXES.'
[12] ''
[13] 'AT THE START, YOU MAY DECIDE TO GO FIRST OR SECOND.'
  ∇

```

```

    ∇START[□]∇
  ∇ START
[1] ε'N',LN,'←10'
[2] ε'M',LN,'←10'
[3] ε'T',LN,'←10'
[4] ε'E',LN,'←10'
[5] G←0
[6] CLOCK←I20
  ∇

```

```

    ∇ASSIGN[□]∇
  ∇ ASSIGN
[1] LEARN←LEARN,2|?100
[2] OPTION←OPTION,2|?100
[3] ((εLN)≠ρLEARN) / 'HAP CHECK'
[4] ((εLN)≠ρOPTION) / 'HAP CHECK'
  ∇

```

DI1

3 3 3 5 5 7

DI2

2 2 4 4 6 6

EVM

1 1 1 1  
2 2 2 2

ODM

1 1 1 0  
2 2 2 2



```

    ∇EW[□]∇
  ∇ EW;M;Q
[1]  G←G+1
[2]  TOTM←TOTA←R←0
[3]  'TO START WITH THERE ARE';B←(ROLL DI1)+ROLL DI2
[4]  (2×B)ρ'□ '
[5]  L1:((G<6)/'DO YOU WANT TO GO '), 'FIRST OR SECOND?'
[6]  (G<4)/'TYPE F OR S'
[7]  →L1×1~∇/'FS'∈Q←□, ' '
[8]  →L2×1'F'∈Q
[9]  L3:'MY MOVE.'
[10] TOTM←TOTM+□←M←MMOVE
[11]  ''
[12] 'NOW THERE ';ARE;B←B-M
[13] (2×B)ρ'□ '
[14] →END×10=B
[15] 'SO FAR, IT'S..... YOU: ';TOTA;'      ME: ';TOTM
[16] L2:''
[17] 'YOUR MOVE.'
[18] TOTA←TOTA+A←AMOVE
[19] TALLY
[20] 'NOW THERE ';ARE;B←B-A
[21] (2×B)ρ'□ '
[22] →L3×1B>0
[23] END:'THAT'S THE END OF THE GAME.'
[24]  ''
[25] 'YOU HAVE';TOTA
[26] ' I HAVE';TOTM
[27]  ''
[28] →L4×10=2|TOTM
[29] RESPONSE;' YOU WIN!'
[30] →L5×1~LEARN[εLN]
[31] ADAPT
[32] →L5
[33] L4:'I WIN THIS TIME.'
[34] L5:''
[35] REMIND
[36]  ''
[37] 'TYPE EW TO PLAY AGAIN.'
  ∇

```

```

    ∇TALLY[□]∇
  ∇ TALLY
[1]  ε'N',LN,'←N',LN,' ,B'
[2]  ε'M',LN,'←M',LN,' ,A'
[3]  ε'T',LN,'←T',LN,' ,T'
  ∇

```

```

    ∇ADAPT[□]∇
  ∇ ADAPT
[1]  ''
[2]  →0×1R=0
[3]  →L1×1PARITY
[4]  →EVM[R;1+STATE]←0
[5]  L1:ODM[R;1+STATE]←0
  ∇

```

```

    ∇MMOVE[□]∇
    ∇ Z←MMOVE;R;C
    [1] →L1×10=2|TOTM
    [2] C←,ODM[;1+4|B]
    [3] →L2
    [4] L1:C←,EVM[;1+4|B]
    [5] L2:→L3×10=ρR←(0≠C)/C
    [6] Z←R←ROLL R
    [7] STATE←4|B
    [8] PARITY←2|TOTM
    [9] →0×1Z≤B
    [10] L3:Z←?B|2

```

∇

```

    ∇AMOVE[□]∇
    ∇ Z←AMOVE
    [1] T←I20
    [2] Z←,□
    [3] T←[0.5+0.001×(I20)-T
    [4] →L1×11=ρZ
    [5] L3:'PLEASE ENTER 1 OR 2'
    [6] ε'E',LN,'←E',LN,',1+ρM',LN
    [7] →1
    [8] L1:→L2×1Zε'12'
    [9] →L3
    [10] L2:→0×1B≥Z←εZ
    [11] 'NICE TRY, BUT THERE IS ONLY';B;' LEFT'
    [12] 'MOVE AGAIN, PLEASE.'
    [13] ε'E',LN,'←E',LN,',1+ρM',LN
    [14] →1

```

∇

```

    ∇RESPONSE[□]∇
    ∇ Z←RESPONSE
    [1] Z←RESPONSES[?(ρRESPONSES)[1];]
    [2] Z←(1+-(φZ=' ')10)+Z

```

∇

```

    RESPONSES
    NICE PLAY OLD CHAP
    *ε!?*o*?ε!?!?*
    RATFINK!!!
    AAAAAAGGGGGHHHHH..
    OH NO....
    AGAIN
    GULP....
    GOOD PLAY
    NO COMMENT.....

```

```

    ∇QUIT[□]∇
    ∇ QUIT
    [1] CON←CON,[0.5+0.001×(I20)-CLOCK
    [2] CPU←CPU,[0.5+0.001×I21
    [3] ((εLN)≠ρCON)/'HAP CHECK'
    [4] ((εLN)≠ρCPU)/'HAP CHECK'
    [5] 'THANK YOU FOR PLAYING EVEN-WINS.'
    [6] 'BYE FOR NOW.'

```

∇

```

    VADJUST[ ]V
  ▽ ADJUST X;D;O;E;R;C;L
[1]  D←X-(O←+/+/O=ODM)+E←+/+/O=EVM
[2]  →0×10=D
[3]  →UP×1D>0
[4]  →0×1(O=0)∧E=0
[5]  →L2×1O>E
[6]  C←ROLL(V/[1]O=EVM)/1-1ρEVM
[7]  R←ROLL(O=,EVM[;C])/11+ρEVM
[8]  EVM[R;C]←R
[9]  D←D+1
[10] →1
[11] L2:C←ROLL(V/[1]O=ODM)/1-1ρODM
[12] ODM[R;C]←R←ROLL(O=,ODM[;C])/11+ρODM
[13] D←D+1
[14] →1
[15] UP:→L3×1O≥E
[16] →0×1∧/∧/L←ODM=2 4ρ0 1 1 0 0 2 0 0
[17] C←ROLL(V/[1]~L)/1-1ρODM
[18] R←ROLL(,~L[;C])/11+ρODM
[19] ODM[R;C]←0
[20] D←D-1
[21] →1
[22] L3:→0×1∧/∧/L←EVM=2 4ρ1 0 0 0 0 0 2 2
[23] C←ROLL(V/[1]~L)/1-1ρEVM
[24] R←ROLL(,~L[;C])/11+ρEVM
[25] EVM[R;C]←0
[26] D←D-1
[27] →1

```

▽

ADJUST 10

EVM

1	0	0	0
0	0	2	2

ODM

0	1	1	0
0	2	0	0

```

  ▽REMIND[ ]V
  ▽ REMIND;Q
[1]  →L1×1OPTION[εLN]
[2]  (G<6)/'HOW DID THE COMPUTER PLAY?'
[3]  'EASIEST      EASY      MEDIUM      HARD      HARDEST'
[4]  ' | | | | | | | | | | '
[5]  →2×10=ρQ←,□
[6]  →0,ρ□←'O.K.'
[7]  L1:(G<6)/'HOW DO YOU WANT THE COMPUTER TO PLAY?'
[8]  ' EASIEST      EASY      MEDIUM      HARD      HARDEST'
[9]  ' | | | | | | | | | | '
[10] →0×10=ρQ←,□
[11] →0×1∧/'EW'=2+Q,2ρ' '
[12] →L3×10≠ρ(Q≠' ')/Q
[13] 'PLEASE TYPE X UNDER A LINE BELOW.'
[14] →L1
[15] L3:ADJUST[0.5+(ρQ)÷5
[16] 'O.K.!'

```

▽

APPENDIX C

DATA SUMMARIES

ALAST-ONE-LOSES

NAMES

TONY TAYLOR  
FRED PARKS  
SHAI KOWAL  
GREG MULVANEY  
MATTHEW SIMON  
LENORA SIMANSKI  
GREG STEVENSON  
CHRIS WITORT  
DANNY SAMMARTANO  
JOY DEAN  
ROBERTA SZALA  
RICK ZUBE  
ERIC MANKIN  
STUART GREY  
AMY HARPER  
JOHN JERNIGAN  
JOANNE KUZMESKI  
JULIE GURSKI  
TOM LENTILHON  
MIKE FORGET  
JOCELYN FORD  
SHANNON WHITTEMORE  
DANIEL SILVER  
TOM CORCORAN  
DAVE EVE  
DAVID YANDO  
PHILIP JENKS  
BRUCE PATTERSON  
MARK DURANT  
DON KUZMESKI  
PAUL PERCHAK  
JAMES BURGESS  
DENNIS STILES  
JEFF DAY  
NANCY WASKIEWICZ  
ALANE PAUL  
ERIC ZUBE  
BILLY IVEY  
CAROL STEIN  
JEREMY LYON  
JOHN WARRINER  
STEVEN PEENE



AEVEN-WINS

NAMES

CHRIS  
STEVEN  
DAVID YA  
PHILIP JEN  
ERIC MANKI  
GREG  
MIKE FORGE  
DENNIS STI  
JOHN WARRI  
RUSTY ROWE  
BRUCE  
ALANE  
JOHN  
SHARON  
NANCY  
JEFF  
ROBBRTA  
STUART GRE  
BILLY IVEY  
DA VID  
LENORA  
RICK  
TOM CORCOR  
BETSY GATE  
MARK  
DON KUZMES  
PAUL PERCH  
SHAI KOWAL  
AMY  
JOY DEAN  
JULIA GURS  
PHIL  
JOHN HUBER  
JOANNE KUZ  
JOHN WYSOC  
JEFFREY GR  
MATT SIMON  
DAVE LITTE  
CAROL  
TOM LENTIL  
JEREMY LYO  
STEVEN

SUMMARY OF VARIABLES

ALAST-ONE-LOSES

VARIABLES←V11,V12,V21,V31,V41,V42,V5,V6

Q11 42ρ(142),LEARN,OPTION,VARIABLES

1	1	1	53.8	0.12	18	8.3	15.2	0.14	7	5
2	0	0	81.3	0.56	10	0	14	0.24	10	6
3	1	1	91.1	0.94	31	6.8	13.4	0.04	14	4
4	1	0	93.8	2.72	45	1.7	12.1	0.03	14	14
5	1	1	100	1	18	6	11.5	0.29	14	14
6	1	1	40	-0.1	18	2.8	16.1	-0.31	8	5
7	0	0	78.6	0.45	8	0	19.3	-0.06	6	6
8	1	1	85.7	1	6	0	21.4	0.83	12	12
9	1	0	89.5	0.68	9	4	14.9	0.17	5	9
10	1	1	81.3	0.8	20	0	18	-0.26	12	5
11	0	1	84.2	0.59	16	11.8	12.2	0.12	10	6
12	0	0	94.9	0.9	24	0	11.5	0.07	14	14
13	0	1	100	1	26	1.9	10.2	0.12	14	14
14	1	1	83.3	0.75	5	0	17.8	-1.64	8	4
15	0	1	52.2	0.1	22	2.1	9	0.02	11	6
16	1	1	20	-0.46	5	90.9	19.8	3.3	5	8
17	0	1	76.7	0.62	22	1.6	14	-0.1	14	4
18	1	1	44.4	-0.17	26	0	13.6	0.02	6	5
19	1	1	46.3	-0.1	41	10.7	15.2	0.05	8	9
20	0	1	90	0.84	25	9.5	13.5	-0.04	14	4
21	0	1	85.4	0.76	22	1.7	15.6	-0.17	14	5
22	1	0	84.1	2.72	71	1.4	13.3	0	14	8
23	1	0	97.7	2.72	46	2.1	11.7	-0.06	14	6
24	1	0	59.5	0.16	23	47.5	12.5	-0.15	13	8
25	1	0	56.1	0.2	30	13	13.7	-0.05	8	6
26	1	0	47.2	-0.08	23	6.7	15.4	0.2	3	5
27	0	0	66.1	0.33	24	1.2	15.2	-0.04	7	6
28	1	0	54.5	0.1	30	6.3	18.1	0.03	5	6
29	1	1	65	0.15	15	5	16.9	-0.23	6	5
30	0	0	66.7	0.41	44	1.8	12.8	-0.03	7	4
31	0	0	42.6	-0.2	23	1.8	11.4	-0.05	3	4
32	0	0	55	0.05	20	0	12.3	0.08	7	8
33	1	0	59.1	0.15	25	0	15.3	1.16	6	6
34	1	0	91.7	2.72	35	0	14.5	-0.02	11	5
35	1	1	87.5	0.81	34	0.1	15.6	-0.23	9	6
36	0	0	61.7	0.17	40	0	14.8	-0.23	5	7
37	0	1	87.5	0.66	18	0	20	-0.74	14	14
38	1	0	66.7	0.7	11	0	19.8	2.69	14	14
39	1	0	94.1	0.88	14	0	19.5	-1.48	14	14
40	0	0	100	1	35	0.1	40	0	14	9
41	0	1	100	1	11	0.3	40	0	7	5
42	1	1	95.2	0.9	42	0	40	0	14	14

(+/LEARN^OPTION),+/(~LEARN)^OPTION

13 8

(+/LEARN^~OPTION),+/(~LEARN)^~OPTION

12 9

SUMMARY OF VARIABLES

AEVEN-WINS

VARIABLES←X11,X12,X21,X22,X23,X24,X31,X41,X42,X51,X61

Q14 41p(141),LEARN,OPTION,VARIABLES

1	0	1	50	0.1	9	1020	4	1.64	6.25	16.7	-0.06	6	4
2	1	1	91.11	0.85	26	3739	9	0.53	1.19	20	0	8	9
3	1	1	72.22	0.55	9	1740	6	1.17	7.41	20.3	-0.38	4	7
4	1	0	62.5	0	4	506	4	3.4	0	17.2	0.91	6	2
5	1	0	94.74	0.95	9	840	3	1.77	0	14.9	0.43	12	6
6	1	0	94.29	0.9	17	2126	13	0.76	3.39	16.2	0.14	7	3
7	1	1	78.57	0.75	8	955	19	1.56	15.79	14.9	-0.5	6	5
8	0	1	82.35	0.7	12	1558	28	1.21	5.56	18.8	0.4	6	5
9	1	1	53.85	0.1	11	1832	37	1.08	13.16	19.7	0.14	5	8
10	0	0	91.67	1	8	807	28	1.8	0	14.5	-0.57	12	4
11	0	1	64.52	0.45	27	3463	18	0.64	4.69	22	0.05	9	10
12	0	1	87.5	0.75	4	600	6	3.62	0	21.7	2.78	-1	-1
13	1	0	87.5	0.7	12	2222	12	1.26	11.11	27.9	8.06	6	5
14	1	0	93.33	0.9	11	1225	10	1.09	17.65	13.4	0.12	-1	-1
15	0	1	89.13	0.8	21	2839	23	0.58	5.88	16.6	0.24	12	9
16	0	1	78.95	0.65	24	2800	23	0.59	0	16.5	-0.01	7	4
17	0	0	83.33	0.8	6	786	29	1.39	29.41	10.9	-0.5	6	6
18	1	1	70.97	0.4	17	2381	37	0.66	4.17	15.8	-0.09	7	7
19	0	1	63.16	0.3	14	1934	32	1.03	2.38	20	0.46	4	10
20	0	1	60.71	0.3	15	2095	16	0.8	33.33	16.7	-0.02	6	6
21	1	1	62.5	0.25	11	1519	25	1.19	6.67	18.1	-0.97	5	4
22	0	1	83.33	0.8	16	1700	13	0.83	5.66	14.1	0.17	8	7
23	1	0	62.5	0.25	6	1852	3	0.81	88.89	15	-0.24	0	3
24	1	1	54.17	0	22	2506	17	0.78	0	19.6	0.02	4	4
25	0	0	100	1	25	3227	24	0.5	5.06	16	0.08	8	7
26	0	0	78.26	0.7	37	3452	53	0.43	5.15	14.9	-0.1	3	4
27	1	1	46.15	-0.2	12	1165	12	1.29	6.45	15	0.27	4	7
28	1	1	78.95	0.65	12	1349	12	1.15	6.06	15.5	0.31	12	12
29	1	0	85.71	0.75	30	3494	37	0.52	1.15	18	-0.05	10	6
30	0	1	84.21	0.8	13	1802	14	1.11	2.38	20	-0.12	8	7
31	0	0	76.47	0.6	35	3039	21	0.51	0	15.4	0.01	10	6
32	0	0	93.67	2.72	39	4378	11	0.32	0	14.2	0.1	12	7
33	1	1	71.43	0.5	12	1816	19	1.35	0	24.5	-0.27	8	6
34	1	0	83.33	0.6	14	1650	27	0.96	2.38	15.8	-0.12	10	5
35	0	0	60	0.3	18	2015	10	0.69	11.54	13.9	-0.24	4	6
36	1	1	82.93	0.55	27	3267	28	0.54	5.19	17.7	0.03	10	5
37	1	1	80	0.5	10	1403	35	1.25	3.03	17.6	0.25	12	5
38	0	1	92.31	0.9	12	1621	44	1.19	11.11	19.3	0.17	6	4
39	1	0	96.05	2.72	40	4743	23	0.38	0	17.9	0.05	12	7
40	0	1	68.42	0.4	13	2282	4	0.85	30.77	19.5	0.68	5	7
41	0	1	90.91	0.9	11	1944	13	0.67	17.24	13.1	0.21	8	6

(+/LEARN^OPTION),+/(~LEARN)^OPTION

12 13

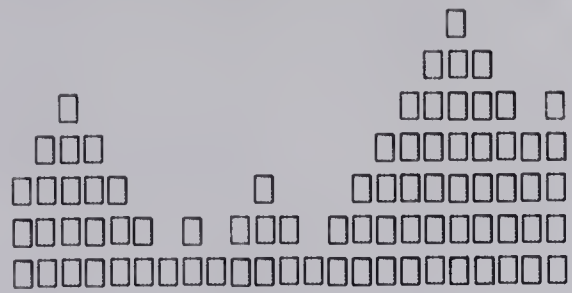
(+/LEARN^~OPTION),+/(~LEARN)^~OPTION

9 7

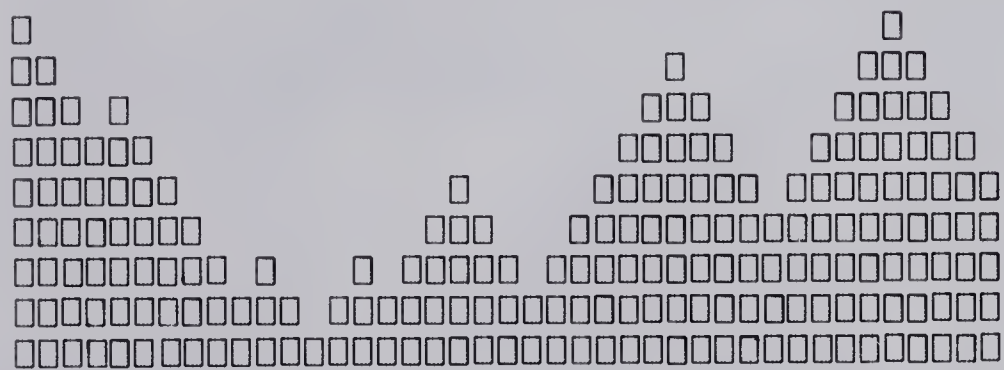
LEARNING CURVES

ALAST-ONE-LOSES

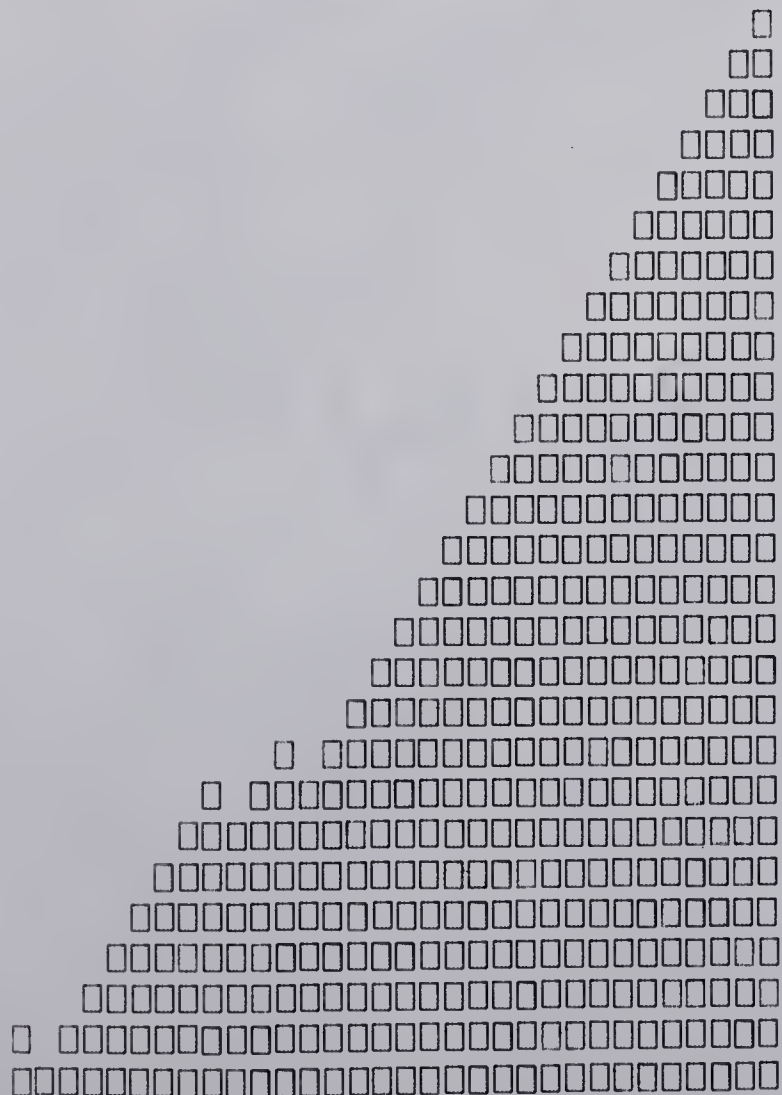
LCURV 15



LCURV 19



LCURV 35





SUMMARY OF STATISTICS

ρ LAST-ONE-LOSES

)LOAD ANOVA1

SAVED 06/29/71

STATS

CELL 1

□:

(LEARN^OPTION)/V11

CELL 2

□:

((~LEARN)^OPTION)/V11

CELL 3

□:

(LEARN^~OPTION)/V11

CELL 4

□:

((~LEARN)^~OPTION)/V11

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
68.74	81.3	80	25.37	84.5	86.45	47.8	15.24
74.5	75.4	50.5	18.86	71.88	66.7	57.4	18.58

STATS

CELL 1

□:

ONLYNOE (LEARN^OPTION)/V12

CELL 2

□:

ONLYNOE ((~LEARN)  
^OPTION)/V12

CELL 3

□:

ONLYNOE (LEARN^~OPTION)/V12

CELL 4

□:

ONLYNOE ((~LEARN)^~OPTION)/V12

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
0.43	0.75	1.46	0.53	0.7	0.71	0.9	0.29
0.35	0.18	0.96	0.35	0.41	0.41	1.2	0.38

STATS

CELL 1

□: (LEARN^OPTION)/V21

CELL 2

□: ((~LEARN)^OPTION)/V21

CELL 3

□: (LEARN^~OPTION)/V21

CELL 4

□: ((~LEARN)^~OPTION)/V21

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
21.46	18	37	12.69	20.25	22	15	4.98
30.17	27.5	62	17.5	25.33	24	36	12.4

STATS

CELL 1

□: (LEARN^OPTION)/V31

CELL 2

□: ((~LEARN)^OPTION)/V31

CELL 3

□: (LEARN^~OPTION)/V31

CELL 4

□: ((~LEARN)^~OPTION)/V31

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
10.05	2.8	90.9	24.58	3.61	1.8	11.8	4.45
6.89	1.9	47.5	13.37	0.54	0	1.8	0.81

STATS

CELL 1

□:  $\bar{1} + (LEARN^OPTION)/V41$

CELL 2

□:  $\bar{1} + ((~LEARN)^OPTION)/V41$

CELL 3

□: (LEARN^~OPTION)/V41

CELL 4

□:  $\bar{1} + ((~LEARN)^~OPTION)/V41$

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
16.21	15.85	9.9	2.79	13.5	13.5	11	3.65
15.07	14.7	8.1	2.75	13.91	13.4	7.9	2.6

STATS

CELL 1

□:

$$\bar{1} \uparrow (\text{LEARN} \wedge \text{OPTION}) / V42$$

CELL 2

□:

$$\bar{1} \downarrow ((\sim \text{LEARN}) \wedge \text{OPTION}) / V42$$

CELL 3

□:

$$(\text{LEARN} \wedge \sim \text{OPTION}) / V42$$

CELL 4

□:

$$\bar{1} \downarrow ((\sim \text{LEARN}) \wedge \sim \text{OPTION}) / V42$$

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
0	0	0	0	0.19	0.04	0.86	0.38
0.21	0.02	4.17	0.97	0	0.03	0.47	0.14

STATS

CELL 1

□:

$$1 \downarrow (\text{LEARN} \wedge \text{OPTION}) / V5$$

CELL 2

□:

$$\bar{1} \downarrow ((\sim \text{LEARN}) \wedge \text{OPTION}) / V5$$

CELL 3

□:

$$(\text{LEARN} \wedge \sim \text{OPTION}) / V5$$

CELL 4

□:

$$((\sim \text{LEARN}) \wedge \sim \text{OPTION}) / V5$$

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
9.67	8.5	9	3.37	13	14	4	1.73
10.08	12	11	4.36	8.11	7	11	3.82

STATS

CELL 1

□:

$$1 \downarrow (\text{LEARN} \wedge \text{OPTION}) / V6$$

CELL 2

□:

$$\bar{1} \downarrow ((\sim \text{LEARN}) \wedge \text{OPTION}) / V6$$

CELL 3

□:

$$(\text{LEARN} \wedge \sim \text{OPTION}) / V6$$

CELL 4

□:

$$((\sim \text{LEARN}) \wedge \sim \text{OPTION}) / V6$$

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
7.58	5.5	10	3.8	7.57	6	10	4.47
8.42	7	9	3.58	7.11	6	10	3.06

)LOAD ANOVA2  
SAVED 06/29/71

STATS

CELL 1

□:

(LEARN^OPTION)/X11

CELL 2

□:

((~LEARN)^OPTION)/X11

CELL 3

□:

(LEARN^~OPTION)/X11

CELL 4

□:

((~LEARN)^~OPTION)/X11

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
70.24	71.83	44.96	13.52	76.58	82.35	42.31	13.61
84.44	87.5	33.55	13.19	83.34	83.33	40	13.36

STATS

CELL 1

□:

ONLYNOE (LEARN^OPTION)/X12

CELL 2

□:

ONLYNOE ((~LEARN)^OPTION)/X12

CELL 3

□:

ONLYNOE (LEARN^~OPTION)/X12

CELL 4

□:

ONLYNOE ((~  
LEARN)^~OPTION)/X12

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
0.41	0.5	1.05	0.31	0.6	0.7	0.8	0.26
0.63	0.73	0.95	0.34	0.73	0.75	0.7	0.27



STATS

CELL 1

□:

(LEARN^OPTION)/X21

CELL 2

□:

((~LEARN)^OPTION)/X21

CELL 3

□:

(LEARN^~OPTION)/X21

CELL 4

□:

((~LEARN)^~OPTION)/X21

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
14.75	12	19	6.65	14.69	13	23	6.2
15.89	12	36	11.78	24	25	33	13.74

STATS

CELL 1

□:

(LEARN^OPTION)/X22

CELL 2

□:

((~LEARN)^OPTION)/X22

CELL 3

□:

(LEARN^~OPTION)/X22

CELL 4

□:

((~LEARN)^~OPTION)/X22

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
1972.67	1778	2784	850.25	1973.69	1934	2863	761.57
2073.11	1852	4237	1327.39	2529.14	3039	3592	1371.47

STATS

CELL 1

□:

(LEARN^OPTION)/X23

CELL 2

□:

((~LEARN)^OPTION)/X23

CELL 3

□:

(LEARN^~OPTION)/X23

CELL 4

□:

((~LEARN)^~OPTION)/X23

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
21.33	19	31	10.98	18.31	16	40	11.64
14.67	12	34	11.93	25.14	24	43	14.42

STATS

CELL 1

□:

(LEARN^OPTION)/X24

CELL 2

□:

((~LEARN)^OPTION)/X24

CELL 3

□:

(LEARN^~OPTION)/X24

CELL 4

□:

((~LEARN)^~OPTION)/X24

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
1.05	1.16	1.03	0.34	1.14	0.85	3.04	0.81
1.22	0.96	3.02	0.92	0.81	0.51	1.48	0.56

STATS

CELL 1

□:

(LEARN^OPTION)/X31

CELL 2

□:

((~LEARN)^OPTION)/X31

CELL 3

□:

(LEARN^~OPTION)/X31

CELL 4

□:

((~LEARN)^~OPTION)/X31

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
5.76	5.63	15.79	4.83	9.63	5.66	33.33	10.96
13.84	2.38	88.89	28.79	7.31	5.06	29.41	10.62

STATS

CELL 1

□:

(LEARN^OPTION)/X41

CELL 2

□:

((~LEARN)^OPTION)/X41

CELL 3

□:

(LEARN^~OPTION)/X41

CELL 4

□:

((~LEARN  
)^~OPTION)/X41

MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
18.22	17.9	9.6	2.8	18.08	18.8	8.9	2.72
17.37	16.2	14.5	4.23	14.26	14.5	5.1	1.64

STATS

CELL 1

□: (LEARN^OPTION)/X42

CELL 2

□: ((~LEARN)^OPTION)/X42

CELL 3

□: (LEARN^~OPTION)/X42

CELL 4

□: ((~LEARN)^~OPTION)/X42

	MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
	0.1	0.01	1.28	0.38	0.38	0.17	2.9	0.76
	1.03	0.12	8.3	2.66	0.17	0.1	0.67	0.27

STATS

CELL 1

□: ONLYPOS (LEARN^OPTION)/X51

CELL 2

□: ONLYPOS ((~LEARN)^OPTION)/X51

CELL 3

□: ONLYPOS (LEARN^~OPTION)/X51

CELL 4

□:

ONLYPOS ((~LEARN)^~OPTION)/X51

	MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
	7.08	6.5	8	2.97	7.08	6.5	8	2.11
	7.88	8.5	12	4.02	7.86	8	9	3.67

STATS

CELL 1

□: ONLYPOS (LEARN^OPTION)/X61

CELL 2

□: ONLYPOS ((~LEARN)^OPTION)/X61

CELL 3

□: ONLYPOS (LEARN^~OPTION)/X61

CELL 4

□: ONLYPOS ((~LEARN)^~OPTION)/X61

	MEAN	MEDIAN	RANGE	S.D.	MEAN	MEDIAN	RANGE	S.D.
	6.58	6.5	8	2.31	6.58	6.5	6	2.19
	4.63	5	5	1.77	5.71	6	3	1.25

*APPENDIX D*  
*STATISTICAL TOOLS*



▽ANOVA2X2[ ]▽

▽ ANOVA2X2

```

[ 1] 'ENTER RAW SCORES FOR CELL 1'
[ 2] R1C1←[ ]
[ 3] 'ENTER RAW SCORES FOR CELL 2'
[ 4] R1C2←[ ]
[ 5] 'ENTER RAW SCORES FOR CELL 3'
[ 6] R2C1←[ ]
[ 7] 'ENTER RAW SCORES FOR CELL 4'
[ 8] R2C2←[ ]
[ 9] R1←R1C1,R1C2
[10] R2←R2C1,R2C2
[11] C1←R1C1,R2C1
[12] C2←R1C2,R2C2
[13] ALL←R1C1,R1C2,R2C1,R2C2
[14] SST←SMSQ ALL
[15] SSC←(((+/C1)*2)÷ρC1)+(((+/C2)*2)÷ρC2)-(((+/ALL)*2)÷ρALL
[16] SSR←(((+/R1)*2)÷ρR1)+(((+/R2)*2)÷ρR2)-(((+/ALL)*2)÷ρALL
[17] SSWC←(+/ALL*2)-(((+/R1C1)*2)÷ρR1C1)+(((+/R1C2)*2)÷ρR1C2)
[18] SSWC←SSWC+(((+/R2C1)*2)÷ρR2C1)+(((+/R2C2)*2)÷ρR2C2
[19] SSRXC←(((+/R1C1)*2)÷ρR1C1)+(((+/R1C2)*2)÷ρR1C2)
[20] SSRXC←SSRXC+(((+/R2C1)*2)÷ρR2C1)+(((+/R2C2)*2)÷ρR2C2
[21] SSRXC←SSRXC-SSC+SSR+(((+/ALL)*2)÷ρALL
[22] ((2 RND SSRXC)≠2 RND SST-SSC+SSR+SSWC) / 'HAP CHECK'
[23] DFC←DFR←1
[24] DFWC←((ρR1C1)-1)+((ρR1C2)-1)+((ρR2C1)-1)+((ρR2C2)-1)
[25] DFRXC←DFC×DFR
[26] DFT←(ρALL)-1
[27] VART←2 RND SST÷DFT
[28] VARC←2 RND SSC÷DFC
[29] VARR←2 RND SSR÷DFR
[30] VARRXC←2 RND SSRXC÷DFRXC
[31] VARWC←2 RND SSWC÷DFWC
[32] F1←2 RND VARC÷VARWC
[33] U←F1≥D05[DFWC;DFC]
[34] 'COLUMN VARIANCE ',((~U) / 'NOT '), 'SIGNIFICANT AT .05 LEVEL'
[35] F2←2 RND VARR÷VARWC
[36] U←F2≥D05[DFWC;DFR]
[37] 'ROW VARIANCE ',((~U) / 'NOT '), 'SIGNIFICANT AT .05 LEVEL'
[38] F3←2 RND VARRXC÷VARWC
[39] U←F3≥D05[DFWC;DFRXC]
[40] 'INTERACTION EFFECT ',((~U) / 'NOT '), 'SIGNIFICANT AT .05 LEVEL'
[41] ''
[42] 'MEANS:'
[43] ''
[44] U←(MEAN R1C1),(MEAN R1C2),(MEAN R1)
[45] U←U,(MEAN R2C1),(MEAN R2C2),MEAN R2
[46] [ ]←U←3 3ρ2 RND U,(MEAN C1),(MEAN C2),MEAN ALL
[47] ''
[48] ''
[49] 'SOURCE          D.F.          MEAN SQ          F'
[50] 35ρ '- '
[51] 'COL VAR.        ';DFR; '          ';VARC; '          ';F1
[52] 'ROW VAR.        ';DFC; '          ';VARR; '          ';F2
[53] 'INTERACT.      ';DFRXC; '          ';VARRXC; '          ';F3
[54] 'ERROR          ';DFWC; '          ';VARWC

```

▽

```

    ∇MEAN[[]]∇
  ∇ Z←MEAN X
[ 1] Z←(+/X)÷ρ,X
    ∇

    ∇RND[[]]∇
  ∇ Z←P RND N
[ 1] Z←(10*-P)×[0.5+N×10*P
    ∇

    ∇SUMSQ[[]]∇
  ∇ Z←SUMSQ X
[ 1] Z←+/(X-MEAN X)*2
    ∇

    ∇SMSQ[[]]∇
  ∇ Z←SMSQ X
[ 1] Z←(+/X*2)-((+/X)*2)÷ρX
    ∇

    ∇SD[[]]∇
  ∇ Z←SD X
[ 1] Z←(VAR X)*.5
    ∇

    ∇VAR[[]]∇
  ∇ Z←VAR X
[ 1] Z←(SUMSQ X)÷-1+ρX
    ∇

    ∇STATS[[]]∇
  ∇ STATS;U
[ 1] 'CELL 1'
[ 2] CELL1←[]
[ 3] 'CELL 2'
[ 4] CELL2←[]
[ 5] 'CELL 3'
[ 6] CELL3←[]
[ 7] 'CELL 4'
[ 8] CELL4←[]
[ 9] ''
[ 10] '      MEAN MEDIAN RANGE      S.D.  MEAN MEDIAN RANGE      S.D.'
[ 11] U←(MEAN CELL1),(MEDIAN CELL1),(RANGE CELL1),SD CELL1
[ 12] U←U,(MEAN CELL2),(MEDIAN CELL2),(RANGE CELL2),SD CELL2
[ 13] U←U,(MEAN CELL3),(MEDIAN CELL3),(RANGE CELL3),SD CELL3
[ 14] U←U,(MEAN CELL4),(MEDIAN CELL4),(RANGE CELL4),SD CELL4
[ 15] []←2 8ρ2 RND U
    ∇

```

APPENDIX E  
ANOVA PRINT-OUTS

SAMPLE:

```

ANOVA2X2
ENTER RAW SCORES FOR CELL 1
□:
    (LEARN^OPTION)/V11
ENTER RAW SCORES FOR CELL 2
□:
    ((~LEARN)^OPTION)/V11
ENTER RAW SCORES FOR CELL 3
□:
    (LEARN^~OPTION)/V11
ENTER RAW SCORES FOR CELL 4
□:
    ((~LEARN)^~OPTION)/V11

```

COLUMN VARIANCE NOT SIGNIFICANT AT .05 LEVEL  
ROW VARIANCE NOT SIGNIFICANT AT .05 LEVEL  
INTERACTION EFFECT NOT SIGNIFICANT AT .05 LEVEL

MEANS:

68.74	84.5	74.74
74.5	71.88	73.38
71.5	77.82	74.06

SOURCE	D.F.	MEAN SQ	F
COL VAR.	1	403.37	0.96
ROW VAR.	1	19.61	0.05
INTERACT.	1	862.30	2.05
ERROR	38	421.62	

**NOTE:** ALL ANOVA RESULTS ARE GIVEN IN CHAPTER IV  
SEE TABLES IV - 1 THROUGH 6

APPENDIX F

STRATEGY UNDERSTANDING TESTS



LAST-ONE-LOSES

RULES

LAST-ONE-LOSES IS A GAME OF TAKING AWAY BOXES.  
THE GAME STARTS WITH SOME BOXES IN A ROW, LIKE THIS:  
□ □ □ □ □ □ □ □ □ □  
WHEN IT IS YOUR MOVE, YOU MAY TAKE 1 OR 2 OR 3 BOXES.  
YOU AND THE COMPUTER TAKE TURNS TAKING BOXES AWAY  
UNTIL THERE IS NONE LEFT. THAT IS THE END OF THE GAME.  
WHOEVER TOOK THE LAST ONE LOSES.

DIRECTIONS

1. LOOK AT THE NUMBER OF BOXES ON THE LEFT
2. CHECK WHETHER YOU WOULD GO FIRST OR SECOND
3. WRITE THE NUMBER YOU WOULD TAKE (IF YOU WENT FIRST)

	I WANT TO GO:		I'LL TAKE:
	FIRST	SECOND	
WHEN THERE ARE 2 □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 3 □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 4 □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 5 □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 6 □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 7 □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 8 □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 9 □ □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 10 □ □ □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 11 □ □ □ □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 12 □ □ □ □ □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 13 □ □ □ □ □ □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 14 □ □ □ □ □ □ □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 15 □ □ □ □ □ □ □ □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

LAST-ONE-LOSES

LOOK  
↙

RULES

LAST-ONE-LOSES IS A GAME OF TAKING AWAY BOXES.  
THE GAME STARTS WITH SOME BOXES IN A ROW, LIKE THIS:  
□ □ □ □ □ □ □ □ □ □  
WHEN IT IS YOUR TURN, YOU MAY TAKE 1 OR 2 OR 3 OR 4 BOXES.  
YOU AND THE COMPUTER TAKE TURNS TAKING BOXES AWAY UNTIL  
THERE IS NONE LEFT. THAT IS THE END OF THE GAME.  
WHOEVER TOOK THE LAST-ONE-LOSES!

DIRECTIONS

1. LOOK AT THE NUMBER OF BOXES ON THE LEFT
2. CHECK WHETHER YOU WOULD GO FIRST OR SECOND
3. WRITE THE NUMBER YOU WOULD TAKE (IF YOU WENT FIRST)

	I WANT TO GO:		I'LL TAKE:
	FIRST	SECOND	
WHEN THERE ARE 2 □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 3 □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 4 □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 5 □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 6 □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 7 □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 8 □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 9 □ □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 10 □ □ □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 11 □ □ □ □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 12 □ □ □ □ □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 13 □ □ □ □ □ □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 14 □ □ □ □ □ □ □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WHEN THERE ARE 15 □ □ □ □ □ □ □ □ □ □ □ □ □ □ □	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

# EVEN-WINS

## RULES

EVEN-WINS IS A GAME OF TAKING AWAY BOXES.  
THE GAME STARTS WITH SOME BOXES IN A ROW, LIKE THIS:  
□ □ □ □ □ □ □ □  
YOU AND THE COMPUTER TAKE TURNS TAKING BOXES AWAY UNTIL  
THERE IS NONE LEFT. THAT IS THE END OF THE GAME.  
WHOEVER HAS AN EVEN NUMBER OF BOXES WINS!

WHEN IT IS YOUR TURN, YOU MAY TAKE 1 OR 2 BOXES.  
THEN THE COMPUTER WILL GO AND TAKE 1 OR 2 BOXES.

## DIRECTIONS

1. LOOK AT THE NUMBER OF BOXES ON THE LEFT
2. CHECK WHETHER YOU WOULD GO FIRST OR SECOND
3. WRITE THE NUMBER YOU WOULD TAKE (IF YOU WENT FIRST)

I WANT TO GO:      I'LL TAKE:

WHEN THERE ARE 3

□ □ □

FIRST      SECOND

WHEN THERE ARE 5

□ □ □ □ □

FIRST      SECOND

WHEN THERE ARE 7

□ □ □ □ □ □ □

FIRST      SECOND

WHEN THERE ARE 9

□ □ □ □ □ □ □ □ □

FIRST      SECOND

WHEN THERE ARE 11

□ □ □ □ □ □ □ □ □ □ □

FIRST      SECOND

WHEN THERE ARE 13

□ □ □ □ □ □ □ □ □ □ □ □ □

FIRST      SECOND



## EVEN-WINS

### RULES

EVEN-WINS IS A GAME OF TAKING AWAY BOXES.  
 THE GAME STARTS WITH SOME BOXES IN A ROW, LIKE THIS:  
 □ □ □ □ □ □ □ □  
 YOU AND THE COMPUTER TAKE TURNS TAKING BOXES AWAY UNTIL  
 THERE IS NONE LEFT. THAT IS THE END OF THE GAME.  
 WHOEVER HAS AN EVEN NUMBER OF BOXES WINS!

WHEN IT IS YOUR TURN, YOU MAY TAKE 1 OR 2 OR 3 BOXES.  
 THEN THE COMPUTER WILL GO AND TAKE 1 OR 2 OR 3 BOXES.

LOOK  
 ←

### DIRECTIONS

1. LOOK AT THE NUMBER OF BOXES ON THE LEFT
2. CHECK WHETHER YOU WOULD GO FIRST OR SECOND
3. WRITE THE NUMBER YOU WOULD TAKE (IF YOU WENT FIRST)

WHEN THERE ARE 3

□ □ □

I WANT TO GO:      I'LL TAKE:  
 FIRST      SECOND     

WHEN THERE ARE 5

□ □ □ □ □

FIRST      SECOND     

WHEN THERE ARE 7

□ □ □ □ □ □ □

FIRST      SECOND     

WHEN THERE ARE 9

□ □ □ □ □ □ □ □ □

FIRST      SECOND     

WHEN THERE ARE 11

□ □ □ □ □ □ □ □ □ □ □

FIRST      SECOND     

WHEN THERE ARE 13

□ □ □ □ □ □ □ □ □ □ □ □ □

FIRST      SECOND



APPENDIX G

GLOSSARY OF TERMS

- algorithm..... a set of rules or procedures for solving a problem
- Artificial Intelligence..... (abbreviated AI) behavior called 'intelligent' when exhibited by human beings
- computer..... a symbol-processing electronic device capable of performing well-defined instructions for the manipulation and transformation of information
- Computer-Assisted Instruction.....(abbreviated CAI) any of a wide range of techniques that rely on a computer to assist in the presentation of pre-specified learning materials to a number of students individually
- computer program..... a set of instructions written in a programming language executable by a computer system utilizing previously stored data and/or user responses to generate output
- computer system..... the entire computer operating system, including central processing unit, tape and disk storage units, drum and core memory, input-output terminals, communications equipment, machine translator, and computer programs
- forced move sequence..... a set of procedures (moves in a game) for which a win is possible for the next player
- heuristic..... a method, strategy, or trick used to improve the efficiency of a problem-solving system
- instructional program..... a set of computer programs written by an author and executed on a computer system for the purpose of instruction

GLOSSARY -- Continued

- intellectual game..... mental competition according to a set of specified rules
- (machine) learning..... progressively (and automatically) improving performance at a specified task--such as winning a game
- optimal strategy..... a set of procedures (moves in a game) which guarantee the best possible outcome
- programmed instruction..... a teaching sequence in which a) information is presented to the student requiring him to make responses, b) the student is given immediate feedback, and c) the student is permitted to study independently
- response..... input (by the student) or output (by the computer) displayed on paper at a typewriter keyboard
- sign-off..... the procedure by which a working session with the computer system is terminated
- sign-on..... the procedure by which a working session with the computer system is initiated
- terminal..... a computer input/output device--capable of receiving input from the user and of displaying output to the user, e.g. telecommunications typewriter

APPENDIX H  
RELATED RESEARCH TOPICS

In order to encourage entrance into the new area of AI in CAI by researchers from related fields, a list of topics for research is proposed:

1. Stylistic Differences in Computer Programming

Given a programming problem, a panel of judges rank-order computer programs written by children on criteria such as a) comprehensibility, b) efficiency in coding, c) efficiency in operation, d) elegance, and e) pedagogical soundness.

2. Games As a Basis for CAI Curriculum Development

Computer-executed games and simulations provide natural and enjoyable vehicles for computer-assisted instruction,

3. Programming As a Conceptual Framework for Teaching Mathematics<sup>1</sup>

Programming a solution to a problem in mathematics demands rigorous, explicit thinking and facilitates critical self-analysis.

4. A Theory of Thinking

The construct of a computer program models certain cognitive processes; for example, hierarchical organization in plan-formulation. Aspects of computer programming also closely parallel the general process of education: 'debugging' one's model of the world.

5. Learning Games As Testing Devices

Games which progressively improve their performance and adapt to changing conditions may serve as viable vehicles for testing decision-making skills, strategy building and execution, powers of generalization, etc.

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<sup>1</sup> Continuance of work begun by Seymour Papert, Director, Artificial Intelligence Laboratory, M.I.T., Cambridge, Mass.

## 6. Man-Machine Collaborative Systems<sup>1</sup>

Instead of perpetuating rabid competition between man and machine, capitalize on the particular strengths of each in development of superior combinations--as in a collaborated artificial intelligence game-player.

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<sup>1</sup> First suggested to this investigator by John W. Ulrich, Professor of Mathematics and Information Sciences, University of New Mexico





