INFORMATION TO USERS

While the most advanced technology has been used to photograph and reproduce this manuscript, the quality of the reproduction is heavily dependent upon the quality of the material submitted. For example:

- Manuscript pages may have indistinct print. In such cases, the best available copy has been filmed.

- Manuscripts may not always be complete. In such cases, a note will indicate that it is not possible to obtain missing pages.

- Copyrighted material may have been removed from the manuscript. In such cases, a note will indicate the deletion.

Oversize materials (e.g., maps, drawings, and charts) are photographed by sectioning the original, beginning at the upper left-hand corner and continuing from left to right in equal sections with small overlaps. Each oversize page is also filmed as one exposure and is available, for an additional charge, as a standard 35mm slide or as a 17''x 23'' black and white photographic print.

Most photographs reproduce acceptably on positive microfilm or microfiche but lack the clarity on xerographic copies made from the microfilm. For an additional charge, 35mm slides of 6''x 9'' black and white photographic prints are available for any photographs or illustrations that cannot be reproduced satisfactorily by xerography.
An analysis of cognitive theories in artificial intelligence and psychology in relation to the qualitative process of emotion

Semrau, Penelope, Ph.D.

The Ohio State University, 1987
AN ANALYSIS OF COGNITIVE THEORIES IN ARTIFICIAL INTELLIGENCE AND PSYCHOLOGY IN RELATION TO THE QUALITATIVE PROCESS OF EMOTION

DISSERTATION

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of the Ohio State University

By

Penelope Semrau, B.S.E., M.A.

** ** **

The Ohio State University

1987

Dissertation Committee:  
Dr. Kenneth A. Marantz  
Dr. E. Louis Lankford  
Dr. Barbara A. Boyer

Approved by

Kenneth A. Marantz  
Adviser  
Department of Art Education
Dedicated to Mabel Dudko, an independent thinker who I admired.
ACKNOWLEDGEMENTS

I want to express my sincere appreciation to Dr. Kenneth A. Marantz, my advisor, for his consistent support, encouragement, advice, and for his humanistic views concerning people and art. I also wish to thank Dr. E. Louis Lankford, my committee member, who provided constructive criticism and thought provoking philosophic discussions regarding my research. In addition, my deepest gratitude is extended to Dr. Barbara A. Boyer, my committee member, who opened my eyes to the significance and pervasiveness of culture and the implications it has for A.I. and art education. I am appreciative of the invaluable opportunity I had in working in the renowned computer graphics lab directed by Chuck Csuri and Tom Linehan. I also wish to thank Dr. Nihai Nadin for introducing me to some of the major issues that cognitive science addresses. Finally, I would like to thank Professor Donald Duncan and Trudi Duncan for their friendship, encouragement, and moral support.
VITA

1972..........................  B.S.B.E., University of Wisconsin, Whitewater

1972-1978.....................  Art Teacher, Fort Atkinson Public Schools, Fort Atkinson, Wisconsin

1976..........................  Coordinated and Designed Community Barn Mural in Jefferson County, Wisconsin, which was featured in *Time Magazine*, May 15, 1977

1978-1979.....................  Graduate Study, Art, Art History, Art Education, and Cultural Anthropology, University of Wisconsin, Madison

1979..........................  "SHIP" National Scholarship Award for Outstanding Young Art Educator and Scholar

1979..........................  Selected for membership in the Alpha Beta Chapter of Pi Lambda Theta, Spring, 1979, University of Wisconsin, Madison

1980..........................  M.A., Department of Art, Illinois State University, Normal, Illinois

1981-1983.....................  Graduate Teaching Associate and Supervisor of Student Teachers, College of Education and Department of Art Education, The Ohio State University, Columbus, Ohio
1983-1984................. Microcomputer Product Developer, Shaffer & Shaffer Research & Development, Columbus, Ohio

1985-Present................ Software Development Editor, Merrill Publishing Co., Columbus, Ohio

PUBLICATIONS


1985......................... Author, MacArt (a book for the Macintosh computers), Publisher: Arrays Inc.

FIELDS OF STUDY

Studies in art education, cognitive science, computer graphics, and education.
TABLE OF CONTENTS

ACKNOWLEDGEMENTS .................................................................................. iii
VITA ........................................................................................................ iv
LIST OF FIGURES ..................................................................................... ix

CHAPTER PAGE

I. INTRODUCTION TO THE PROBLEM ............................................ 1
   Statement of the Problem ................................................................. 1
   Limitations ..................................................................................... 4
   Background of A.I. Research ........................................................ 5
   Epistemological Claims and Major Issues in Developing A.I. Systems .... 9
   Art Theories Related to Cognition and Emotions .............................. 19
   Methodology .................................................................................. 22
   Significance and Implications for Art Education ............................... 22

II. A.I. CONCEPTS AND PROGRAMMING TECHNIQUES ............... 30
   Introduction .................................................................................... 30
   Representation and Use of Knowledge ............................................ 33
   Logic ............................................................................................. 33
   Frames ......................................................................................... 37
   Scripts .......................................................................................... 39
   Semantic Networks ...................................................................... 40
   Problem-Solving Methods ............................................................ 42
   Heuristic Search .......................................................................... 43
   Forward and Backward Chaining .................................................. 45
   Bidirectional Search .................................................................... 47
   Decision Trees and Graphs ............................................................ 47
   Matching ....................................................................................... 50
   Weak Methods ............................................................................. 56
   Conclusion .................................................................................... 74
<table>
<thead>
<tr>
<th>FIGURES</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. A semantic network</td>
<td>40</td>
</tr>
<tr>
<td>2. Breadth-first search tree</td>
<td>48</td>
</tr>
<tr>
<td>3. A search graph</td>
<td>49</td>
</tr>
<tr>
<td>4. OR graph</td>
<td>58</td>
</tr>
<tr>
<td>5. AND-OR graph</td>
<td>59</td>
</tr>
<tr>
<td>6. Mini-max search algorithm</td>
<td>64</td>
</tr>
<tr>
<td>7. An alpha cutoff</td>
<td>65</td>
</tr>
<tr>
<td>8. Alpha and beta cutoffs</td>
<td>66</td>
</tr>
<tr>
<td>9. Breadth-first search at the first level</td>
<td>67</td>
</tr>
<tr>
<td>10. Breadth-first search at two levels</td>
<td>68</td>
</tr>
</tbody>
</table>
CHAPTER I
INTRODUCTION TO PROBLEM

Statement of Problem

The purpose of this study was to analyze selected cognitive theories in the research areas of artificial intelligence (A.I.) and psychology. The major focus was to examine the cognitive research in A.I., which is a digital, quantitatively based system, and qualitative aspects of human cognition to determine what role, if any, emotions play in the cognitive or intellectual processes and if such an arbitrary process as emotions could be accounted for in an A.I. model. Understanding the relationship of emotions to processes of intelligence has implications for constructing theories of art learning that explain the relationship between emotions and aesthetic response.

Research has indicated the significance of the relationship of intelligence or mental processing to experiences of creating or perceiving works of art. Pittard (1970) posited that intellectual development is an integral component in the aesthetic experience. Pittard stated:

My thesis is that art is a mode of constructing and organizing knowledge that not only originates with
intellectual development but also presupposes it.
(p. 21)

Gardner (1983), in his research on aesthetic behavior in the Harvard Project Zero, noted that "artistry is first and foremost an activity of the mind" (p. 47).

Meyer (1974) advocated that theories of art explaining aesthetic response need to stress the significance of cognition in the aesthetic experience:

to account for the ways in which works of art are understood by and affect competent audiences, hypotheses must be formulated that relate the processes and patterns in works of art to human cognition and responses. (p. 191)

Hofstadter (1980) stressed that A.I. would have to include higher types of cognitive skills, such as appreciation and imagination, in addition to the lower types, such as recognition and memory, to constitute a human notion of intelligence. Hofstadter stated:

If intelligence involves learning, creativity, emotional responses, a sense of beauty, a sense of self, then there is a long road ahead, and it may be that these will only be realized when we have totally duplicated a living brain. (p. 573)
This study focuses on basic research analyzing:

(1) programming techniques in A.I. related to basic concepts in artificial intelligence and cognition and ways of processing knowledge,

(2) theories in psychology related specifically to cognition and emotion,

(3) an A.I. model for cognition which is adopted for factors in emotion using data from the above two areas of research, and

(4) the cumulative data to draw implications and speculations for potential A.I. systems in the areas of aesthetic response and art learning.

The subcommittee of the Doctoral Advisors' Roundtable of the National Art Education Association (1970) noted the significance of basic research in art education, and delineated significant areas for research:

The unanswered questions in art education might be said to be those concerned with intent or purpose in art education; concepts upon which we build our theories; behaviors inherent in the act of making or responding to art; and the interrelations of these concerns. (Johnson, I., et al., p. 2)

In the same report, Chapman (1970) observed that modes of inquiry appropriate to art education include such basic research areas as ontology, epistemology, axiology, ethics, and aesthetics (p. 2).
Limitations

Inquiry into research can be categorized into the following areas:

(1) A.I. technology that is a demonstration of an "intelligent behavior," regardless of relationship to human capacities. This area concerns such topics as computer performance, speed of operation, efficient algorithms and use of computer memory,

(2) A.I. modeling, which is concerned with the internal structures and processes of computers in examining plausible modes of the way people think (psychologically oriented), and

(3) Research in A.I. and psychology that is directed toward a theory of "intelligence" emphasizing human cognition in consideration of its implementation on a computer.

The criteria for selection of the research data to be analyzed was:

(1) Research in A.I. concentrating on cognitive science which is the study of the mind drawing primarily from the fields of psychology, philosophy and computer science. An exemplar cognitive model by Pylyshyn (1985), a leading authority in cognitive science, was analyzed, and
Research in psychology focusing on cognitive-emotional theories that could possibly be extended or adapted for use in a cognitive A.I. model. A primary reference selected for analyzing the cognitive-emotive theories was Strongman (1973) who examined the different emphases and orientations to the study of cognition and emotion.

Background of A.I. Research

In 1950, Turing expressed the belief that, at the end of the century, "one will be able to speak of machines thinking, without expecting to be contradicted" (p. 433). Many human mental activities, such as writing computer programs, engaging common-sense reasoning, and understanding language, are said to demand intelligence. Over the last couple of decades, several computer programs, among them SHRDLU (Winograd, 1972), STUDENT (Bobrow, 1967), and ELIZA (Weizenbaum, 1966) have been implemented to perform "mentalistic" processes. For example, Winograd's SHRDLU was a computer program that understood natural language in a limited context of blocks and things to do with blocks. SHRDLU was a program that existed in an imaginary world composed of colored blocks that could be manipulated, stacked, and moved about on a table top. SHRDLU was able to carry on a conversation by answering questions about the blocks. In discussing SHRDLU's intelligent capabilities, a
prominent A.I. researcher, Dreyfus (1982), defined the system's cognitive capabilities as "an integrated system which makes use of syntax, semantics, and facts about blocks" (p. 161).

Another conversational type program was developed by Weizenbaum at MIT (Massachusetts Institute of Technology) in 1966. Weizenbaum's program, ELIZA, was the first interactive A.I. program. ELIZA consisted of a language-analyzing portion and a script portion. As the user typed in responses on the keyboard, ELIZA's language analyzer cued in on keywords detected in sentence fragments and phrases, as guided by preestablished rules in the program. The script portion consisted of numerous rules, referred to as heuristics, that allowed the program to improvise sentences that were based on the themes assessed by the language-analyzing portion. Weizenbaum gave ELIZA a script for mimicking a Rogerian therapist, whose statements are typically neutral and often merely mimicked the client's own words. Weizenbaum thought this script would be especially easy for ELIZA to carry out. Systems such as ELIZA and SHRDLU reflect some of the early work done in A.I.—a rapidly evolving new research area rooted in cognitive science. The field of cognitive science studies processes of the mind, using the computer as a model to explain the cognitive processes.
The term "intelligence" is derived from the Latin intelligentia, meaning to understand. The Dictionary of Philosophy defines intelligence as the capacity of the mind to meet effectively, through the employment of memory, imagination, and conceptual thinking, the practical and theoretical problems with which it is confronted (Runes, 1962, p. 147).

Philosophical controversy exists as to what computers can and cannot do in performing tasks equivalent to human thinking processes. Steps are being made in A.I. research to move from passive models of information processing to those accounting for an individual's interacting with the world. Weizenbaum's ELIZA was one of the first programs that people could interact with without having any specialized background or preparation in math or computer science. ELIZA vividly demonstrated the computer's capability for information processing and did so in an interactive fashion. Computer novices from various fields could now actively participate in a computer's operation, rather than standing back as passive observers.

Searle (1981) has described the computer as a manipulator of symbols, but without the ability to interpret the symbols. According to Searle, "the computer has a syntax (symbol manipulator-structure), but no semantics (meaning). Thus if you typed '2 plus 2 equals' it will type 4, but it has no idea that '4' means '4' or that it means
anything at all" (p. 303). He maintained the view that humans may do something like information processing, but computers certainly do not. In contrast to Searle, Pylyshyn (1979) believed that computers can be programmed for a wide range of behaviors and that a psychological programming language can be developed.

According to Boden (1977), A.I. "is not the study of computers, but of intelligence in thought and action. Computers are its tools, because its theories are expressed as computer programs that enable machines to do things that would require intelligence if done by people" (p. xi). Webber and Nilson (1981) have said that A.I.'s objective is to "endow machines with reasoning and perceptual abilities" (p. vii).

Another A.I. researcher, Marr (1982), directed his work to the study of complex information-processing problems, rather than to the large array of human attributes: "The goal of the subject is to identify interesting and solvable information-processing problems, and solve them" (p. 127).

In clarifying her attitudes towards A.I., Boden cited Feigenbaum's definition: "Intelligent action is an act or decision that is goal-oriented, arrived at by an understandable chain of symbolic analysis and reasoning steps . . ." (p. 422). Boden emphasized that intelligence in A.I. cannot be interpreted as a literal expression any more than the word intelligence in Central Intelligence.
Agency can. Boden described A.I. as the study in and for knowledge, rather than as the possession of knowledge itself (p. 422).

Epistemological Claims and Major Issues in Developing A.I.

Systems

Minsky (1982), Dreyfus (1982), and Pylyshyn (1985) dealt with epistemological assumptions related to what people actually do when they think and perceive. How people think and perceive might provide information about reproducing human performance with digital computers. Pylyshyn's cognitive model is presented and examined in chapter IV.

Two epistemological claims that are recognized as significant to understanding A.I. are:

Claim 1) all nonarbitrary processes can be formalized, and

Claim 2) formalisms can be used to reproduce the processes in question.

These claims require an understanding of what is meant by "nonarbitrary" behavior and "formalism." Nonarbitrary can be defined as any behavior that is not random and has a definitive purpose, reason, or goal. Formalism refers to a set of symbolic objects that are related through operations or manipulations. For example, numbers are related to one another through the arithmetic operations of addition, subtraction, division, and multiplication. Certain rules
are learned and applied to an arithmetic operation to achieve the correct result.

A programming language like LOGO is also a kind of formalism. In contrast to arithmetic, the rules of LOGO are learned along the way through trial and error debugging procedures. Eventually, one masters the language by applying the rules in the correct fashion. However, LOGO requires "perfection" as much as any other formalism in the sense that "When one is committed to a specific result, specific operations must be performed in the correct order to achieve that result" (Lawler, 1983, p. 132).

Dreyfus (1982) referred to two examples of nonarbitrary behavior that can be formalized. Although planets are not following any rules, they demonstrate a behavior that can be translated into laws. Differential equations express this planetary behavior as motion according to a rule. Another example of behavior that can be designated as nonarbitrary and can be formalized or translated into a rule or equation is bicycle riding. Dreyfus explained how bicycle riding can be formalized, but noted that major components of the full explanation are still missing:

A man riding a bicycle may be keeping his balance just by shifting his weight to compensate for his tendency to fall. The intelligible content of what he is doing, however, might be expressed according to the rule: wind along a series of curves, the curvature of which
is inversely proportional to the square of the velocity. . . . This formalization enables us to express or understand his competence, that is, what he can accomplish. It is, however, in no way an explanation of his performance. It tells us what it is to ride a bicycle successfully, but nothing of what is going on in his brain or in his mind when he performs the task. (p. 190)

Dreyfus was critical of applications of physical laws to explain cognitive processes involved in human performance. He argued that observable physical acts in behavior can be reduced to a set of rules and mathematical equations—but not thinking. Cognitive processes cannot be explained using observable laws of physics.

Minsky (1982) supported the claim that all nonarbitrary processes can be formalized, and that the resulting formal rules can be used by a digital computer to reproduce that process. According to Minsky, a digital computer is a machine that is a rule-obeying mechanism. If one is able to formulate rules for a specific behavior or cognitive process, then a rule-obeying computer could reproduce the competence level of the specified process.

In response to this argument, it is important to note that there are processes involving performance which cannot be described with formalisms, such as hallucinations and dreams, which are also carried out by the mind.
Furthermore, the claim that all nonarbitrary behavior can be formalized also involves the possibility that there may be arbitrary components or processes within nonarbitrary behavior. Neither Minsky nor Dreyfus dealt with this. Can these processes be ignored, or is it possible to formalize nongoal-oriented behavior? Although Minsky and Dreyfus do not account for such arbitrary nongoal-seeking behavior, Dreyfus would respond that no human performance can be formalized to account for cognitive processes.

In developing theories of A.I., researchers have resorted to using human intelligence as a model. But, does the computer have to resemble or replicate human intelligence in order to function in an intelligent manner? Is it possible for computers to possess a form of intelligence that can perform and solve higher order cognitive tasks and problems, yet not resemble or replicate the human mentalistic processes?

Minsky admitted that it is not possible to formulate a set of rules describing what a human should do in every conceivable situation, but argued that a set of rules could describe what this individual could do. Dreyfus argued that this suggested some sort of "laws of behavior," which in itself is ambiguous. Behavior is lawful, if lawful simply refers to a form of order, but whether these types of laws can be inputted into a computer program and whether human cognitive processes actually follow a set sequential order,
requires further justification. When one refers to laws of behavior, the question must be raised as to whether these laws refer only to physical movement that can be expressed in formalistic terms that can be manipulated on a digital computer, while ignoring other kinds of behaviors and processes.

Dreyfus noted that formalists try to confuse the difference between physical laws and information processing rules in order to defend the claim that human behavior and cognitive processes can be formalized. He emphasized that a digital computer does not really process information, but only appears to process it. A computer does not understand the meaning of "2 plus 2," yet it seems to be performing an intelligent mathematical operation when it provides the correct answer of "4." Dreyfus elaborated on the computer's capability to simulate cognitive processes, "One can only show that for any given type of information a digital computer can in principle be programmed to simulate a device" which appears to process that information (p. 195). Thus, the computer is not cognitively processing and understanding information, it is calculating and solving mathematical and logical operations. Through programs, the computer is able to simulate information processing. The computer does not directly deal with the original information--it works with conversions of that information.
Dreyfus postulated that there is an impossibility involved in any attempt to simulate the brain as a physical system, and that the very laws of physics and information theory may preclude the enormous calculations necessary. Dreyfus supported this position by referring to the laws of physics demonstrating the enormous tasks involved in calculating with detail the motion of human bodies (p. 196).

Such a view may be challenged in light of the rapid advances in technology. The way problems are structured in areas like theorem proving, robotics, A.I., and the calculation of human body movement may be so different that what appears to be a problem today in terms of computer time, speed, and efficiency in data processing will no longer be a major problem in the future.

Another problem that Dreyfus observed was that A.I. theories were built around how the computer responds to bits of context-free, completely determinant data. This appears to create a major obstacle to computer-based cognition, especially at more sophisticated levels of cognition. As Dreyfus noted, "the world cannot be analyzed in terms of context-free data" (p. 205).

Dreyfus concluded that "the formalist is caught between the possibility of always having rules for the application of rules and the impossibility of finding unambiguous data" (p. 205). Therefore, the data required for the computer must be such that no further interpretation of the data is
necessary for it to be understood. In other words, the data must be finite, discrete and unambiguous.

In contrast, Minsky believed that computers can demonstrate creativity, intuition, and emotion. He completely supported the epistemological claim that all nonarbitrary behavior will eventually be formalized, and will therefore be reproducible by computers. However, Minsky was aware that there were major obstacles to overcome before researchers could even begin to formalize specific behaviors and cognitive processes. It is difficult to determine both the exact nature of creativity, and what is involved in creative behavior. Minsky attempted to resolve this by asserting that there is "no substantial difference between ordinary thought and creative thought" (p. 5). It appears that he believed that the creative artist just does ordinary thinking better because of practice. He elaborated:

Each better way to learn would lead to better ways to build more skills—until that little difference had magnified itself into an awesome, qualitative change. In this view, first rank "creativity" could be just the consequence of childhood accidents in which a person's learning gets to be a little more "self-applied" than usual. If this image is correct, then we might see creativity happen in machines (computers), once we
begin to travel down the road of making machines that
learn—and learn to learn better. (p. 6)

Why isn't everyone capable of this higher order of
thinking? Minsky responded that the tails of distribution
curves are small by definition. There are fewer people in
both the highest and lowest measured achievement bounds by
the very definition of those thresholds. Thus, Minsky
posited that there is no such thinking as creative
thinking—only better kinds of ordinary thinking, which is
somehow easier to explain than an ambiguous, arbitrary form
of thinking.

Minsky concentrated his work on what he referred to as
"common-sense" knowledge (p. 82). He admitted, however,
that more research is needed in this area, indicating that a
limited definition exists as to what is contained in this
type of common-sense knowledge. He used terms such as cause
and effect, purpose, locality and process as synonymous
components of common-sense knowledge, but provided no
explanation for the identification and classification of
knowledge in general. Nor did he explain how this common-
sense knowledge differed from other types of knowledge, or
what other types of knowledge existed, if any.

Minsky has relegated all knowledge to the realm of
ordinary, everyday knowledge in his attempt to formalize or
structure it. He referred to this new knowledge structure
as a "frame" for representing stereotypic or common
situations. He created what he termed a "micro-world," or schematic, of everyday situations, which simplifies those situations into small sub-data structures. In response to this framework, Dreyfus criticized Minsky for creating "a fairyland in which things are so simplified that almost every statement about them would be literally false if asserted about the real world" (p. 164).

**Summary of Dreyfus and Minsky's positions.** Dreyfus criticized Claim One (see page 9) that all nonarbitrary processes can be formalized, by demonstrating that it is an unjustified generalization from physical science. According to Dreyfus, Claim Two, that formalisms can be used to reproduce cognitive processes, is a theory of competence demonstrating equivalence between the model and cognition, rather than a theory of performance reproducing the cognitive process on a computer. He stated:

> unlike the technological application of the laws of physics to produce physical phenomena, a timeless, contextless theory of competence cannot be used to reproduce the moment-to-moment involved behavior required for human performance; that indeed there cannot be a theory of human performance. (1979, pp. 190-191)

Minsky, in contrast, posited that all nonarbitrary behavior can be formalized. He claims that digital computers can, *in principle*, do anything that human beings
can do, that it has only those limitations it shares with man.

Dreyfus developed an anti-formalist claim that there are processes that simply cannot be described through formalisms. Yet, these processes can, nevertheless, be carried out by human minds.

Minsky countered this claim by noting that it is impossible to develop a set of rules to describe what a human being should do in every conceivable set of conditions. The supposition is that there is an absence of complete laws of behavior. However, rules can be established that formalize what an individual could do in various situations.

Antithetical positions. Minsky and Dreyfus take antithetical positions on the subject of epistemology. An investigation of the claim that all nonarbitrary processes can be formalized is basic to understanding philosophical issues in A.I. Minsky and Dreyfus represented polar positions. It appears that there exists nonarbitrary behaviors that can be formalized and that computers will be able to reproduce these behaviors. However, Dreyfus identified the complexity of the problem of creating an artificial intelligence model and the problem of understanding what human intelligence is.
Art Theories Related to Cognition and Emotions

Two highly influential educational researchers who have made an impact on art educational research are Dewey (1964) and Langer (1958). Following is an analysis of their theories as related to cognition, emotion, and art. According to Langer (1958), the essence of art is the expression of human feelings. Art works are able to convey an expression of human emotions that are part of experience. Through art, emotions such as vitality, excitement, joy, and sadness can be experienced. Art gives form to feelings by objectifying feelings, "so that we can contemplate and understand it" (Langer, 1958, p. 91).

Regarding the role that one's past experiences play in the aesthetic experience, Dewey (1964) stressed that ideas, attitudes, values, and feelings from one's life are naturally involved (though not always intentionally) as one responds to a work of art. Dewey stated:

when excitement about subject matter goes deep, it stirs up a store of attitudes and meanings derived from prior experience. As they are aroused into activity they become conscious thoughts and emotions, emotionalized images. (p. 608)

The work of art, according to Dewey, is filled with meanings derived from associations made by the viewer. Art conjures up previous experiences in one's life. But the work of art also has unique qualities and characteristics of
its own that we experience aesthetically. These meanings are intellectually based, in that they are thought of, remembered, and understood as part of the aesthetic experience. Langer agrees with Dewey regarding this role of cognition in the aesthetic experience. Langer believed that perceptions of art objectify one's inner, subjective feelings, making them outward and objective.

Fry's (1965) notion of the aesthetic experience also included an aesthetic emotion derived from the significant form of the work of art, excluding any thoughts of feelings that may exist outside of the work. Fry, a proponent of "formalism," believed that the aesthetic emotion is focused and derived from the form of the artwork alone. Formalism is an art theory based on the structure of art. This structure, referred to as "significant form," means that the artwork is viewed as a whole composition, an intrinsic form that does not depend on anything else, such as representational associations. The significant form itself should be worthy of contemplation, and one should be able to realize the significance of the form. Formalism involves cognition in the aesthetic response as a means of "establishing the completest relationship of all parts within the system . . ." (p. 307).

Fry noted that the aesthetic emotion is an emotion about form that is derived from the artwork itself. It is an immediate experience with the artwork that does not rely
on past experience. Whereas, the aesthetic experience in Langer's and Dewey's perspective, also involves a perceived response where feelings are associated with past experiences. It arouses one's imagination and memory, and excites one's senses. At the same time, there is an objectified experience, according to Langer, when viewing art. An individual has a cognitive-affective experience with the work of art in the conceiving, contemplating, and understanding of one's emotions as experienced through the art. Dewey defined emotion as being "to or from or about something objective, whether in fact or in idea. An emotion is implicated in a situation, the issue of which is in suspense and in which the self that is moved in the emotion is vitally concerned" (p. 609).

Dewey clarified his idea of emotion in his theory of art:

I have spoken of the esthetic quality that rounds out an experience into completeness and unity as emotional. . . . emotions are qualities, when they are significant, of a complex experience that moves and changes. (p. 602)

Dewey and Langer emphasized the role of experience associated and derived from the work of art. The viewer naturally makes connections with personal experiences and the feelings perceived as being expressed by the art work. Langer suggested that certain emotions were realized through
the experience of works of art, and that the emotion one had with a work of art was different in type and degree from other kinds of emotions, such as being in love, feeling grief, etc. Fry posited in his theory that the artwork itself had significant inherent value to warrant an aesthetic experience, disregarding any exterior, personal associations made between it and one's life.

Methodology

This study was designed (1) to analyze the cognitive theories found in research in A.I. and psychology to determine the role of emotions in cognitive processes; and (2) to suggest implications for the development of A.I. systems in the areas of art learning and aesthetic response.

Analytic research procedures include: (1) rephrasing and explaining claims or arguments; (2) analyzing for specific issues or problems; and (3) identifying relationships and discontinuities between the research data, with implications for the use of cognitive theories and A.I. systems in art learning processes.

Significance and Implications for Art Education

As the research in A.I. develops and is integrated into software applications, an individual's use of computers will become a more interactive, integral part of his/her world. A.I. is contributing to the interaction between individual and machine/program through the increasing user-friendliness of software products. As this interactive friendliness
increases, many more people will be able to use the information-processing capabilities of computers.

Computers can perform assorted functions for users in different professions. Each specialized career field is a micro-world of specific terminology, techniques, and values. Current research in A.I. has been applied toward occupational groups, such as pharmacists, physicians, and engineers, in an attempt to develop user-specific or knowledge domain-specific software. This software eliminates the need for learning computer languages and programming. The program contains an occupational context of words, techniques, and functions and it will accept word commands similar to the user's natural language. Such user-friendliness will develop for use by artists in an interactive context. For example, an artist could use word commands like "draw," "brush," and "paint" instead of programming language. Better yet, the artist could talk to the program with a built-in voice recognizer.

The relationship between research in A.I. and the artistic process has implications for the art educator, particularly those working with computers in educational settings. There has been increasing interest in computer art, and questions have been raised as to whether computers can be programmed for such intelligent activities as art appreciation. The potential exists to create computer programs that could simulate thinking processes involved in
aesthetics and art criticism. In fact, researchers like Bense (1971) and Franke (1977) have been concerned with the synthesis of computers and art, and are developing what they call a "cybernetic approach" to aesthetics. Cybernetic aesthetics began in the 1950s with the work of Bense, who delineated a theory of "generative aesthetics"—an aesthetic approach to computer graphics derived from mathematical formulas (Bense, 1971).

Several other researchers have been concerned with making computer art. They have maintained a position consistent with formal theories of A.I. and logic that describe human processes in terms of rules that can be followed by a computer. Mezei (1971) saw the artist using the computer as a subject for research on creative behavior and noted, "The element implicit in using the computer for making designs is that all the decisions have to be made specific and explicit which makes them open to study" (p. 165). Richards (1983) also suggested a formalistic approach to computer art in which the exploration levels involved in aesthetic decision making would be defined and explicit. Various levels of cognitive processing involved in the artistic procedure, compositional techniques, as well as accident and chance would be programmed into the computer (p. 22).

In opposition to a formalistic approach to creative processes using computers, Cohen (1971) noted that logically
treated and explicitly described processes can be limiting. He advocated the position that certain cognitive processes cannot be formalized or reduced to words and definitions. According to Cohen, the communicative, semantic processes are much more complex:

This world of ours is not bounded by words or by covers of a dictionary. Our commerce with it provides the cues which reduce the intrinsic ambiguity of language and hence make communication possible. Only if a computer engaged in similar transactions with the world beyond its own linguistic store could it acquire our mastery of language. (p. 36)

Continued analysis of what is involved in thinking and knowing in artistic processes and computer intelligence provides information necessary to research in art education. Jones (1980-81), an art educator, has noted:

This task of individuals trained in the arts and humanities is to ask questions about the nature of the new technology and its relation to human needs and values to determine appropriate modes of development and application. (p. 47)

Research in areas such as visual perception, Gestalt principles of visual organization, and aesthetics utilizing the interactive component of computers could enhance our present concepts of creativity and aesthetic response to
art. Csuri (1974) advocated the interactive use of computers in analyzing visual perception and stated:

The frontiers of computer art are in the arena where definitions, procedures, and techniques are being developed to extend our conceptions of information processing and what we might mean by human intelligence and creativity. (p. 515)

There is much to be learned about the creative process, aesthetics, and art appreciation; the use of computers and A.I. in these areas would provide art education another perspective. While there seems to be some cognitive processes involved in the aesthetic experience that would better lend themselves to a formalistic treatment, there are other processes of the mind that cannot be so easily defined. In working in A.I. and art, it seems that there is as much to learn about artistic accidents, perceptual illusions, mistakes, and misunderstanding as there is about understanding. Reichardt (1971) expressed this view about analyzing misunderstandings in art:

In art there are no rules defining its proper realm or specifying prescribed attitudes to technology and the world at large . . . there is no reason why significant works should not be based on misunderstandings and partially digested information, although this is not a prescription. (p. 17)
Hofstadter (1980) is one of the few A.I. researchers concerned with arbitrary behavior, intelligence, randomness, and computers and the arts. He described computer processes involved with creativity and randomness as still quite mechanical. He added, however, that although researchers are not close to simulating the way we think, they are getting closer. He posed a strong humanistic argument against formalistic techniques and emphasized the uniqueness of the individual. He proposed that intelligence, consciousness, and free will cannot be automated:

On a gut level, each of us probably has about as good an understanding as is possible of those things, to start with. It is like listening to music. Do you really understand Bach because you have taken him apart? Or did you understand it that time you felt the exhilaration in every nerve in your body? Do we understand how the speed of light is constant in every inertial reference frame? We can do the math, but no one in the world has a truly relativistic intuition. And probably no one will ever understand the mysteries of intelligence and consciousness in an intuitive way. Each of us can understand people, and that is probably about as close as you can come. (p. 680)

Hofstadter's research is concerned with the more ambiguous areas of cognitive processes and art that will help in providing research to educators interested in the
areas of art, artificial intelligence, and computers. This kind of research will provide a new perspective for looking at computers and their functions. New frameworks for thinking can be developed that will enable researchers to expand beyond formalistic approaches to an A.I. that will more closely resemble human experience in art.

Innovative languages, programs, and new systems of computers that do not require input from the artist in the format of mathematical equations or formalistic procedures (i.e. a program) could be developed from such research. These computer-related innovations would be more amenable to natural language and a wide range of cognitive processes in such areas as creative thinking and aesthetics. To do this, a change in society's belief that cognition and A.I. are scientific and precise is needed. We must admit that there is also a qualitative element. At present, computers are not able to deal with the ambiguities and the imprecision of the real world. Zadeh (1984) suggested a unique approach to formal logic, which

will also call for a certain fundamental shift in attitudes, particularly in theoretical computer science. . . . We may have to retreat from this tradition in order to be able to say something useful about complex systems and in particular about systems in which human reasoning plays an important role. (pp. 209-310)
Research in A.I. will help to expand the boundaries of what can even be imagined about computers and forms of intelligence in the future.
CHAPTER II
A.I. CONCEPTS AND PROGRAMMING TECHNIQUES

Introduction

In this chapter, I have presented an overview of A.I. concepts and programming techniques with selected examples demonstrating the historical evolution of the research. This chapter covers standard A.I. programming tools and methods such as semantic networks, frames, heuristic search, and decision trees. Characteristics of A.I. problems, techniques, and systems are presented as well as specific means to represent knowledge and methods for problem solving. The major resource for this chapter was Artificial Intelligence by Rich (1983) which is a foundational text used in A.I. courses. This chapter is divided into the following sections:

I. Introduction—brief overview and description of an A.I. system from a programming perspective.

II. Representation and Use of Knowledge—standard A.I. formalisms for representing, acquiring, and using knowledge, such as logic, semantic networks, and frames.
III. Problem-Solving Methods—several standard paradigms determining the flow of control, such as heuristic search, decision trees and graphs, matching, and and-or graphs.

IV. Conclusion—brief summary of A.I. concepts and some implications.

Basically, an A.I. system is a reasoning system that does problem solving. Thus, the system may be designed to reason about the most appropriate move when playing a game of chess or to understand human speech as it matches certain external sounds to its own database. To solve these problems, an A.I. system needs a certain amount of knowledge, a way to characterize the knowledge that is useful to the computer, and a means to solve the problem. For use by a computer, knowledge from the everyday world needs to be represented in a format acceptable, readable, and usable to the computer. The information needs to be standardized and formalized. Formalism refers to a set of symbolic objects, such as alphabetic letters and numbers, that can be related to one another through operations and manipulations. For example, numbers are related to one another through the arithmetic operations of addition, subtraction, and multiplication. Certain rules are learned and applied to an arithmetic operation in order to achieve the correct result. A formalism is a way in which knowledge
(data) and reasoning (control) are represented symbolically by an A.I. program.

Two important components of an A.I. program are: (1) A knowledge-representation framework, such as one or more databases, which provide knowledge and information about the particular task that it is designed for and a set of rules called heuristics; and (2) Problem-solving and inference methods indicating the flow of control or the order in which heuristics will be compared to each other and the database(s). A controlling strategy specifies the process, order, or method of exploring the various paths in determining the appropriate path to the solution (goal). This process of searching through various paths to determine the appropriate one is fundamental to the problem-solving nature of an A.I. system. The search process uses both rules and knowledge as the paths are explored. Heuristic search can involve two kinds of heuristics: heuristics that define the control strategy specifying the order and ways that rules are compared; and the rules themselves that convert one system of communication into another (Rich, 1983, p. 37).

Fundamentally, an A.I. program should demonstrate the best technique(s) for representing the knowledge and for problem solving and then apply these to the particular problem. A.I. programs are a collection of written formalisms proving the relations among objects. The
following section identifies techniques commonly used for knowledge representation and problem solving with example programs.

Representation and Use of Knowledge

In setting up a database of information, certain questions need to be asked about the nature of the knowledge. Is the knowledge consistent or will it change due to the particular problem, situation, context, or other factors?

How much knowledge is needed and what exactly is the role of knowledge in solving the problem: is it a significant and necessary requirement or is it there to provide help, if needed? This kind of question effects the design in that too much knowledge in some problems can constrain the search process, whereas in other problems, an abundance of knowledge may be required in order to recognize the solution (Rich, p. 46). The standard formalisms for characterizing knowledge include the following.

Logic

Knowledge representation using logic is a way of representing facts and objects to form a complete description of the world. The world according to this view is static: it does not change, it is consistent (Rich, p. 62). For example, mathematics is a static form of information; it remains consistent and does not vary.
Propositional logic. Simple real-world facts can be easily represented as logical propositions written as well-formed formulas using propositions. With propositional logic, we could deduce that it is not sunny if it is raining. The following example is in propositional logic (the \( \rightarrow \) means equal and \( \sim \) means not).

It is raining.

RAINING

It is sunny.

SUNNY

It is windy.

WINDY

If it is raining then it is not sunny.

RAINING \( \rightarrow \) \( \sim \) SUNNY \quad \text{(Rich, pp. 137-138)}

Predicate logic. Predicate logic is used for more generalized representations where one statement covers several references, such as Socrates is a MAN and Plato is a MAN, and where individual statements are not going to be written for each reference or use. Predicate logic is a better way of representing knowledge than propositional logic because real-world facts can be represented as statements written as well-formed formulas (Rich, p. 138).

In propositional logic, a well-formed formula written for the statement Plato is a man appears as PLATOMAN. In predicate logic, it would appear as MAN (PLATO), which is more generalized because this could also be extended to MAN.
(SOCRATES); whereas propositional logic is very specialized with individual facts being represented as separate statements as in SOCRATESMAN and PLATOMAN (Rich, p. 138).

In predicate logic, the situation becomes more complex because of all the possible ways of substituting values for variables. In the predicate logic example that follows, individual facts are represented in the statements following the leading sentences (V-means all and --> means equal to).

1. Marcus was a man.
   \[ \text{man (MARCUS)} \]

2. Marcus was a Pompeian.
   \[ \text{Pompeian (MARCUS)} \]

3. All Pompeians were Romans.
   \[ V-x \text{Pompeians (x)} \rightarrow \text{Roman (x)} \]

4. Caesar was a ruler.
   \[ \text{ruler (Caesar)} \]

Predicate logic is purely syntactic, which means that no concern is given to the actual meaning being portrayed by the formalisms. Syntactic representations are adequate for simple, straightforward problems using static information.

Predicate logic provides a way of deducing new statements from old ones. But, unlike propositional logic, it does not provide a decision procedure for cutting off all possible inputs.

Prolog, an A.I. specific programming language, developed by Warren in 1977 is a production rule-based
language built on top of a predicate logic theorem prover (Rich, p. 392).

**Computable predicates.** With computable predicates, English sentences are converted into logical statements which can be evaluated as true (true = 1) or false (false = 0). Clauses are compared for their value or truth and then the final value is returned. A drawback to this method is the difficult task of converting English sentences into logical statements (Rich, p. 141).

**Computable functions.** Computable functions use arithmetic statements to evaluate the truth. In the expression ab(3+5,2) the value of 3+5 is first computed and then the values of 8 and 2 are sent to ab, respectively. Using a combination of computable predicates and functions, equal quantities can substitute each other as in "It is now 1987," the word now can be substituted by 1987 since they are equal. This procedure can become more complex, thus determining if MARCUS is alive or dead based on previous statements indicating when he was born compared to today's date (Rich, p. 146).

**Resolution theorem proving.** Rich described resolution as a proof procedure "that reduces some of the complexity because it operates on statements that have first been converted to a single canonical form" (p. 148). Resolution produces proofs by refutation. To prove a statement is valid, it shows that the negation of the statement produces
a contradiction with the known statements. It operates on statements that have been converted to a very convenient form, called clause form, such as

\[
\begin{align*}
\text{winter } \lor \text{ summer} \\
\neg\text{winter } \lor \text{ cold} \\
\text{summer } \lor \text{ cold}
\end{align*}
\]

In these statements, \( \lor \) means "or" as in comparing the first clause with the second, as in this or that. In this example, clauses are compared for their value or truth. Resolution is a simple procedure that compares two parent clauses at each step of the way yielding a new clause inferred from the two parent clauses. Thus, \( \text{summer } \lor \text{ cold} \) will be inferred from the previous clauses (Rich, p. 151).

**Frames**

A knowledge structure is a data structure (database) in which information about a particular problem domain can be stored. Sometimes, this knowledge is composed of smaller knowledge structures, called schemas, which represent information about commonly occurring patterns of things, such as past experiences and past reactions that can be organized, accessed, and are an assumed, integral part of the present, current knowledge. A type of schema is a frame which is used to represent complex knowledge (Rich, p. 203).

Frames take into account that some facts change and others do not. For example, if a plant is sitting on a table and the table is moved to the middle of the room, can
we assume that the plant has also moved (Rich, p. 63)? Frames are a collection of attributes and details for describing an object, such as a table or plant. In analyzing new experiences, the frame system updates the appropriate stored structures with details from the new information.

Frames are semantically oriented, general structures used to represent objects, usually complex objects from different viewpoints. To consider an object from many perspectives, a frame system is needed.

AM was a discovery program developed by Lenat in 1977 that represented knowledge as frames containing slots specifically chosen for the discovery domain (Rich, p. 375). Rich defined discovery as a restricted form of learning where an entity independently acquires knowledge without assistance from the knowledge experts (p. 375). Learning and knowledge are acquired through experimentation and discovery. The AM program exploited a variety of general-purpose A.I. techniques, such as knowledge representation and problem solving. Two hundred and fifty rules were used to qualify activities as interesting or uninteresting discoveries. AM was limited by the static nature of its heuristics, that is as the frames evolved, the heuristics could not keep the pace. The heuristics were only able to work with the initial concepts; they did not change and evolve.
To resolve this, in 1983, Lenat developed another learning program, EURISKO, based on the discovery paradigm AM (Rich, p. 383). EURISKO treated heuristics as concepts, that is, they could be changed and modified, they were not static as in AM. Heuristics must be capable of change and created through the same procedures used to create and modify concepts: through generalization, specialization, and analogy. Analogy allows for similarities among objects to be stated, as in "Bill is like a fire engine." To understand the information presented in this statement, one has to determine how Bill is like a fire engine. According to Rich, if knowledge about objects is represented in a collection of frames, "then learning by analogy can be described as the transfer of values from the slots of one frame (the source) to the slots of another (the target)" (p. 384).

Scripts

Another type of schema, a script, is used to describe an activity or event, such as what happens when dining out at a restaurant. Scripts are used for the representation of common clusters of facts and common sequences of events. Scripts are similar to frames, but they reason about situations, whereas, frames reason about objects. The real world is composed of patterns of events. Scripts can indicate the relationships among events and how they relate to each other. Scripts are able to predict unobserved
events inferred from what is already is known. Like frames they are semantically based (Rich, p. 237).

**Semantic Networks**

A semantic net is typically used to represent the meanings of words. A semantic net can be thought of as a graph where the information is represented as nodes connected to each other with labelled arcs showing the relationships between the nodes. The example in Figure 1 (Rich, p. 215) illustrates a semantic net.

![Semantic Network Diagram](image)

**Figure 1.** A semantic network.
Semantic nets can be elaborated on to represent a sentence describing an event. Winston's program in 1975 used semantic nets to capture the representations and relations amongst simple shape concepts, such as house, tent, and arch (Rich, pp. 370-371). The program would analyze a drawing and then construct a semantic net representation of the structural description of the objects. For example, a structural description of house is that it is composed of two basic shapes, a wedge on top and a brick block shape supporting the wedge. The semantic net description would illustrate node A as representing the entire structure of the house that is composed of the two parts--node B is the wedge roof and node C is the brick support. Winston's approach can be broken down into the following steps: (1) Begin with the concept definition, that is, the structural description of one known instance of the concept, such as house is composed of a brick and a wedge; (2) Generalize this concept definition to include other similar structural descriptions of other types of houses with narrower wedges or thicker and taller blocks; and (3) Depict near-misses of the concept definition, that is, an instance that closely resembles the concept in question but is not an instance of it, such as a wedge is similar to a house but not completely identical to it (Rich, pp. 370-371).
Problem-Solving Methods

In setting up designs, various questions need to be asked to analyze problems and determine appropriate techniques for solving them. Can a specific problem be broken down into a number of smaller problems and solution steps?

Is it possible to ignore or undo a step in solving a problem? For example, chess is a game where the steps, called moves, are not recoverable or cannot be undone; whereas, the steps to moving the numbered tiles in a framed box called 8-puzzle can be undone.

If necessary, can the system step backwards through the steps as well as forward? (This is referred to as backward and forward chaining).

Is a good solution absolute or relative, in that, if one path leads successfully to the correct answer, is it necessary to even consider further backtracking to try out other possible paths. In other kinds of problems, other paths will have to be explored to determine not only the correct path but the best path among several plausible solutions.

Does the task require interaction with a person? And most important, is the universe predictable, allowing one the ability to design a good plan predicting the outcome or solution and the sequence of steps necessary to solving the problem (Rich, pp. 40-44)?
Heuristic Search

Heuristic search is the A.I. technique used to solve problems whose solutions are not deterministic. That is, the answer is not readily deduced from preceding material; the preceding information does not automatically determine or render the result nor can it be causally determined by the previous events.

The problem is viewed as a state space search, that is, the movement through a space where each state is a legal position or move. Solving the problem is seen as exploring all possible moves within the space to find a path leading from the current state to the goal state.

The heuristics are the rules, clues, directives, and parameters used in reaching the goal. They control the flow of action. The heuristics provide guidance and advice in exploring the problem space and they recommend the directions to take in reaching the solution. Problem solving by heuristic search means exploring various alternatives in arriving at a solution.

The process of search is a fundamental problem-solving mechanism in A.I. To begin, the problem must be defined formally indicating the starting state or kind of input expected. The problem-solving process begins at this initial starting state(s), that is, all possible situations at which the problem solving can start. Next, the search space or problem space needs to be defined in terms of all
possible and potentially relevant moves as well as impossible moves and conditions. In addition, it is necessary to specify a set of heuristics that describe the actions or operators available determining the moves. A problem space is a way of stating a problem so that it can be solved with search techniques. In heuristic search, the heuristics improve the efficiency of the search process by directing and controlling the flow. Finally, all acceptable solutions to the problem (goal states) must be described as output. The space is then explored in an attempt to find the appropriate path to the solution.

The process of search is fundamental to almost every A.I. program. Rich noted that heuristic search is "based on a sound understanding of the underlying structure of the problem domain" forming the core for an A.I. program (p. 409). Most programs contain a search algorithm. Solving complex problems, such as medical diagnosis and playing chess, involves heuristic search. A.I. can be described as a process of heuristic search to solve problems by applying the most appropriate rules to individual problem states in order to generate new states to which the rules can then be applied, this generative process is repeated until a solution is found. Choosing among the rules to select the most appropriate rule, which will eventually lead to an acceptable solution, is the basic premise of heuristic search. Some heuristics define the control structure,
specifying the order and ways that rules are compared and
guide the selection and application of rules in the search
process, while others are encoded as the rules themselves.
Problems can be solved using the heuristics to move about
the search space until an acceptable solution, goal state,
is determined.

Determining which A.I. technique is best to use
requires a thorough understanding of the various techniques
and their advantages as well as an in-depth knowledge of the
problem itself. Popular A.I. techniques of problem solving
follow.

**Forward and Backward Chaining**

The goal of a heuristic search is to discover a legal
path leading to an acceptable solution. The flow of the
search can go in two directions: **forward** from the starting,
initial state and **backward** from the goal state, backtracking
to a starting state. The same rules can be used for either
backward or forward reasoning. The difference between the
two is illustrated in an example by Rich, who asks why it
always seems easier to drive home **from** an unfamiliar place
than to drive **to** an unfamiliar place (p. 58). According to
Rich, this is because we already know familiar and good
routes to getting home and therefore we can eliminate many
unnecessary attempts or paths. Whereas in driving to the
unfamiliar place, we are unfamiliar with the best routes and
therefore must consider many more alternatives, so that
reaching the goal becomes more difficult and complex. The branching factor, determining the number of paths, increases in forward chaining and decreases significantly in backward chaining because forward chaining is confronted by many more paths to be explored. Backward reasoning is also called goal-directed reasoning because the search backtracks from the final goal state (Rich, p. 57).

An example of a backward reasoning technique is Mycin developed in 1976, an early rule-based medical program designed to recommend appropriate therapies for patients with bacterial infections (Rich, p. 59). Mycin reasons backward from the disease-causing organisms to the clinical data. It backtracks from the goal state of determining the patient's illness to diagnosing the patient's symptoms (starting states). Mycin's purpose was to help physicians in diagnosing infections and selecting the appropriate antibiotic for bacterial diseases. Since doctors would not accept unfounded diagnoses from a computer program, it was necessary for the program to explain its reasoning process with coherent justifications. Mycin obtained its knowledge, the clinical data, from interactions with the physician. Rich explained how Mycin used rules, "It uses rules that tell it such things as 'If the organism has the following set of characteristics as determined by the lab results, then it is likely that it is organism X' and 'Why should I perform that test you just asked for?' with such answers as
'Because it would help to determine where organism X is present'" (Rich, p. 59).

**Bidirectional Search**

In a bidirectional search two concurrent searches occur: one starting from the goal state and backtracking to the initial state, the other search proceeding forward from the starting state to the goal state. The search will continue until the two paths meet. A drawback to this method is the possibility that the two paths may run parallel to each other and never cross. But, if they do cross, this method is particularly efficient. A bidirectional heuristic search does not require domain-specific knowledge (Rich, p. 60).

**Decision Trees and Graphs**

A decision or problem tree is a mechanism for controlling forward and backward chaining. A problem tree can be compared to the roots of a tree, where the branching and number of roots expand exponentially throughout the system. Each juncture point where new roots or paths are extended is referred to as a node.

If several rules can be applied in a particular situation, then the system must resort to both forward- and backward-chaining mechanisms in finding the rule relevant to that instance. The total set of possible legal alternatives that could be applied in a situation is referred to as a tree. A structured search through nested If . . . . Then
statements is conducted in order to select the most appropriate rule to apply.

A decision tree is a generative process where a node is generated at each step of the search. Problem trees generate families of nodes that can result in duplicate nodes at different paths with the same node or step being processed more than once. Although the tree may be a simple technique, it can also be inefficient. For example, in Figure 2 (Rich, pp. 60-61), note that the node (4,3), representing 4 gallons of water in one jug and 3 gallons in the other, is repeated twice in the tree. It appears as a result of first filling a 4-gallon jug and then filling the 3-gallon jug, or the reverse. Another node that repeatedly occurs in this tree is node (0,0). It appears as the starting node and as the alternative solutions. Since (0,0) is not an acceptable solution to the problem, these two nodes should be deleted (Rich, pp. 60-61).

![Figure 2. Breadth-first search tree.](image)
A search graph is like a tree except that several paths may come together at the same node, thus eliminating the duplication of the same node at different paths. Figure 3 (Rich, p. 61) is an example of a search graph corresponding to the tree in Figure 2.

![Search Graph Diagram]

**Figure 3.** A search graph.

A tree search could be converted to a graph search simply by changing the action performed at each step rather than automatically generating a node each time. This would be done by analyzing the set of existing nodes to ascertain that the new one does not already exist before adding it to the graph. If it already exists, the direction of the path is changed to point to the existing node and then the duplicate node is eliminated. Or, the shortest distance
obtained by using either node is determined then the node with the longest distance is eliminated and the directions of the paths are changed so that they both point to the same node (Rich, p. 62).

Matching

Matching in a rule-based system means selecting the most appropriate rules from a collection of rules, any of which could be applied to the situation. This is done by matching the current state with the preconditions of the rules and pulling from this collection all the rules that match the preconditions, thus indicating the paths that potentially lead to the solution (Rich, p. 65).

Problems with matching arise when the preconditions are not described as exact situations but as properties of varying complexity that the situations must have. Another problem in the search process is the time-consuming act of exhaustively searching through a huge number of rules that could be applied. To address these particular problems, several unique matching techniques have been developed: indexing and approximate matching.

Indexing. To search effectively and efficiently through a large collection of rules, an index, such as a number, is assigned to each search state. All possible rules that could be applied in a particular situation are grouped and stored together under a key for easy access. All rules describing a similar precondition are found
together. Rather than searching through all the rules that might apply, the current state is used as an index to a selective collection of applicable rules. From this group, the search process immediately selects the matching ones.

Although writing rules in as general a way as possible allows them to be applied to numerous similar conditions, the matching process as described here calls for rules to contain specific descriptions rather than general applications. The rules in this situation are tied too specifically to the particular state and thus loose generality usually needed for more complex problems (Rich, p. 66).

Approximate matching. Approximate matching is more desirable than exact matching in such situations as speech recognition, where an approximate match is made between the preconditions describing a particular physical waveform and the actual input. Selection of the appropriate rule to apply to the particular situation is deduced from the use of a set of rules describing how some properties can be inferred from others, thus narrowing the selection to a few applicable rules. The program becomes more complex as the sound recognition capabilities of the program become more perceptive and discriminating. The number of rules is directly proportional to the program's capacity to recognize a greater number of sounds of varying qualities.
ELIZA developed by Joseph Weizenbaum in 1966 is an early example of an approximate matching program (Rich, p. 68). ELIZA simulated the behavior of a Rogerian therapist in the type of questions asked of the client/user. ELIZA was able to have an interactive dialog with the client by matching certain keywords in the client's response to its own database of rules indexed by keywords. In the following example, ELIZA's dialog has been capitalized to distinguish it from the client's:

Men are all alike.
IN WHAT WAY
They're always bugging us about something or other.
CAN YOU THINK OF A SPECIFIC EXAMPLE
Well, my boyfriend made me come here.
YOUR BOYFRIEND MADE YOU COME HERE
He says I'm depressed much of the time.
I AM SORRY TO HEAR YOU ARE DEPRESSED
It's true. I am unhappy.
DO YOU THINK COMING HERE WILL HELP YOU NOT TO BE UNHAPPY
I need some help, that much seems certain.
WHAT WOULD IT MEAN TO YOU IF YOU GOT SOME HELP
Perhaps I could learn to get along with my mother.
TELL ME MORE ABOUT YOUR FAMILY (Rich, p. 68).
In this activity, the program matches the applicable rules to the current state using a technique referred to as
keyword matching. Major words in the input sentence are identified and matched against simple templates of keywords. Once the keywords are recognized, the rest of the sentence is disregarded. The following program script is used by ELIZA to interpret input sentences:

(HOW DO YOU DO. PLEASE TELL ME YOUR PROBLEM)

START

(ME = YOU)

(I = YOU)

(REMEMBER 5

((0 YOU REMEMBER 0) (DO YOU OFTEN THINK OF 4)

(DOES THINKING OF 4 BRING ANYTHING ELSE TO MIND)

(WHAT ELSE DO YOU REMEMBER)

(WHY DO YOU REMEMBER 4 JUST NOW)

(WHAT IS THE CONNECTION BETWEEN ME AND 4)

((0 DO I REMEMBER 0) (DID YOU THINK I WOULD FORGET 5)

(PERHAPS ((0) (YOU DON'T SEEM QUITE CERTAIN)

(WHY THE UNCERTAIN TONE)))

(COMPUTER 50

((0) (DO COMPUTERS WORRY YOU)

(WHY DO YOU MENTION COMPUTERS)

(DON'T YOU THINK COMPUTERS CAN HELP PEOPLE)))

(MACHINE 50 (=COMPUTER)

(MOTHER DLIST(/NOUN FAMILY))

(MOM = MOTHER DLIST (/NOUN FAMILY))

(DAD = FATHER DLIST (/NOUN FAMILY))
Each keyword template is associated with an output template or templates that produce an acceptable response by ELIZA as related to the client's input sentence. Each input template is associated with one or more output templates. If several outputs exist, then ELIZA cycles through them and randomly selects one.

Instead of recognizing a whole sentence, ELIZA's script is organized by primary keywords, such as remember, which has two input templates:

(0 YOU REMEMBER 0)
(0 DO I REMEMBER 0)

Here, 0 matches any number of words in the sentence, including none. The script automatically converts common
words like me into you and I into you. Thus, if the input
was "I screamed," ELIZA would respond with "Why did you
scream?," substituting you for I in its response.

In the example of ELIZA's program script, the number 4
indicates parts of the input statement that have to be
matched and generated at that corresponding location in the
output statement. For example, in response to the input
statement, "I remember the first time I went to the beach,"
ELIZA would respond "Why do you remember the first time you
went to the beach just now?" In this example, the sentence
fragment the first time I went to the beach is represented
by the number 4 in the script, which is repeated in the
output which has substituted I for you.

In Weizenbaum's program, similar keywords are grouped
together, as the word class "family" represents mother, mom,
dad, and father. Words also are prioritized by assigning
words with numbers, as the word computer is ranked as 50.
If a sentence contains several keywords, the program selects
the word with the highest priority, such as computer. Words
used less frequently are given a higher priority than words
used commonly. The prioritizing helps narrow down the
search process by defining a few select rules that apply. 0
was assigned to input words that are not matched by the
keywords in the script. In response to the 0 template,
ELIZA responds with some general purpose responses, such as
"Can you elaborate on that?" and "Tell me more about that!."
The program does not understand the meaning behind the dialog nor does it attempt to. Once the matching is complete, the input is forgotten.

Conflict resolution. In conflict resolution, the matching process possesses some decision-making power, determining the order of the rules that will be applied. This is generally handled by the search method rather than the matching process. It can reason in both forward and backward directions (Rich, p. 59).

The decision making resides in the use of special case rules, such as the use of priority matching in ELIZA, where words with a higher priority rating are considered to be more semantically significant and selected for the match over other words.

Weak Methods

Weak methods are general-purpose heuristic techniques, general in the sense of no direct tie to a specific knowledge domain or task. They can be described independently of the domain, yet they are able to provide the framework in which the domain-specific knowledge can be placed. Weak methods typically are not used to solve complex problems.

A variety of heuristic search techniques are considered weak because their power in solving a problem is dependent upon the way that the domain-specific knowledge is searched. In this sense, these techniques are not as general as a
search technique, which can be described independently of the task, problem, or knowledge domain. The strength of a weak method is tied directly to the particulars of the problem. Weak methods are very popular in A.I. due to their ability to solve domain-specific problems.

**OR graph.** Most weak methods, such as generate-and-test, hill-climbing, breadth-first search, and the best-first search are based on a transversal OR graph. An OR graph starts with an initial state generating a set of arcs (paths), representing each alternative move than can be made. Like a decision tree, at the end of each arc is a set of successor nodes pointing to the alternative paths that can be transversed from here. An OR graph is generative in its reproductive ability to create successor nodes from an originating node. To solve a problem with an OR graph, the search must find a path through the graph to a final state by beginning at the starting node and transversing down to a successor node and then down to the successor of the second node. Figure 4 shows an OR graph.
Other kinds of problems require the use of the AND-OR graph, in which each node points to a group of successor nodes. The AND-OR graph is used to decompose a complicated problem into smaller and perhaps easier subproblems, which is referred to as problem reduction. The AND-OR graph will be explained next.

**AND-OR graph.** Unlike an OR graph, where only two successor nodes emerge from one node, the general purpose AND-OR graph can have a group of successor nodes extend from a node (Rich, p. 73). An AND-OR graph is useful for problems that can be reduced into smaller subproblems, which are then solved in addition to the larger problem. The process of problem reduction generates AND arcs from the problem leading to the group of smaller subproblems. One AND arc may point to several subproblems, all of which need solving. Like an OR graph, there are two alternatives leading to the solution. One of the alternatives may involve an AND arc, thereby requiring the solution of
several smaller problems before this arc can point to the solution. Illustrated in Figure 5 is an example of a simple AND-OR graph demonstrating the use of the AND arc with successor subproblems on the right half of the figure.

![AND-OR graph](Rich, p. 87)

Both subproblems generated by the AND arc, "earn some money" and "buy TV set," need to be accomplished in order to be considered an acceptable solution. Either one of the AND arc paths by itself does not provide a solution.

An example of problem reduction is seen in moving all the furniture out of a room. In order to do this, the problem is decomposed into smaller subproblems, such as removing the books from a bookcase and removing the lamp and candy dish from an end table; then the bookcase or table can be moved.

It is often useful to solve more complicated problems by decomposing the major problem into smaller, hopefully easier subproblems. Then, the partial solutions are
combined into a unified whole representing one solution step or alternative path pointing to the big goal.

**Depth-first search.** A depth-first search, also referred to as a brute-force algorithm, is the simplest kind of search algorithm and does not require domain-specific knowledge. A depth-first program will search a single branch of a tree until a solution is generated or until a requirement is met, at which point the search starts over by exploring the next branch (Rich, p. 34). Several depth-first techniques include nearest neighbor algorithm, generate-and-test, hill-climbing, and the mini-max algorithm.

**Nearest neighbor algorithm.** The nearest neighbor algorithm is a general purpose heuristic search that selects the locally superior alternative at each step. This technique is particularly useful for narrowing the search in exponentially explosive problems, which typically generate numerous families of subtrees with their successors. For example, this control structure starts by arbitrarily selecting the first path to search. Then, if a solution is not found, other paths are analyzed and the path most similar to the one just visited is then explored. If a solution is not found, then the next most promising or similar path is transversed. This procedure continues until either all the paths have been investigated or the goal is reached (Rich, p. 35).
**Generate-and-test.** The generate-and-test method is a simple approach. First the program generates a possible solution which is either a particular state in the problem space or a path leading to the acceptable goal. Then, it compares the possible solution against acceptable goal states to determine if the solution is acceptable. An acceptable solution ends the search process, otherwise, the search starts over from the beginning.

The generate-and-test approach is considered a depth-first procedure since it explores and tests an entire path to determine its validity as a solution before trying another path. This procedure is very exhaustive and systematic in its search and will usually find a solution. On the other hand, it is not very efficient because it explores paths that eventually turn up being futile.

A generate-and-test program that overcame the weakness of futile search was DENDRAL developed by Lindsay in 1980 (Rich, p. 74). DENDRAL builds models or organic compounds from mass spectrographic and nuclear magnetic resonance data through an adapted approach, called plan-generate-test, which includes a planning strategy. The planning component compares substructures to a set of constraints or restrictions in producing lists of recommended substructures that satisfy a specified set of criteria and lists of unadvisable ones. Then, the generate-and-test component
explores and tests only the recommended lists, thus limiting its search for an acceptable solution.

**Hill-climbing.** Hill-climbing is a locally superior depth-first method like the nearest neighbor algorithm. It is also a variation of the generate-and-test method whereby the testing component provides feedback to the generate component and thus helps its search. The testing part analyzes the chosen path in terms of an approximation to the solution and communicates this closeness to the generate function. The node with the closest estimate then is explored generating successor nodes. Nodes with a low approximation are disregarded. The search stops when an acceptable solution is found. If the node turns out to be useless, then backtracking to a prior node and trying that may be in order (Rich, pp. 75-76).

**Mini-max algorithm.** The mini-max algorithm transverses forward and backward through the various alternative nodes of a tree to determine the best possible node to be pursued as compared to alternate moves. Alternate means every other move, as in a game of chess. The best node is determined by analyzing the opponent's (the alternating level's) position and its consequences for the current move. The program then projects potential moves of the opponent, assuming that the opponent will move to maximize the chances for winning the game while minimizing ours. Knowing the consequences of the opponent's future move, the program moves in a direction
that maximizes our potential for winning the game while minimizing the opponent's chances.

In Figure 6, Rich (p. 188) diagrams a mini-max algorithm. If we were currently at position A and chose to move to B, we would find ourselves in trouble because our opponent would then move to either E, F, or G to maximize their potential while minimizing ours. To determine the best move, we have to look at possible successor nodes to see the future moves of our opponent. To determine which move would be appropriate, note the values of the bottom row of nodes. Pass the value of the worst node, with -10 being negative and +10 positive, up to the preceding node, that is, B is -6 because it took on the value of F, C takes on a value of -2, and so on. A look at these new values would indicate that the most appropriate move for maximizing our potential while minimizing the opponent's would be to move to C. The minimum or lowest, negative value is backed up to the current node level and then the move is made by selecting the node with the highest, positive value. Mini-max is a depth-first, depth-limited procedure where each path is explored as far down as possible, then that final value is passed up to the preceding node. This method is more effective than exploring the whole tree in that once a path is determined as unproductive it is not explored any further (Rich, pp. 117-118).
Alpha-beta cutoffs to the mini-max algorithm help in refining the search process by cutting off needless searching of branches. An alpha cutoff would be where a move is cut off because a preceding successor node has a higher value, therefore it is not necessary to continue the search of the remaining subtree branches. For example, in Figure 7 (Rich, p. 121), the evaluation begins with the left node in the bottom row and moves sequentially to the right. The lowest value derived from the successors is passed up to the originating node. Therefore, the value of 3 as derived from node D is passed up to node B. This value is referred to as the alpha value. In analyzing the next subtree C, it is observed that F has a value of -5 which is lower than the alpha value of 3. This value of -5 is then passed up to C and the search to node G eliminated. This is considered to be an alpha cutoff.
Alpha-beta pruning requires two threshold values: an alpha value, which is a low bound value that a maximizing node may possibly be assigned; and a beta value, which is a high bound value that a minimizing node may be assigned. Moves are made on alternating levels between maximizing and minimizing levels like game playing. The minimizing level can be thought of as the opponent's move. In Figure 8 (Rich, p. 123), the subtree of B is searched and the lowest value that B can have is 3, which is then passed up to B. The lowest value of A as derived from searching B would be 3. The alpha value for the maximizing player is 3 or more, which is then compared to the search of C's subtree F. When the subtree of F is searched, it is discovered that I is guaranteed a value of 0 from K. Because this value is less than the alpha value of 3, it is not necessary to transverse node L since the value passed up to I is already less than what can be achieved by moving to node B. Cutting off moves at the maximizing level is referred to as an alpha cutoff.
After cutting off the exploration of I's subtree, node J is pursued. J yields a value of 5 which is passed up to F, since it is greater than the current alpha value assigned to A. At this point, the value of F is equal or less than 5 and 5 is passed up to C guaranteeing that C will achieve a value of 5 or less. C's value is referred to as the beta value. Now node G is transversed starting with M, which yields a value of 7 that is passed up to G and compared to the beta value of 5. Since the maximizing player is trying to minimize the opponent's score, the subtree of G will not be explored since the value of 7 is greater than 5 and searching the subtrees of C will guarantee a value greater then the beta value of 5.

At the maximizing level, a move can be cut off if the current value is less than the alpha value. At the
minimizing level, the search will be cut off if the current value is greater than the beta value (Rich, pp. 121-122).

**Breadth-first.** A breadth-first search tree is a transversal problem tree in which each node of the tree is exponentially expanded by a generation of successor nodes, which in turn are expanded and so on. A breadth-first program will explore all the nodes at the same level then generate the next level of successor nodes by applying the appropriate rules. For example, Figure 9 (Rich, p. 33) illustrates the initial state and successor nodes.

![Diagram](image)

**Figure 9.** Breadth-first search at the first level.

Figure 10 (Rich, p. 33) shows how the tree would look if the subtrees were expanded. This generative process continues level by level, until a solution is found.
Figure 10. Breadth-first search at two levels.

A breadth-first search will explore all the nodes on one level of the tree before examining any others at the next level. Some weaknesses of the breadth-first technique are that many irrelevant nodes could be searched needlessly; redundant nodes could be generated, which will also increase the time expended in searching; and the breadth-first technique requires a lot of memory, since the number of nodes in each subtree increases exponentially and they must all be stored.

Best-first search. Is a solution absolute or relative? If one path will lead successfully to the correct solution, then is it necessary to even consider trying out other alternatives? In some problems, it may be necessary to search through the other paths in order to determine if the first path is also the best path. Determining the best path rather than the correct path is referred to as the best-valued or best-first search (Rich, p. 44). Best-first combines the best elements from breadth-first and depth-
first search techniques. At each level of the search, the most promising nodes are selected and only these nodes are expanded. The selection is made using a heuristic function that estimates the quality of each successor node and determines its priority rating. The search pursues the most promising node and its branches until either a solution is found or searching the subtree turns out to be futile. If a solution is found, then the search process ceases at this point. Otherwise, the search starts again at the second most promising node and its subtree. Again, the search pursues this subtree and its branches until either a solution is determined or the search of this subtree is abandoned. The sequential, prioritized searching of most promising nodes and their subtrees continues until all of them have been explored or a solution is found. If all of them have been explored without turning up a goal, then the most promising nodes from these subtrees are then selected and expanded. The search begins again, starting with the most promising node and transversing its branches until either a solution is found or the search of its branches is exhausted; then the second most promising node is explored. A best-first search is selectively generative.

Agenda. A type of best-first search is an agenda-driven system, which uses an agenda to determine the most appropriate task to perform next. An agenda is a list of tasks to be performed, each task associated with the reasons
justifying its existence on the list and a rating indicating the quantity and quality of useful evidence supporting the task (Rich, pp. 84-85). Heuristics are used to determine which tasks are to be proposed or included on the agenda and how promising and interesting they might be, based on substantial evidence supporting the fruitful characteristics of the task.

An agenda-driven system first selects the most promising, highly rated task from the agenda and executes it, which might in turn generate additional tasks or successor nodes. Each newly generated task is compared to the agenda to see if it already is listed. If listed, the reasons behind the task are checked against the list of justifications to see if these are new or different. If the reasons are the same, then the task is ignored; if they are new, then the task and justifications are added to the agenda. Next, the newly added task is rated by averaging the weights attached to its justifications. Then, the next most promising task is chosen from the agenda and the cycle starts over.

One way of inserting new tasks to the list is by comparing their priority ratings against those already on the list. If the justifications of a task change, then the ratings change and its revised rating is used to correctly place it in the list.
Another way to insert a task, which is more efficient than the last method, is to compare its rating to the top 5 or 10 tasks and, if it is equal or better, insert it at the appropriate place; otherwise, just add it to the bottom of the list. Then, begin the next cycle at the top of the list. Occasionally, reorder the tasks to ensure their proper sequential positions.

An agenda system is a good means for incorporating a variety of information from various sources, where all of the information is useful and relevant at different times. These systems are particularly useful for complex A.I. systems, which draw upon several forms of knowledge (Rich, p. 86). Lenat's program AM developed in 1977 uses an agenda (Rich, p. 84). It operates in cycles choosing the best task from the agenda and then performing it (Rich, p. 375).

Means-end analysis. The means-end analysis technique reasons both forward and backward in order to reduce the differences between the current state and the goal state (Rich, p. 59). Means-ends analysis first defines the differences between the current state and the desired goal state, and then chooses rules that have been identified as relevant to reducing those differences. A variety of heuristic functions can be applied to pick the most appropriate rules from a group of rules that reasonably could be applied.
To perform means-end analysis, first select an operator that detects and defines the difference between the current state and the goal state. Once this is defined then it is the job of the operator to reduce this difference. A table is usually set up identifying the various operators available for reducing the differences between the given state and the goal state. A problem that might arise is when for some reason the operator cannot be applied directly to the current state and, therefore, a smaller subproblem is set up. Within the subproblem, the operator can work, reducing the difference between the subproblem and the current state that it desires to be at. Another problem is when the operator produces an undesirable goal state. Then, another subproblem must be set up allowing the operator to reduce this difference.

The means-ends analysis relies on a set of heuristics to transform one problem state into another. The first kind of heuristics described the conditions that must be met in order to be able to apply the rule and the second kind of heuristics were those that described specific characteristics of the problem state that would be modified as a result of applying the rule (Rich, p. 100).

The means-ends technique could be applied to the problem of having a robot move a desk with items on the desktop across the room without breaking anything. The problem would be to reduce the difference between the
initial state of where the desk is currently located and the goal state, which is the position across the room. To move the desk, the robot could either push or carry the desk. Moving the desk would imply the reduction of some small differences between the present state and what needs to be done, such as removing the items from the desktop with pickup and putdown routines. Then, the desk could be pushed across the room using walk and push routines. Once the desk is in the proper location, then the difference between where the items were left on the other side of the room and the new location of the desk must be reduced with pickup, carry, walk, and place routines (Rich, p. 102).

To make the search effort efficient, the significant differences should be reduced before lower priority ones. The means-end analysis technique goes about solving the big problems first and then returns through recursive programming means to working on the small problems. Significant problems can be given a priority rating to ensure that they are tackled first by the means-ends approach.

An early means-ends analysis program was the General Problem Solver developed by Newell in 1963 (Rich, p. 368). Newell modelled his program after the steps he thought people took in thinking when they solved problems. The most significant result that came out of Newell's program was the notion that programs can be constructed to show the
performance of the system in learning a task where learning is correlated to the reduction of differences existing between the present state and the goal state.

Conclusion

This chapter provided an extensive overview of A.I. programming techniques with examples for problem solving and knowledge representation. Commonly used A.I. means of acquiring, representing, and reasoning with knowledge that were covered included frames, semantic networks, scripts, and predicate logic. These methods showed how knowledge is represented symbolically as formalisms in an A.I. system and how the system was used in order to draw inferences, conclusions, and solutions for problems from the domain-specific database(s).

Heuristic search involved finding a solution to a problem by exploring a problem space for a path from the initial state to the desired goal state. Research on heuristic search focused on ways for formulating a problem so that it could be solved with heuristic search techniques. All search techniques follow this basic pattern of exploring various alternatives in search for the solution, but their methodology may differ in order to accommodate the type, quantity, complexity, and approximateness of the knowledge being explored. Popular heuristic search methods for problem solving discussed were problem trees and decision
graphs, forward and backward reasoning, weak methods and matching.

A.I. programmers are concerned with writing A.I. algorithms that concentrate on finding a solution in an efficient and economical manner. Efficiency involves reducing and possibly eliminating the need to perform the same tasks repeatedly or perhaps to perform futile tasks needlessly in the search. Other concerns include reducing the amount of time it takes for an algorithm to execute its tasks, reduction of the amount of computer memory required, and elimination of duplicate nodes or tasks that are generated through the generative process of problem solving (e.g., tree structures). A.I. researchers are interested in finding a universal formalism or algorithm to represent cognition that could be applied to an infinite variety of problems without having to revise the algorithm to fit the unique specifics of every problem.

The field of A.I. research has much to offer cognitive scientists in the opportunity to use algorithms to test out psychological theories of intelligence. By using a computer to perform cognitive tasks perhaps a better insight into understanding human intelligence and processing of knowledge can be gained by observing how a machine performs various cognitive functions.

A.I. research has drawn primarily from the fields of psychology, computer science, and electrical engineering in
developing models of human cognition. Much of what has been studied in cognition in A.I. concentrates on the semantic and logical aspects of intelligence while ignoring such influences upon cognition as emotions, mood, feelings, attitudes, and values. A basic assumption underlying the A.I. techniques presented in this chapter is that cognition is synonymous with linear problem-solving processes. This approach assumes that thinking is discrete and stops when the goal is reached and the problem is solved, and only begins again when another problem is presented. This assumption does not address the issue that not all aspects of cognition can be explained as problem solving including such areas as day dreaming and hallucinations. A strict logical approach to cognition ignores the wide range of processes involved in thinking while assuming that all thinking is linear and not continuous. In the next chapter, I reviewed the basic cognitive theories of emotion drawing from the field of psychology and related these to the cognitive research in A.I. and Best’s aesthetic concepts related to cognition.
CHAPTER III
COGNITIVE THEORIES OF EMOTION

Introduction

In this chapter I reviewed and analyzed the background and historical literature from the areas of the psychology and philosophy of emotion. This literature described the evolution of emotional theory from, first, a physiological perspective, to one involving cognition, intent, and arousal, to the more current interactional, phenomenological view. Some of the literature was definitional, drawn from the different psychologists and philosophers concerned with theories in emotion and cognition. One of my major sources was Strongman (1973), who described, categorized, and analyzed significant emotional theories in cognition. In the last section of the chapter, literature was presented that emphasized the relationship between emotional research, A.I., and art.

Neurophysiological Theories of Emotion

Much of the early research analyzed the physiological aspects of emotion, focusing on physical changes in the central and autonomic nervous systems resulting from emotional change. For example, Cannon's neurophysiological
theory of emotion of 1927 emphasized the importance of the thalamus, a part of the brain, in stimulating neural emotional responses (Strongman, 1973, p. 16). His theory viewed emotion as occurring almost simultaneously with the bodily changes. Because much of the experimental work behind Cannon's theory was carried out by Bard, the thalamic theory is commonly referred to as the Cannon-Bard theory. Basically, the Cannon-Bard theory explained emotion as resulting from a series of events. First, the individual physically perceives the environmental stimulus, which triggers impulses to the cortex. The cortex then sends messages to the thalamus, which releases a nervous discharge referred to as an emotional expression. Particular emotional responses are tied to the specific chain of events. The Cannon-Bard theory was significant in that it drew attention to the neurophysiology of emotion.

Papez's theory of 1937 also had a neurophysiological basis (Strongman, p. 59). Papez differentiated between the behavioral expression of emotion involving the hypothalamus, a theory similar to the Cannon-Bard theory, and subjective emotional experience, which is felt by the individual but not necessarily expressed. According to Papez, the difference is caused by how the thalamus mediates the incoming receptors of the stimulus, resulting in different neural outputs. Papez's theory stressed the significance of
cortical mediation in determining emotional expression or experience.

In 1968, Bindra presented a neurophysiological theory of emotion and motivation that can be accounted for by what he termed the central motive state (CMS), that is, an interaction between environmental stimuli and physiological change that causes a change in neurons in the brain (Strongman, pp. 19-21). The environmental stimulus and physiological action must occur at the same time to produce a CMS, and the resulting CMS is dependent on this particular interaction. Bindra's theory is unique in that both physiological and environmental stimulus are considered integral components of the CMS, rather than separate and distinct elements.

These studies described the causes of emotion in an experimental, scientific manner. Although studies noted the changes in the subject's physiology, they were not able to explain the makeup of emotions in terms that distinguished among the various emotions and the varying degrees of emotional intensity. The matter was further complicated by the fact that identical physiological changes could be associated with different emotions. Furthermore, these studies were not able to explain why it was also possible to experience an emotion without any physiological changes.

Theories with a neurophysiological orientation generally viewed emotion as a change in one's normal
physical processes, of which there may or may not be awareness. For example, physiological change could be as simple as a change in pulse rate or an increase in blood pressure.

The neurophysiological orientation does not take into account the individual's thoughts or interpretation of the event. A neurophysiological orientation looks strictly at the physical changes, such as a neural change in the brain, and labels these changes *emotions*. According to the neurophysiological view, emotions are innate; individuals are born with the capacity for emotions.

**Behavioristic Theories of Emotion**

Later studies on emotion tried to demonstrate a causal relationship between behavior and its stimulus. Studies such as these are referred to as *behavioristic*, since they deal with changes in behavior as a response to the stimulus. In this view, emotional behavior is simply a reaction to stimulus, and environmental stimuli play a significant role in affecting an individual's behavior.

Moving beyond a strict neurophysiological account of emotional behavior, to one that recognized other, nonphysical factors, was a 1950 study by Rapaport (Strongman, p. 31). Rapaport proposed a psychoanalytic, behavioristic theory that asserted, "the substrates or psychic processes underlying emotion were unconscious" (Strongman, p. 31). According to Rapaport, emotion was
instinctual and innate, but other forces, such as the psyche and dreams, influenced the emotional behavior. Persons were born with the capacity to experience emotions, given the appropriate stimuli.

McDougall’s 1910 theory distinguished between emotion and feeling (Strongman, p. 16). According to McDougall, feelings were rooted in cognition, such as anxiety and hope, and were conditioned by positive or negative experiences and influenced future feelings. Emotions, such as curiosity and fear, were instinctive and neurophysiological, and did not affect later experiences. All behavior stemmed from avoiding negative things and responding to the positive ones, such as food. Two emotions, pleasure and pain, modified all goal-directed behavior.

A study that divided the realm of emotions into two distinct, polar categories was Young’s, whose 1961 study spoke of emotion in terms of pleasantness and unpleasantness, as affective processes arranged on an hedonic continuum (Strongman, p. 28). The affective processes would vary in degree from extremely negative to extremely positive, and in length of duration. All behavior was accompanied by an underlying affective process that directed and influenced the resulting behavior.

In 1929, Watson formulated a behaviorist theory of emotion, which emphasized the resulting external behavior rather than internal feelings and thoughts (Strongman,
In differentiating between emotion and instinct, Watson identified three fundamental types of emotions that were built in from birth—fear, rage, and love—which he labelled X, Y, and Z in his model.

In 1967, Millenson presented a modern behaviorist theory of emotion by studying it as one aspect of behavior. According to Millenson, all emotions were based on three fundamental emotions—terror, pleasure, and anger (Strongman, p. 35). Some emotions, such as sorrow, were more intense versions of a fundamental emotion, while others were a combination of these three. Millenson constructed a three-dimensional model of emotional intensity: dimension one was terror, anxiety, and apprehension; dimension two was elation, ecstasy, and pleasure; and dimension three was anger, rage, and annoyance. Even the more complex emotions were still rooted in the original three. Millenson's emotional coordinate system was only a model representing primary emotions, since many more emotional terms could be added to these. Watson's X (fear), Y (rage), Z (love) theory of 1929 was the model for Millenson's postulate of these three basic emotional dimensions (Strongman, p. 18). His strong behavioristic theory emphasized the roles of empirical behavior and environmental conditions, which he believed to be entirely responsible for an individual's emotional reaction. Although the environmental conditions controlled the behavior according to Millenson, he proposed
three methods for controlling emotions that were drawn from a behavioral perspective. Continual exposure to (1) the emotion-producing stimulus could lead to adaptation of behavior, e.g., from tolerance to frustration; (2) learning to control outward physical gestures, such as maintaining a poker face; and (3) avoidance of emotion-producing situations (Strongman, p. 35).

Some of the behavioristic studies took on a more psychological explanation, as in James' theory of 1884. James proposed that emotion was an after-effect of the stimulus-response reaction. For example, "we hear the lion roar, run and then feel afraid" (Strongman, p. 3). The emotional response is felt as a visceral and muscular reaction prior to the cognitive assessment and labelling of it. James emphasized three significant emotional components: (1) emotional stimuli, that is, the physical or social environmental features triggering the response; (2) the emotional behavior—the felt bodily changes; and (3) the emotional experience—the internal cognitive effect and labelling of the physiological response. Although all emotions are felt in some way (for example, increased breathing or sweating), and different emotions are felt differently, some emotions are more obscure than others. Perception of the external environmental stimulus will automatically lead to a neurophysiological reaction. The cognitive acknowledgement of these neurophysiological
reactions is the emotional experience, or what James referred to as the emotion.

James' theory was considered the first psychological theory of emotion. He placed the visceral bodily reaction before the cognitive experience. For example, "We feel 'happy' because we are laughing" (Strongman, p. 44). James' theory was significant because it moved the research away from physiological explanations toward an emphasis on psychological factors. As a result, psychologists discovered that individuals could learn how to control their emotional responses. This discovery was particularly helpful to psychologists working with emotionally disturbed clients.

In Feeling and Reason in the Arts (1985), Best, a British art educator, was critical of studies that made large generalizations about emotion based on physiological or behavioristic theories. According to Best, measuring physical changes, such as a rise in blood pressure or number of heartbeats, does not explain an individual's emotions. Analyzing emotion from a strict neurophysiological perspective does not provide answers to several important questions. How can we determine which emotion is experienced based solely on pulse rate? How can we determine the degree and intensity of the emotion being experienced by the individual? Best pointed out that there were times when an emotion may be experienced without any
physical signs. He was strongly opposed to the measurement of emotions: "Emotions cannot be measured, not because it is too difficult but because the very notion of measuring emotions makes no sense" (p. 91). According to Best, if a correlation is to be made between an individual's emotional state and physiology, this correlation should be made only after first identifying the emotion and then observing the physical condition, and not the reverse.

Best noted that behaviorism could only account for those emotions that are expressed outwardly in an observable physical manner. Behaviorism, according to Best, cannot begin to explain those emotions that are felt internally but not expressed externally (p. 94).

Behavioral analyses of emotion, as a whole, have added very little to general theories of emotion. Except for Milleson's model of emotion based on the three fundamental emotions of terror, pleasure, and anger, most of the behavioral analyses "are deficient in one or more respects" (Strongman, p. 125). Behavioral analyses of emotion tend to be too speculative, cannot be tested empirically, or draw conclusions that are too broad when tested. Theories of emotion need to describe characteristics of the specific behavior and the situations in which the behaviors occur.

Cognitive-Behavioristic Theories of Emotion

Several behaviorist studies emphasized the relation between cognition and emotion, therefore extending emotion
theory beyond behavioristic stimulus-response concepts. Studies by Schachter and Singer in 1962 suggested that emotion depended on cognition, as well as both the autonomic nervous system and the situation (Purcell, 1984, p. 192).

Schachter believed that cognition and arousal were strongly interrelated and he emphasized heavily the role of cognition as a determinant of the emotional state. By that, Schachter meant that the emotional state is due to and caused by the individual's interpretation, appraisal, and perception of the stimulus, and thus results in general arousal of the physiological nervous system. Schachter's 1959 theory of emotion was a cognitive-physiological one (Strongman, p. 25). Emotion presupposes a physiological arousal, and this arousal is due to the individual's cognition, derived from internal and external cues about the stimulus. According to Schachter, there is no basic difference among the physiological symptoms of emotional states. Differences among emotional states are due, instead, to cognitive labelling.

According to James' study in 1884, an individual first perceives the stimulus, then reacts in a behavioristic manner, and finally experiences the emotion afterwards. Emotion is not simply a behavioristic stimulus-response theory, it also involves cognitive appraisal, thus demonstrating an interaction between the internal and external cues involved in emotion.
Three Major Cognitive-Emotive Approaches

Cognition involves the individual's thoughts and interpretation of the perceived stimulus. The cognitive interpretation or evaluation of the stimulus influences how an individual will respond to the stimulus. Studies that looked at the relationship between cognition and emotion have basically emphasized the sequence of processes, that is, which occurs first, the emotion or cognition? The majority of research in the area of cognition and emotion has been of three types: (1) thought precedes emotion; (2) emotion precedes thought; and (3) emotion and thought are viewed as a holistic process, in which both processes occur at the same time. In surveying the various studies on cognition and emotion, Strongman noted, "there have been sufficient cognitive approaches to emotion to ensure that this type of analysis is firmly entrenched" (p. 90). The following material describes these three cognitive-emotive approaches in greater detail, along with their related theories.

Thought precedes emotion. According to this view, emotion occurs as a consequence of cognition. An individual first perceives the stimulus in a neurophysiological manner, then interprets the perception. Finally, the individual responds emotionally to the situation as a result of the cognitive analysis. This theory is illustrated in the following example, "My emotional response would be very
different if I believed that the object lying on the ground was a twig than if I believed it to be a snake." The individual interprets and evaluates the stimulus before responding. The emotion is the behavioral output resulting from the perception and interpretation of the stimulus. The environmental stimulus in this example is considered the external cue. The individual's cognitive appraisal of the situation is based on prior knowledge and experiences, which are referred to as internal cues.

In 1970, Valins recognized the significance of internal cues in determining the emotional response and conducted research in this area (Strongman, p. 75). He added a third dimension to the analysis of internal and external cues in emotion. He termed this dimension veridicality, which means the ability to safely read and reasonably interpret the situation with some degree of accuracy. This activity required that the individual be able to distinguish between relevant and irrelevant input in determining the appropriate course of action.

The veridical approach has been illustrated in Schachter's work. Schachter noted that perception of bodily change is distinct from the bodily change itself. Schachter was a strong proponent of studying cognitions to gain an understanding of emotions. Cognition can help individuals identify and label their emotions. From his experiments, Schachter concluded that there was little physiological
differentiation between emotional states and that how these states were labelled was a cognitive matter (Strongman, p. 70). Schachter was careful in separating cognition from emotion and recognized that, perhaps, the emotion occurred prior to the cognitive recognition of that emotion.

Valins interpreted Schachter's concepts to mean that individuals label their experiences with words, which then are associated with the emotions. Valins' research in 1970 emphasized the significance of language and cognition in labelling emotions with descriptions, words, and explanations (Strongman, p. 75). This labelling can further individuals' understanding of themselves and their emotions. It is difficult to determine from Valins' work if he believed the emotional experience influenced the internal, cognitive interpretation and labelling or the reverse. Valins work could be interpreted in this way: Prior emotional experiences influenced cognition, and emotions occurred before thoughts, since words label the emotional experience after it has been experienced. Valins' methodology, in which individuals label their emotional experiences with words describing the phenomena, can help us understand individuals in terms of their emotional responses. Valins elaborated on this view by pointing out that, if a certain stimulus can be identified and associated with an emotion, it would be possible to predict that a particular emotional behavior will result. Once this
process is understood and the appropriate stimulus associated with the emotion, it would be possible to predict, explain, and control the resulting emotional behavior. Valins criticized Schachter's work because Schachter made no explicit connection between how the internal and external cues affected the resulting emotional behavior (Strongman, pp. 75-76).

To distinguish the role of internal and external cues in influencing emotion, in 1966 Valins conducted research aimed strictly at "nonveridical" perceptions, emphasizing the role of cognition in determining the emotion (Strongman, p. 76). Some of Valins' studies on nonveridical perceptions involved deceiving subjects about their bodily reactions, such as telling the subjects that they were aroused and that their heartbeats had quickened while viewing a particular nude photo, even though this was not actually the case. Valins would then observe the effect this deception had on the subjects' behaviors. To do so, he displayed the same pictures again while noting if the subjects experienced any physical changes, such as an actual increase in heart rate, when viewing the photos that they were told had aroused them. Valins' study showed that individuals could be deceived about their emotional response and this deception affected how they responded in future situations when subjected to the same stimulus. Cognition could influence and, ultimately, control emotional behavior.
In 1960 Arnold posited a theory of emotion that was a mixture of cognitive and physiological approaches (Strongman, p. 81). Her theory depended on the concept of appraisal as a determinant of emotion. Appraisals intervened between environmental stimulation and the physiological, behavioral responses. Appraisals were the cognitive evaluations of each incoming stimulus as to whether it was good or bad. Strongman was critical of Arnold's sketchy conclusions, and found it difficult to make such broad generalizations about the role and influence of appraisals, particularly when these appraisals were themselves unobservable, with only the resulting behavior observable (p. 81). Arnold concluded that more research was needed to investigate the relationships among perception, emotion, and action.

Lazarus's work in 1968 was unique in that he stressed the importance of cognitive, biological, and cultural influences on emotion. He suggested that a cognitive/phenomenological approach that accounted for biological and cultural factors would put research of emotion into the "forefront of psychology" (Strongman, p. 29). Like Arnold, Lazarus viewed emotion as a response to appraisal. Both believed that appraisal was essential to emotion. Cognition preceded emotion and caused physiological and behavioral change. Each incoming stimulus was evaluated to determine whether it was good or bad.
In 1965 Lazarus demonstrated that emotional reaction could vary in intensity due to cognitive appraisal (Strongman, p. 84). He compared reactions of subjects who viewed a benign kind of film and a "stressful" kind of film that illustrated an Australian Stone Age culture's ritual subincision of the young male's penis and scrotum using a sharpened stone. The subincision film generated more emotional reaction and disturbance than the benign type of film. In addition, the intensity of the emotional reactions varied when different sound tracks were used with the subincision film. From experiments like this, Lazarus concluded that emotional reaction was the result of cognitive appraisal and that emotional appraisal could be manipulated. Although Lazarus found it difficult to define emotion and the defining criteria distinguishing among the various emotions, he believed that emotional states eventually would be differentiated from one another by defining the specific physiological, cognitive, behavioral, and stimulus characteristics.

According to Lazarus, the individual was first aroused in a neurophysiological way in the perception of the stimulus. The individual then made a cognitive appraisal of the phenomena with, finally, an emotion resulting. Strongman was critical of Lazarus's appraisal theory of emotion for the same reasons that he opposed Arnold's--these theories were difficult to evaluate empirically.
In contrast to Lazarus's concept of emotions as an organizing, adaptive, coping mechanism was Pradines' theory of 1958. Pradines regarded emotions as maladaptive, disruptive, and disorganizing. Concerned with distinguishing between adaptive and maladaptive processes, Pradines differentiated between feelings and emotions and noted, "Emotions are simply sentiments in extreme, explosive, crisis form" (Strongman, p. 32).

In 1960 Berlyne introduced a theory that was similar to Lazarus's in that an emotional response was recognized as an adaptation function resulting from cognitive appraisal of the situation (Harvey, 1965, p. 247). An emotion was the way an individual coped with the situation. Unlike earlier theories, such as James of 1884, which viewed the individual somewhat as a helpless, inhibited being reacting to environmental stimuli without having an impact on the input, Berlyne's theory of emotion emphasized the role of cognition and, in particular, the cognitive aspect of how an individual seeks out novelty. Negative emotions could result from too much complexity, where the individual was bombarded with more stimuli than he or she knows what to do with and, as a result, became nervous and anxious. At the other extreme, the individual would become tired and bored as a result of too few stimuli. Berlyne's theory accounted for an individual's maintenance of a satisfactory level of arousal and excitement and an effort to reduce tension.
resulting from too much or too little stimulation. Berlyne viewed emotional response as far more complex than just stimulus-response. His theory also brought attention to individual differences in emotional response. For example, an individual who was familiar with a situation because of past experiences and knowledge would react somewhat disinterestedly to the newly presented stimulus. An individual who considered this situation novel because of unfamiliarity with the stimulus might act anxious and excited (Berlyne, 1974, pp. 325-326).

Lindsley viewed arousal and motivation as underlying mechanisms for emotion in his 1950 psychological activation theory, which emphasized arousal of the automatic nervous system and/or limbic-cortical system, which controls the resulting emotional behavior. The resulting emotion is expressed in neurophysical terms (Strongman, p. 19).

Nowlis and Nowlis's research took into account an individual's interpretation of the perceived stimulus and how this interpretation could affect the emotional response (Strongman, pp. 78-9). The Nowlises looked at both internal and external cues and their relationship to mood. Their research spanning from 1953 to 1970 differentiated between mood and emotion. In terms of breadth, mood was related to emotion (and some moods might be emotional), but mood was more enduring than emotion as in the expressions "I am in the mood," or "He is moody." More specifically, emotion
occurs at the onset of behavioral change, while mood occurs thereafter. A mood, such as depression, is long-lasting. An emotion, such as fear of heights, is experienced immediately in direct response to the stimulus and is short-lived. According to the Nowlises, mood was seen as less intense but more enduring and continuous; emotion was seen as more intense and explosive. This sense of endurance and sequence of occurrence, referred to as breadth, is the Nowlises contribution to the study of emotion.

**Emotion precedes thought.** This approach viewed the individual as first responding emotionally to a stimulus, then analyzing cognitively, and, finally, labelling the emotion afterwards. For example, an individual planning a trip to an unfamiliar location will emotionally prepare for the new experience. Upon leaving the site, the individual’s feelings will be firmed up as a result of cognitive evaluation and appraisal of the newly experienced situation. Often times, these emotions will vary in intensity when compared to both those emotions experienced prior to the actual trip and the cognitive analyzation of the trip.

In 1984, Lewis, Sullivan, and Michalson observed that some emotions occur before cognition, as in a student preparing for a test or for a new learning experience. They noted,

> it seems clear that some emotions occur before what is traditionally viewed as the solution of a problem, or
learning, and others come later. The particular emotions observed, rather than causing or resulting from a cognitive process, seem to interface with learning, providing the setting for each learning phase as well as resulting from that learning. (p. 285)

According to their theory, emotions are like motives or drives that do not require cognition prior to occurrence. This study suggested that positive and negative feelings could have a bearing on one's thoughts and particularly on how one learns.

Leeper emphasized the role of emotion as a motivating force organizing cognitive and behavioral processes. Going beyond Lazarus's theory of emotion as an adaptive, coping function, Leeper argued against the idea that emotions arise from disorganization and, in fact, suggested that they are organizing. Leeper's theory of 1948 recognized emotional processes as motives that involved arousal activities and provided direction and persistence (Strongman, p. 86). Emotion was equivalent to motives, which Leeper regarded as perceptual and cognitive processes. He also argued against the separation of emotions and motives and suggested, according to Strongman, "that emotions should be seen as part of a continuum of motivational processes ranging from physiological motives through to clearly emotional motives" (pp. 86-87). Emotions were also viewed by Leeper as cognitive in that they convey information perceived from the
stimuli to the individual. Leeper considered emotion, motive, and perception as an interwoven process.

Similar to Leeper's concept of emotion as a motivating, organizing force is Izard's and Tomkins' 1966 theory, which regarded emotion as a motivational affect influencing cognition and behavior (Meichenbaum & Butler, 1980, p. 142). Izard and Tomkins differentiated between the results occurring from negative and positive affects: a positive affect provides the motivation for effective functioning, which is critical to creativity, learning, perception, and personality, and, conversely, negative affect is disruptive and suppressive. They identified three components of affect: (1) neurological, (2) behavioral, facial, bodily, and visceral responses, and (3) phenomenological, affect as a motive. Their theory, although somewhat obscure, suggested that one's cognitive constructs were made up of perceptions and that memories are goal-directed; that is, the images of one's desired end results strongly influence one's affect and the resulting behavior. In studies conducted individually by Izard, emotion clearly took into account many interrelated factors, such as physiological, hormonal, and cognitive.

**Emotion and cognition as an inseparable holistic process.** Unlike the preceding two approaches, which viewed emotion as an entity independent of cognition, this approach posited that emotion and cognition are in a continuous
symbiotic relationship, with both processes occurring at the same time, like the biological process of osmosis. Depending on the circumstances, either one may influence the other in a given situation, but neither occurs before the other as a separate, isolated process. Lewis, Sullivan, and Michalson (1984) described the relationship between emotion and cognition as an interwoven process that created a fugue or holistic composition (pp. 285-286).

Lewis, Sullivan, and Michalson emphasized the significance of studying cognition and emotion as an interwoven process when they stated, "Discussions of global emotional states (i.e., positive or negative) obscure interesting and significant aspects of the dynamic interplay between emotional and cognitive threads of behavior" (p. 285). Studying emotion as an isolated event and then drawing universal generalizations from isolated results obscures the rich and significant aspects derived from examining the interplay between emotion and cognition.

In a phenomenological study, Averill (1977) had subjects report their feelings during the experiment (Meichenbaum & Butler, 1980, p. 142). Averill recognized that other qualitative factors, such as values and attitudes, were influencing cognition, emotion, and behavior. Specifically, Averill emphasized that cultural values also affected cognition, emotion, and behavior. Although this method provided lengthy descriptions, the data
was difficult for Averill to categorize. In a 1975 study, Averill looked at language and emotions and discovered more negative words present in our language than positive ones. His study went on to provide criteria for identifying an emotion as positive or negative.

Plutchik's model of 1970 showed emotion as multidimensional, that is, emotions varied in terms of intensity, similarity, and polarity. For example, emotions varied in intensity, differing in degree from perhaps pensiveness to grief; emotions varied in degree of similarity to other emotions, that is, joy and anticipation are more similar than loathing and surprise; and, all emotions have polar extremes, e.g., repulsion is the opposite of acceptance. He discussed three sorts of languages used with emotion: (1) an everyday subjective language used to describe emotion, as in the example "we may be experiencing joy"; (2) a purely descriptive language based on behavioral observation, as in "behaviorally we are mating"; and (3) a functional language based on the adaptive function of what the organism does, as in "functionally we are reproducing" (Strongman, p. 22). In the three preceding examples, the same phenomenon could be described in three different ways or in what Plutchik refers to as languages. Plutchik's theory was formal in that it was structured with rules and definitions that could be empirically accounted for (Strongman, p. 5).
**Significant Factors of the Cognitive-Emotive Theories**

**Internal and External Cues.** As indicated in the cognitive-behavioristic theories, emotional response is not simply a matter of stimulus-response; internal and external cues affecting the arousal should be considered. For example, the internal interpretation or appraisal of a stimulus as to whether it is congruent with the individual's existing structure of meanings plays a significant role in determining the resulting emotional response, as demonstrated in the research by Schachter, Valins, Nowlis and Nowlis, Arnold, Lazarus, all cited in Strongman (1973). In addition, the individual's preferences and curiosity towards the event affect the emotion, as Berlyne in 1960 indicated (Berlyne, 1974, pp. 325-326). An individual's preferences, the cognitive selection one stimulus over another, definitely influenced the emotional response. These preferences can be either innate or learned. While it is possible to precisely study any one of these aspects as an individual, isolated factor, the richness of emotion is embodied in the interrelationship among the multiple variables, as noted by Lewis, Sullivan, and Michalson (1984). Emotion involves a multiplicity of variables and is multisensory, involving the whole individual interacting with the environment. Studying emotion as an independent element isolated from culture and environment is like attempting to understand a movie by looking at one still
frame. The "frame" may give some superficial idea of what an emotion is and show its characteristics, but it does not provide the human perceptions and depth of the emotion, as when the research considers emotion from a phenomenological, interactive view.

**Cognition as an organizing force.** James theory of 1884 stressed the role of cognition in emotion and viewed emotion as a means of maintaining cognitive order and consistency among experiences. According to James, we mentally perceive some fact, which produces a mental effect (emotion), which in turn causes a bodily expression. Emotional response is the result of resistance to change in light of new experience in an effort to maintain organization and a state of equilibrium (Harvey, 1965, p. 243). An individual will tend to maintain the existing cognitive structure of meanings about himself or herself and the world. The cognitive ordering system provides a way to show how an individual reads the world and integrates new input into the existing system. Conflict arises when the input is not easily assimilated into the existing system.

Although this theory was put forth by both James and Lange in 1884 and called the James-Lange theory, James was the strongest proponent of it over the years (Strongman, p. 38). James viewed individual emotional response (even in low-level animals) as an establishment and maintenance of its cognitive ordering system in the face of new stimuli.
This ordering system resists change and strongly enforces the existing system. Psycho-physiological theories, such as James' theory relied on external, environmental, or social sources for stimuli that cause general arousal. Empirical measurement of emotional behavior (or its physiological aspects) can be quite imprecise when correlated with the source of stimulus.

**Role of cognitive appraisal.** Harlow and Stagner's theory of emotion of 1933, which was based on a conditioning model, differentiated between those emotions that were learned ways of behaving and innate feelings (Strongman, p. 34). According to Harlow and Stagner, emotions were not innate; they were learned as a result of conditioning, and feelings were innate. Emotion was different from feeling because it involved cognition of the external stimuli. Individuals were born with the capacity for physiological feelings, which became emotions through cognitive analysis of the external stimuli. Individuals evaluated the stimulus to determine their meaning for them and behaved accordingly. Emotions were cognitively conditioned ways of behaving. In describing the difference between feeling and emotion, Harlow and Stagner provided an example in which fear and rage were basically viewed as the same with one exception: the external stimulus that brought them about was different. If the situation was threatening and attack was appropriate,
the emotion was labelled rage. If running away was appropriate, the emotion experienced was fear.

In delineating the various cognitive aspects that made up emotion, Duffy in 1934 presented a behaviorally oriented activation theory that regarded emotion as the same as arousal (Strongman, p. 33). Motivation, expectation, and arousal were predeterminants influencing the emotional response. According to Duffy, individuals prepared themselves to react in a certain manner based on expectations and an appraisal of the situation, as negative or positive, and as significant or not important. Duffy's theory was an activation theory because emotion was viewed as a change in energy level, which she referred to as an activation level, that changed depending on how the individual felt and acted towards an external stimulus. For example, an individual who felt depressed was experiencing a low-energy level and one who felt excited was experiencing a high-energy level. Behavioral action and energy level depended on the individual's cognitive expectations of the situation, that is, what was expected to be important and positive or negative. In Duffy's opinion, emotion shouldn't be a phenomenon separate from other responses, because all responses, not just emotional ones, require some change in energy level. She advocated a theory of "nonemotion" and actually suggested that the term emotion be dropped from
scientific usage, since it was like all behavioral responses in that it represented a change in energy level.

Arnold's work also looked into specific cognitive aspects, such as appraisal and how appraisal influenced the resulting emotional response (Strongman, p. 24). Her theory, which stretched across three decades from 1945-1970, was a mixture of phenomenology (cognition) and physiology. According to Arnold, emotion can best be understood by studying the brain's function in emotion, that is, by cognitively analyzing the physiological processes occurring from perception to emotion. Her cognitive analysis of emotion depended on a phenomenological analysis of appraisal. All perceived external stimuli were cognitively evaluated in terms of their value. As a result, the individual may act or ignore the situation depending on the appraisal. Arnold regarded cognitive appraisal as producing a tendency to do something. When the tendency was strong, it was called an emotion. Like Harlow and Stagner, she distinguished between emotion and feeling. Emotion arose from positive or negative appraisals of perceived or imagined objects, and feelings resulted from appraisals that were regarded as beneficial or harmful for functioning.

In 1970 Pribram presented a cognitive-phenomenological/information theory of emotion. In setting up his argument, he first distinguished between two kinds of experiences: (1) those from the external, "objective world
of sense data," those empirically based in the senses, which included all that can be seen, heard, smelled, tasted, or touched; and (2) those experiences from the "subjective world of feelings," those based on subjective, internal, and personal evidence and not tied to the outside, objective world of sensory data (Strongman, p. 25). Pribram differentiated between feelings and emotions and referred to feelings as monitors, which monitor and appraise internal, neurophysiological changes. Pribram favored the studying of feelings over emotions, since he was able to justify this concept with substantial empirical neurophysiological evidence. Pribram described emotions as emotional plans, which were neural-based programs set into motion when the individual was in a state of disequilibrium (Strongman, p. 24). He distinguished the concept of emotional plans from those he termed motivational plans, in that motivational plans were those carried out or executed, while emotional plans were those blocked or thwarted. The emotion resulted when the normal plans were blocked. Otherwise, if everything was in equilibrium and operating as per normal expectations, the plans were carried out and no emotion occurred. Although his theory distinguishing between feelings and emotions was presented in a confusing manner, it was similar to Arnold's, in that it was a cognitive/phenomenologically based theory of emotion that
drew upon neurophysiology for empirical support (Strongman, p. 25).

A problem with appraisal theories of emotion, such as Lazarus's and Arnold's, was that the cognitive appraisal factors intervening between the stimulus and the emotional response were difficult to test empirically. Appraisal theorists can only speculate about the hypothetical nature of cognitive/phenomenological appraisal inferred from behavior and neurophysiological reactions.

Role of information. Similar to Berlyne's theory, that too many stimuli or too much complexity can turn off the individual, who gets bored, was Siminov's 1970 cognitive/information theory of emotion (Strongman, p. 26).

This cognitive/information theory of emotion emphasized the role information plays in an individual's neurophysiological system. It affects whether an emotion occurs, its degree of intensity, and its type. In Pribram's theory, discussed earlier, emotion and feeling were associated with internal, subjective data. Simonov developed his information theory around the quantity of information; that is, insufficient information needed by the individual to reach an important goal results in disequilibrium, disorganization, and confusion, making the individual nervous and thus leading to a physiological change and a negative emotion. Pribram's "plans" could be compared to Simonov's reference to "need" or goal. What
Pribram called motivational plans were like Simonov's positive emotions. According to Simonov, a positive emotion resulted when an individual attained more information than was needed to satisfy a goal. An overabundance of information was associated with a positive emotion, while a deficiency of information resulted in a negative emotion. Tranquility resulted when sufficient information was acquired to fulfill a need. An individual confronted with too little information experienced negative emotions because of feeling unfulfilled, desperate, and not in control.

Emotion viewed as an interwoven process. Walk (1984) emphasized the significance of studying emotion as an interwoven process and the complexity of this kind of research (p. 212).

Meichenbaum and Butler (1980) stressed the interwoven relationship among cognition, emotion, and behavior and pointed out that the relationship between cognition and emotion is "bidirectional;" sometimes emotion precedes cognition and at other times, just the reverse (p. 142). They viewed this interrelationship as ongoing and continually changing. They also emphasized the role of values, attitudes, or concerns in affecting emotional states or behavior.

When appraising a situation, an individual brings a background of personal motivations, concerns, values, attitudes, and meaning systems which will have an impact on
the accompanying cognitions, behavior, and emotional response. Meichenbaum and Butler stressed the role of emotions not, only within an interwoven process, but also as a significant factor influencing the other processes. They advocated studying emotion outside of the laboratory, where the subject could be observed in a familiar environment, and argued that "studies that examine emotion in the laboratory, essentially, are taking a snapshot which captures only one element of a rich, ongoing movie" (p. 142). Their theory also emphasized the function of emotion in preparing an individual's mind set for a new learning situation. In their view, emotions interacted with cognition and positive as well as negative feelings had an impact on thoughts and the learning process (pp. 264-288).

The research also noted that differences in individual interpretations directly relate to differences in emotional responses. The phenomenological research of Averill in 1977 argued that individual differences, such as varying cultural, educational, or experiential backgrounds, result in differing emotional behaviors when the individuals are subjected to the same stimulus. In an experiment by Harvey (1965), it was noted that individuals who are used to a higher level of diversity in stimulus and ambiguity seek more challenging and diversified situations. Harvey elaborated:
we have found experimentally that more abstract individuals, those presumably from a developmental history of diversity and intensive exploration of their environment, are less motivated toward the resolution of dissonance or cognitive conflict than are the more concrete individuals, those presumably who have undergone prolonged restricted and structured environments in the course of their development.
(p. 258)

Another researcher, Payne (1980), emphasized the holistic approach to emotions as a mechanism capturing the entire experience, which he termed affect. Affect does not exist independently, it captures cognitive, behavioristic, and cultural aspects under the same roof. He stated that affect "is a unitary concept, and such conventional rubrics as interests, attitudes, and values are commonly used to describe various aspects of the domain" (pg. vii). Emotion, cognition, and behavior viewed as an interwoven process presented certain problems, according to Strongman, who observed that there was no theory that successfully explained experiential feelings, physiological change and emotional behavior (p. 193). Each of the theories of emotion appeared to be lacking in some particular way. Some were too narrow, others too broad; some centered in empirical data only, while others were more speculative.
Individual differences. The research also noted that differences in individual interpretations directly related to differences in emotional responses. The phenomenological research of Averill of 1977 and the experimental research of Berlyne (1974) noted that individual differences, such as varying cultural, educational, or experiential backgrounds, resulted in differing emotional behaviors when the individuals were subjected to the same stimulus. In the 1965 experiment by Harvey, it was noted that individuals who were used to a higher level of diversity in stimulus and ambiguity sought more challenging and diversified experiences. They were better prepared to cope with risky and ambiguous situations.

Difficulty in testing. The problem with studying emotion using a cognitive or phenomenological approach was that there were many unobservable conclusions drawn about the processes occurring between the stimulus and the resulting emotional response. A drawback to this kind of research from Strongman's perspective was the inability to empirically assess the internal cues (p. 91).

Conclusion

Emotional-Cognitive Research and Art

Studies investigating the relation of emotion to cognition can help explain how individuals experience their environments and, more specifically, how they experience art. Cognition can broaden the range of feelings through
analysis and labelling of emotions, and emotions, conversely, can provide a rationale for ideas. Best stated, "The natural responses give sense to reasons, yet reasons can open vast ranges of feeling which could not be experienced without them" (p. 10).

Like Lewis, Sullivan, and Michalson's (1984) research, which proposed that emotions set the way for cognition, Best believed in the power of emotions and response to art as significant determinants to learning and understanding in art. As an example emphasizing the unique role of emotions in understanding art, Best noted that, while it is a fact that war involves death and suffering, this fact is better understood if it has a vivid emotional impact (p. 183). Someone who has personally experienced war has a deeper understanding of it than someone who has not. Learning through emotional experiences like this can be applied to learning in the arts. An aesthetic experience with a work of art that involves emotional experiences and various levels of cognitive processing brings about a richer and deeper understanding of that work of art than if one merely knew facts about the work. Responding to art necessitates cognition and emotion and is helped by prior experience and learning about art. Unlike animals, humans are unique in that they possess both cognition and emotion, both of which facilitate the response to art.
Our responses to art can expand our knowledge and feelings about art by enriching our understanding of ourselves in relation to the artwork, in relation to the world, and, in general, by helping us understand what it means to be human. According to Best, response, understanding, and involvement with art can give depth and sensitivity to an individual's understanding of experiences in life. Understanding art can add to defining the shape of one's emotions. The emotions not only help in understanding of art but are the basis for the inferences that help create such understanding. In fact, Best saw understanding of art and responding to art as an inseparable process (p. 194).

According to Best, feelings about an art form cannot occur without some thoughts and notions about the artwork. All aspects—cognition, behavior, the stimulus (artwork), and emotions—must be present in order to have an aesthetic experience. The aesthetic experience is rooted in the characteristics of the artwork, as well as in the physical, emotional, and cognitive aspects of the person.

One's understanding and learning about art grows as a result of having an emotional experience with the work of art. Marantz (1972) noted the importance of knowledge and emotion when viewing a work of art,

The artist deals in ideas, in emotions, in the process of becoming and shaping experience. You do not have to
understand how a medicine works to use it. The only way you can "use" a painting is by understanding how it works—understanding can be in the sense of knowing the technique, the formal structure, the iconography: all of these aspects can provide kinds of meaning, but understanding also comes from an emotional response, from rich associations stimulated by the painting, from a sense of excitement and "rightness" about the manner of its being. (p. 10)

Cognition adds to the emotional experience by labelling feelings with descriptions and explanations using language. Valins' research in 1970 emphasized the significance of language and cognition in labelling emotions with descriptions, words, and explanations. This labelling can further understanding of people and their emotions (Strongman, p. 75).

The function of labelling as applied to artwork was explored by Kirsch and Kirsch (1985) in a study that employed the use of a "shape grammar" to define the structure of an artwork. In their study, they investigated the possibility of a computer viewing and recognizing the design element of dominant form in artworks (p. 65). Although acknowledging that there was more to art appreciation than perception of shape (e.g., interpretation, judgment, and evaluation of properties like emotion), their study focused on the formal quality in
artworks as a beginning. To accomplish their objective, they wrote a "shape grammar" to describe the structure of the paintings being analyzed. Kirsch and Kirsch offered two ways to validate the computer's analysis of the painting using their shape grammar: (1) the original artist can be consulted to determine if the computer's analysis corresponds to the actual organization of the painting; and (2) scholars who are familiar with the artist's works can be consulted (p. 66).

According to Purcell (1984), an aesthetic response was one in which arousal and the blocking of appraisal results from unexpected stimuli provided by the artwork. His theory demonstrated that emotion was the result of a neurophysiological interaction with the stimulus, such as an artwork. The type and extent of the emotional aesthetic response can vary from intense negative emotions to pleasant, positive feelings. The emotional response is dependent on the exposure to the artwork (p. 192).

In his experiment, Purcell had 42 students rate 43 slides of houses for "goodness of example" (i.e., good prototypes or examples of a particular style), interest, and preference. The architectural students responded in a more rational and cognitive manner to the stimuli (houses) than the non-architectural majors. In other words, the architectural students were able to dialog about the styles of the houses and their historical contributions.
Purcell's analysis of aesthetic response related closely to the studies on emotion that viewed emotional arousal resulting from a cognitive appraisal of the stimulus, such as the studies of emotion by Schachter and Singer in 1962. In this case, the appraisal viewed the stimulus as too dissimilar to what is already known, therefore blocking the processing of information, which ultimately causes an emotional experience. The results in Purcell's study showed that architectural students had a greater interest in the subject matter (houses) than other students. This observation demonstrated that individual differences, such as education, among the subjects had effected their responses (p. 194). Arnold's theory of emotion of 1960 also viewed emotion as a result of appraisal, where the cognitive evaluation of the stimulus determines the emotion (Strongman, p. 80).

Emotion is valuable to the understanding of art; that understanding grows as experience and learning are acquired. Best emphasized that emotion and cognition were both important to such understanding and appreciation (p. 193).

Best's premise was that consciousness and rationality are essential to responding to art. An individual cannot unconsciously have an aesthetic experience. All aesthetic experiences, in Best's opinion, necessitate cognition, in that the individual is conscious while having the experience (p. 194). He was critical of the strict behaviorists, who
studied an aesthetic experience from a limited neurophysiological perspective, devoid of cognition, because the cognitive processes of rationality and consciousness are essential in an aesthetic experience, which cannot occur without these cognitive processes.

The interactionalist, phenomenological approach to the study of emotion views emotion as an interacting process rather than an isolated element. Factors such as environment, culture, learning, and past experience are important considerations to this approach. The individual’s values, attitudes, and beliefs are intertwined with the cognitive, emotive, and behavioral processes. In fact, one’s cultural system can actually determine the emotion, behavior, and thought. Emotions cannot be isolated from everyday, interactional living in the world.

An individual’s cultural system of beliefs, attitudes, and values shapes his or her perceptions, emotions, and meaning system. Individuals understand and respond to a work of art from their particular cultural orientation. Boyer (1987) noted the pervasiveness of culture in a society’s aesthetic experiences:

Culture can be defined as the learned shared values, attitudes, and beliefs of a specific group of people that are continually reworked and reformulated. This sharing and reworking of culture provides a basis for the socialization process and the way in which cultural
assumptions about art are transmitted and become internalized. The enculturation process, that is the transmission of culture from generation to generation, or sharing of mental constructs, provides strategies for dealing with an individual's perceived sense of reality, as well as the ways in which members within society control, embellish and maintain their quality of life. Aesthetic experience is a complex and multidimensional phenomenon, influenced at every level by the pervasiveness of culture. (p. 7)

To fully understand and appreciate a work of art from a different culture would require an understanding of that particular culture. In explaining the difficulties in appreciating another culture's artwork, Best provided the following example: "An artistic appreciation of the dancing of Ram Gopal . . . would require an understanding not simply of an independent activity but, to some extent, of the traditions and ways of life of a different society" (p. 194).

According to the view presented by Best, emotions are conceptually oriented, that is, emotional labelling was derived from language (words), which were learned everyday by interacting in society. For example, Best stated, "The meaning of 'I am in pain' is learned by the public criteria given with language" (p. 96). Language that is culturally determined shapes one's ideas and feelings. Through
interaction with the world, individuals learn the meanings and feelings of words such as sadness, fear, anger, and so on. By learning the differences among the different phenomena, one also has learned the language and criteria for distinguishing the various feelings. Even though one subjectively knows and experiences emotion, emotions can be objectively labelled with words. Like other feelings, feeling towards an artwork also can be objectively labelled.

Theories of Emotion as Related to Artificial Intelligence

The majority of A.I. research has been devoted to the collection of objective knowledge, that is, knowledge usually obtained through the senses and semantically described with physical data, noting such characteristics of an object as the color, shape, and size. A.I. is concerned with producing programmable models of intelligence that can be performed by a computer. As indicated in the cognitive-emotive studies, not all human knowledge is objective, some knowledge is acquired through emotions. Emotions have been generally considered by A.I. researchers as irrational, noncognitive, and nonobjective. A.I. has focused primarily on knowledge that is rational and that can be objectified, quantified, and written as a neat formula. This perspective emphasizes the quantifiable aspects of emotions.

Sowa (1984) investigated the use of language in describing in a computer program indiscrete, continuous phenomena, such as temperature, distance, and emotional
state. He noted that language represents them with the use of discrete words. For example, temperature can be described with words like cold, cool, tepid, lukewarm, warm, and hot; an emotional state can be described as happy or sad; and distance can be expressed as far or near (pp. 39-40). Characterizations such as these can be further refined with what he termed fuzzy descriptors like somewhat, very, almost, rather, more or less, approximately, just about, and not quite. These fuzzy words help provide a more precise description recognizing that these descriptors are not precise and discrete; they vary in degree. Even though these discrete words are not able to provide a continuous range of variability, they do provide us with a means for verbal communication and computer representation.

Another researcher exploring the fuzziness and variability of language was Zadeh (1974), who developed a theory of fuzzy logic to assign precise values to fuzzy terms. However, Zadeh's work noted distinctions among the various words in order to be able to account for them on a discrete, calculating digital computer. Sowa observed that work like Zadeh's makes distinctions and differentiations among words that are not as distinct and precise as when people use them in everyday language.

As a result of trying to make a continuous, indiscrete word into a discrete, precise word for use on a digital computer, Sowa recommended the use of both analog and
digital means for inputting language into a computer. According to Sowa (1984), a combination of methods may be required in order to simulate the analog and digital processes of a human activity.

While most of the theorists believed that knowledge is cognitively based, rational, and objective, Dennett (1984) proposed that knowledge can also be emotional, psychic, and innate. According to Dennett, some knowledge may be acquired through feeling, and perhaps some sensory knowledge, like instincts and intuition, is even present at birth.

While there is much information demonstrating the role of emotions in influencing cognition, learning, language, and response to art, much more research in A.I. is needed to incorporate emotions into an A.I. system. Research could be initiated on determining preferences toward certain stimuli, invoking curiosity toward novel events, and directing learning and cognitive labelling of emotions. As the studies in this chapter have shown, emotions are a significant force in establishing and maintaining one's conceptual structure. Emotions play a dynamic, interactive role in perception, interpretation, and assimilation of cultural values, attitudes, and beliefs. Emotions can act as a stabilizing force, maintaining a state of equilibrium, as well as a disorganizing force. In fact, emotions are so fully intertwined with cognition as described in the
phenomenological, interactional research by Lewis, Sullivan, and Michalson (1984) that the two processes are seen as combined into one process. Intelligence in this view is regarded as a qualitative process rather than a semantic, rational, digital process. The interactional, phenomenological view is in contrast to the behavioristic approaches to A.I., which proposed intelligence to be a stimulus-response phenomenon that could be neatly written as a precise and discrete algorithm. Researching and modelling human intelligence from a strict behavioristic view does not account for the significant role of emotions and provides a limited view of intelligence and, more importantly, of what it means to be human. Research on emotions is the means to providing a full substantive understanding of the human processes of cognition.

Researchers have been able to delineate models and theories of emotions, making programming for emotions possible. Although the work on emotions is continually changing and growing, emotions can be studied and potentially written as quantifiable algorithms for a computer. The first algorithms would replicate some of the traditional psychological theories, with cognitive approaches to emotion. The researchers could begin with simpler theories that looked at emotion as an isolated process and studied a particular kind of emotional response, such as anger, rather than trying to develop a generic
algorithm encompassing all emotions. Through time, the work in developing these algorithms could demonstrate the complexity of emotion, and take into account other emotional aspects and processes, such as preferences, depth, degree, culture, cognition, and learning. The goal would be to produce a computer algorithm that considered emotion as an interwoven process, including cognition, behavior, and the environment. The growth of the work in emotions performed by A.I. programmers would reflect the psychological and philosophic advances of the research in emotions. In order to develop a holistic A.I. approach to emotions, it will be necessary for the researchers to shift their orientations away from strictly modelling intelligent semantically-oriented tasks to those that acknowledge the influence of qualitative and cultural aspects.

In the next chapter, I will present an A.I. model for cognition that is semantically based. Then, I’ll adapt this model to take into account emotions. The adaptation can be correlated to the studies by Valins and Kirsch and Kirsch in which language was used to label emotional experiences.
CHAPTER IV
AN A.I. MODEL

Introduction

In the previous chapter I described two significant components found in theories of emotion: cognition and neurophysical processes derived from psychological theories of emotion. The various theories of emotion demonstrated the significance of these two components and raised other associated issues, such as sequential occurrence. Which occurs first, the neurophysical response to the external stimuli or the cognitive interpretation of the stimuli? Conversely, theories were identified that suggested both components occur simultaneously as an interwoven process, rather than occurring as separate processes.

In this chapter I will suggest how emotions might be accounted for in a computational theory. To do this, I will first present Zenon W. Pylyshyn's (1985) model for computing for cognition. Pylyshyn is one of the leading researchers in artificial intelligence. He has developed an A.I. model which incorporates both neurophysiological and psychological processes. I will adapt his model to take into account
emotions and correlate the adapted model with several theories of emotion from psychology.

Pylyshyn's Computational Model

In his book *Computation and Cognition* (1985), Pylyshyn examined various issues related to the developing field of cognitive science, which is the study of the mind using the computer as a model to explain cognitive processes. The role of a cognitive model, according to Pylyshyn, is to explain cognition by "showing how specific instances of behavior are generated by the mind, as well as relating this performance to certain cognitive capacities" (p. 260).

In explaining his model for computing cognition, Pylyshyn proposed three distinct, independent levels that interact with each other, yet are composed of unique qualities not replicated at another level. The three levels are (a) a physical-biological level, (b) a symbolic-functional level, and (c) a representational-semantic level. These three levels will be described in detail.

**Three Levels of the Model**

**Physical level.** At the physical level, the computing system focuses on how the machine works in terms of its electronics, electrical currents, and changes in the flow of energy. The human equivalent of this is the neurophysiological central nervous system's activities, as in the optical reception of light rays in the visual perception of environmental stimuli. An increase in heart
rate of someone anticipating a knock on the door or the sweating palms at a job interview are instances of neurophysiological responses. At this level, A.I. is discussed in scientific terms drawn from the fields of electrical engineering, physics, and biology. Visual perceptions are described using terms common to physics and optics. Stimuli are optically perceived and discussed in terms of light rays bouncing off the retinas.

**Functional level.** The next level, identified as functional-symbolic, is related to syntactic symbol-processing computational functions. The symbolic level describes patterns or regularities of phenomena as symbols. A symbol explanation is provided for all similar, predictable occurrences. The following statement is an example of a symbol explanation, "S wants G and believes that G cannot be attained without doing A; therefore, everything else being equal, S will tend to do A" (Pylyshyn, 1985, p. 132). At the symbolic level, behavior is explained in terms of the symbolic computational code, not requiring a semantic rule-governed explanation. Other examples where symbols are used to capture generalizations would be in the areas of math, physics, music, and computer programming.

In a cognitive model, the functional symbolic level is expressed symbolically as a computer program recognizable by the machine. Emphasis is placed on the "syntax" of the symbolic notation; that is, proper use and relations among
the formal properties, operations, data structures, and functions of the computer code. According to Webster's Dictionary, the study of syntax, referred to as syntactics, is a branch of semiotics dealing with the formal relations among signs (e.g., #, /, -, and +) or expressions in abstraction (e.g., FOR X = 0) from their significance and their interpreters. The phenomenon is discussed at this level in symbolic computational terms or programming code complementing the physical machine-level experience.

Empirical, physical events, such as the optical perception of an image, are explained in mathematical computational programming code. Symbolic notation is used to capture generalizations describing events that reoccur predictably and similarly, as derived from the observable phenomenon. The human counterpart for the computer program is the sensual experiencing of stimuli as realized through the senses instead of through thought, interpretation, and inference. For example, a branchlike shape on the ground is visually perceived as values of light and dark, curves, length, thickness, etc. No interpretations about what the object might be are made here.

Semantic level. The third level delineated in Pylyshyn's model is termed the representational-semantic level, which is knowledge dependent. Inferences, conclusions, interpretations, and meanings are drawn at this
level and phenomena is explained in terms of representations.

This level is operational in the computer as the inferences and deductions derived from running a computer program that deals with the use of rules and relations among signs and expressions that produce results. In running an A.I. program, the semantic level indicates the timing, order, and selection of rules to apply; it points to acceptable paths to take in problem solving; and it produces satisfactory solutions for a particular problem. The human mirror for the semantic phase cognizes a physical occurrence by drawing upon past experiences and acquired knowledge. Empirical activities are understood through such high-level cognitive activities as analysis, inference, deduction, interpretation, and synthesis in addition to the low level cognitive tasks of recognition, recall, etc.

Behavior is explained in terms of how the organism or system interprets the phenomena. At this level, the explanation is deduced from regularities observed in the real world or from possible and acceptable inferences about situations not necessarily observed but still understood as a result of meanings drawn from an analysis and application of past experiences and knowledge.

For example, the shadowy curving linear figure on the ground is analyzed and interpreted at the semantic level to be either a branch or a snake. The acceptable conclusions
can be real or imagined, at this level. Cognitive understanding of visual imagery depends upon imagination, past experiences, prior knowledge, and inferences deduced from analyzing the situation. Thus, conclusions are drawn by determining the nature of the phenomenon or imagined, as illustrated in the example.

Transduction Function

Operationally, all three levels are related and interacting with one another through the mapping of one state of conditions at one particular level to another. Each level has an effect on the other levels in producing a response and no one level acts as an isolated factor controlling behavior. Thus, at each level, the information is assimilated and passed to the other levels.

The intermediary action between the mapping of physical states to symbolic computational ones is termed by Pylyshyn as transduction and the agents responsible for passing the information as transducers. A transducer is not a level but rather a function.

Basically, the major function of the transducer is to receive physical phenomena and transmit this nonsymbolic physical information to the computational symbolic level by transforming the physical events into computational symbols.

Although the transducer plays a major role in mapping the physical to the computational form, the transducer
itself is nonsymbolic. Pylyshyn clarified the role of the transducer as a nonsymbolic function,

A transducer is just another primitive operation, albeit one responsive primarily to the environment rather than the cognitive process. Just as one does not generally consider a thermometer, voltmeter, analog-to-digital converter, or any other piece of equipment connecting a physical environment to a computer as performing a computation, so a psychological transducer is considered nonsymbolic in its internal operation. (p. 154)

Transduction takes into account the physical and biological variables of the system or organism, such as a stomach ache, and incorporates these internal influences in the mapping from the physical to the computational. For example, an individual may respond negatively to a situation not because of any opposition to the stimulus but because of a stomach ache. The transduction process takes into account the effect of internal variables and processes. The transducers act as the links or interfaces between the physical and cognitive levels.

Transduction is a physical process described in physical terms. As Pylyshyn defined it, a transducer function,

In its most general sense, as used, for example, in electrical engineering, a transducer is a device that
receives patterns of energy and retransmits them, usually in some altered form. Thus a typical transducer simply transforms or maps physical (spatiotemporal) events from one form to another in some consistent way. (p. 151)

The three levels are associated via transduction but have autonomous discrete, and distinctly unique, operations, in that the operations performed at separate levels do not intermix or merge together. The operations unique to one level are not replicated in any shape or form at any other level.

Transduction is explained mechanically in physical terms familiar to the computer architecture. It converts the physical perception of light rays into computational content.

Constraints

A system is better able to explain results if it is highly constrained. Constraints are the specific conditions indicating the nature of the process under which permissive rules are involved. A constrained system has captured the cognitive processes as generalizations, so specific and unique to the process that a strong equivalence can be demonstrated between the computational model and the mental process. A system is better able to explain results if it is constrained with limited, yet flexible and controlled degrees of freedom.
Pylyshyn outlined the requirements expressing a computing system's validity and strong equivalence that must be met before the algorithm can be considered a mirror for cognition: (a) the input must be described in discrete, finite, specific physical terms, (b) the transducer function must be considered input bound; that is, it must always produce a particular output whenever it received an input regardless of its current status or condition (p. 141). Transduction is in a constant state of activity.

In order to meet the first requirement of defining the incoming input as a precise and discrete formalism defined in terms of physics, the algorithm has to be written in a form acceptable to the computer, such as a program. This level of representation also may include a flowchart graphically presenting the algorithm as well as a written natural-language description or pseudo code. Pylyshyn cautioned one to be thorough in formulating a representation of a cognitive process:

What is often overlooked when this is done is the extent to which the class of algorithms that can be considered is conditioned by the assumptions made regarding the basic operations possible, how they interact, how operations are sequenced, what data structures are possible, and so on. Such assumptions are an intrinsic part of the descriptive formalism
chosen, since it is that formalism which defines what I call the "functional architecture" of the system.

(p. 96)

In addition to the first requirement, the model must also meet the second requirement—an output must always be produced whenever an input is received. The act of transducing is considered to be an input bound function because it acts solely upon the incoming physical data, converting the data to a computational form. Regardless of the current state of context, the transducer must always manufacture a particular output in response to the input.

In relation to visual perception, transduction is the active force mapping neurophysical optical data onto the symbolic level, which in turn affects the semantic, inferential interpretation of the physical data resulting in a behavioral output. Perception embodies cognitive inferences about the visual image that are transferred to the optical behavioral component influencing what one believes he/she is seeing. Using the example of the twig-snake cited earlier, one who thinks he/she sees a snake will see a snake, because the act of visual perception is penetrated by cognitive influences.

Pylyshyn recommended a descriptive breakdown of the cognitive process into those cognitive functions that are semantically and symbolically oriented and those that are directly associated with the physical, biological state. He
provided an example of an auto-maintaining robot to support his suggestion for detailed, discrete definitions of the various steps and functions and all the possible interrelatable associations:

Suppose a robot is provided with the capability of altering its own hardware architecture, say, by mechanically removing an integrated-circuit chip when it is faulty and replacing it with a new one from a storage bin. Clearly, an account of how this is done requires both a description of the computational process, in terms of the program and data structures, and a description of the physical manipulation process. The first part of the account is entirely symbolic, whereas the second is physical and mechanical. The overall account of altering the hardware architecture by symbolic processes involves showing how the symbol structures affect transducers, which affect the behavior of the manipulators (here, the regularity is explained under a mechanical description), which, in turn, affect the architecture by changing the circuitry. (p. 144)

Dividing and defining the various activities of a computational cognitive model will provide explanatory credence to associations drawn between the model and cognition, in terms of relations between empirical,
physical, nonsymbolic events and those that are symbolic, unobservable, and semantic.

Physical Terms

The system's initial behavior where it first receives input and converts it must be stated with physical terms. Conversion to the computational, symbolic level begins at this basic physical level of description. The language of physics are used to describe physical phenomena, such as light, energy, density and the environment. Conversely, physical terms are not used to describe nonphysical events, such as cognition, inferences, emotion, or psychological phenomena. Physical terms are those used or that could be used, in physics, chemistry, biology, and other sciences; for example, length, time, mass, force, energy, momentum, speed, charge, temperature, cellular discharge, potential gradient, contrast boundary, reverberatory circuit. These terms can be converted into the laws of physics.

Since similar physical events may vary in terms of intensity, distance, repetition, duration, etc., the transducer can be weighted in degrees to reflect the magnitude of the event. As Pylyshyn noted, a system could record these finite differences in a manner similar to the libraries' Dewey decimal system, which would provide the necessary precision and quantification.

Physical descriptions do not involve perceptions of the physical world. Terms used to describe perceptions of the
physical world can be vague and ambiguous when compared to terms used by the laws of physics, which are more consistent and can provide unity and coherence to the system. For example, perceptual terms could include shadow, curvy, and opaque and physical terms, hue, saturation, and depth. However, both types of terms are essential to a computational model of cognition, in order to reflect how people think and communicate their understanding of the physical world. The terms and mental processes used to account for phenomena in perceptual terms differs from those used for physical terms. Physical terms imply the use of physical laws and perceptual terms imply symbolic, cognitive, psychological terms and processes, such as inference and problem solving.

Criteria for Equivalence

Computational A.I. models can be assessed to determine their validity, or how legitimately they imitate a mental task. A comparison can be made at various levels of the A.I. system to determine how strong of an equivalence exists between the human and machine processes. A claim for strong equivalence could start by investigating the physical relationships between the functions of the model and the mentalistic process. Does the model have similar if not identical input and output as the cognitive process being modelled? An analysis at this level does not provide an understanding of how the mentalistic process works, merely
insights about how an organism might respond to a particular stimulus in providing specifics about the nature of the stimulus and its relation to the resulting behavior. An analysis at this level focuses on the biological, physical, and mechanistic aspects of the cognitive process and the model. A comparison at this level might be considered weak because the model is extremely limited in its equivalence to the input-output functions. Obviously, a stronger claim for equivalence could be made where the model used the same method as the mental process being replicated.

At another level, an analysis of the method or algorithm could be made emphasizing aspects of concern to the computational, symbolic, syntactic level. The individual steps, operations, and variables as well as the sequence of steps could be inspected. Many variables and issues need to be addressed when determining the strength of equivalence between a computational model and a mental process and whether the algorithm is at the appropriate level of comparison.

Two requirements are recommended by Pylyshyn for a computing A.I. model to show strong equivalence:

1. The model must be described as a descriptive formalism, specifying the acceptable basic operations and their interactions and ordering, including a detailed description of the appropriate data structures, etc. All functions,
operations, and states of the problem space need to be precisely defined. Emphasis is placed on the performance of the model at this level.

2. The model should be able to explain its selected method of performance; that is, it should be able to express why it works a certain way, why certain rules are used and paths explored, and how it arrived at solutions for the problem. Here, the criteria emphasizes the explanatory nature of the model.

Descriptive Formalism

In defining a computational model, Pylyshyn noted that a descriptive formalism of the model should identify the basic, transducible, cognitive states. The formal structure of the system, referred to as the functional architecture, needs to be defined explicitly, noting fixed variables and universal variables. The functional architecture is the basic information processing mechanism of the system, which is noncognitive, nonrepresentational, and nonsemantic. It is described in physical and biological terms. The physical input needs to be clearly defined, as well as any beliefs about the input, stated as rules and inferences, that may affect the output.

The rules and inferences need to be stated explicitly, as should the biological processes that also affect the cognitive process. Distinctions must be made between
biological and cognitive symbol-processing levels and the transducers functioning between them. Pylyshyn recommends factoring the process into a symbolic stage, a nonsymbolic, nonpenetrable stage, and transduction stages, with a well-defined explanation differentiating among the functions. Distinctions should be made differentiating the semantic-level or symbol-level principles and those at the physical level (p. 145).

The strong equivalence method is used to determine the validity of the functional architecture and the way it operates to how cognitive processes work and function in performing the same tasks. A comparison could be made between the neurophysiological changes in the brain while performing a particular cognitive task and the functional architecture.

Cognitive processes typically are explained in terms of semantics; that is, within the rules or occurring regularities. The functional architecture explains the same process in terms of the physical level content, such as functions.

Pylyshyn recommended that each function be written in a fixed, computational format equivalent to a constant that cannot be freely changed to accommodate another situation (p. 105). A constant is a formal notation fixed over a certain range of properties. Constant functions are assigned to the functional architecture that can explain the
results of the model upon a specific, determined occasion (p. 106).

In order to compute for a cognitive process, such as problem solving, all specific criteria defining the phenomena of problem solving must be stated explicitly. The method, basic operators, and states of the problem space need to be defined precisely.

**Explanatory Nature**

Functional architecture is the foundation for building a computational system modelling a cognitive process. The functional architecture is the innate, fixed, biological or physical system that cannot be changed and cannot be explained by rule-governed or semantic-governed principles. The functional architecture should have the functions necessary to perform specific tasks efficiently. In addition, it is equally important that there be an explicit explanation as to why the resulting computational model works the way it does based, on assumptions from the functional architecture and empirical observations. The behavior in question requires a physical, functional, input/output explanation. The most important aspect to emphasize here is that the computational model should be used "in an explanatory mode rather than simply a performance mode" (Pylyshyn, p. 101).

In developing an explanatory computational model of cognition, it is important that the formalism explain the
cognitive process it is modelling. Confusion sometimes results when cognitive scientists equate the model's output with the cognitive process itself. For example, the output in terms of reaction time cannot be equated to a cognitive process for it does not provide an explanation of the human cognitive process it models. Rather, it provides an insight to the steps and operations required in solving the problem. Cognitive theorists need to shift their focus to interpreting "the model as computing the output in the same way as the subject that is, by using the same algorithm" (Pylyshyn, p. 124). A cognitive model's reaction time cannot be viewed as an adequate explanation for an underlying human cognitive process but should be observed in relation to the reaction time required by the human subject.

Without precise definitions with explanations the computational model cannot begin to explain its results as equivalent to the cognitive process. Pylyshyn emphasized that the computational model of a cognitive process must provide an explanation of that phenomena, not a mere description. He stated, "Thus generalizations of such a nature that no one has any idea (however sketchy) how they can possibly be realized by some mechanism are interpreted as descriptions of phenomena, not explanations" (p. 110).

Unique Machine Considerations

Pylyshyn cautioned one about the unique properties of the machine itself (the computer) that need to be considered
when comparing a computed model to a cognitive process. Sometimes a time delay in the computational model arises when "a signal has farther to travel on a particular (or token) occasion because of the way the machine is wired or the way the algorithm is implemented in it" (Pylyshyn, p. 127). The researcher has to be aware of such differences. In this case, measurements involving time or number of steps cannot be taken literally as a measure of the mental process because they do not provide an explanation for the behavior. Criteria such as time and number of steps should be viewed as "indirect indicators" and should be matched with other sources of evidence, such as complexity of the task and the number of variables involved, in order to infer anything about the underlying mental process. Yet, the importance of observable criteria cannot be undervalued because they are instrumental to the evaluation, since the underlying mental processes themselves cannot be viewed. "All methodologies are based on assumptions. The proof of the correctness of these assumptions is the continued success of the methods in revealing interesting, general properties of the system under study" (Pylyshyn, p. 128).

**Empirical Methods**

**Empirical methods** can be used to ascertain the strength of equivalence and validity of the A.I. model. For example, an analysis of the number and sequence of steps taken could be observed or the amount of time taken to perform a
particular task by the A.I. model could be measured and compared to the human equivalent. Criteria such as total time and total number of steps taken can be further delineated to take into account particular aspects of the computer itself. For example, what counts as a step needs to be qualified. The criteria must be general enough to account for all similar occurrences of the same phenomena, yet specific enough so that the formula does not have to be changed for each new observation:

the purpose of theories is to cast light on what seems like chaos by finding the most general and revealing, lawlike generalizations that lie behind the observations. To be explanatory, a theory cannot have as many free parameters as there are data points. Put another way, we would not be content with a theory that must be changed each time a new observation is made even if, at any given time, the theory accounts for all available observations (that is why the pre appears in the word prediction). (Pylyshyn, p. 122)

A computational model should be able to explain the cognitive process that it is modelling. Pylyshyn cautioned researchers in their zeal not to make broad, sweeping generalizations based on specific, empirical, yet limited and narrow information. For example, the measurement of time is a step or phase in the whole cognitive process, which helps in gaining a better understanding of the process
but does not tell the whole story, nor should it. The element of time describes the performance of the system at a particular level but it does not explain how the system works in solving the problem. And, the steps comparing the two cannot be taken literally because certain unique machine considerations need to be accounted for.

Cognitive Penetrability

In addition to the notion of strong equivalence as discussed earlier, a second criteria used in assessing a computational model of cognition is cognitive penetrability (p. 130). Cognitive penetrability explains the influence of internal and external cues in affecting the behavior. For example, the behavioral act of visual perception is highly susceptible to cognitive inference, interpretation, and conclusions drawn from prior experience and knowledge. Cognitive penetrability refers to the explanation of a behavior with cognitive, nonbehavioral content such as beliefs, attitudes, and feelings. Even in the perception example cited earlier, where the shadowy figure on the ground perceived as a snake actually turned out to be a twig, more is involved in the perception than the mere optical processing of light rays on the retinas. Perception involves inferences about the images being viewed and these inferences are transduced to the biological component.

Whereas, the notion of strong equivalence compares the functional architecture and the way it runs to how cognitive
processes work when performing the same task, the issue of cognitive penetrability explains any influence that cognitive beliefs and other cognitive factors may have on the behavior in question. The behavior in question requires a cognitive explanation. A process is referred to as being cognitively penetrable when any aspect of the function cannot be explained strictly using functional architecture principles and requires a cognitive, computational explanation. The effect of some goals and beliefs on behavior requires a rational or inferential explanation. Thus, a noncognitive activity such as behavior can be cognitively influenced. Pylyshyn provided the following perceptual example in describing the notion of cognitive penetrability:

Without doubt, the perceptual process is cognitively penetrable in the sense required by our criterion. What one sees—or, more accurately, what one sees something to be—depends on one's beliefs in a rationally explicable way. In particular, it depends in a quite rational way on what one knows about the object one is viewing and on what one expects. (p. 134)

When the biological, functional, physical explanation does not suffice because its explanation depends on cognitive influences then it is considered to be cognitively penetrable.
Perception, which is a cognitively penetrable act, involves various kinds and levels of data, such as the objective, neurophysiological, biological type of information as well as cognitive data, inferences, past knowledge, attitudes, beliefs, and values. This cognitive data constitutes an individual's perceived reality; that is, what is perceived as reality is previously determined and is influenced by cultural values, attitudes, and beliefs. These cognitive factors affect the perceived reality at the neurophysical, biological level. Perception involves the cognitive processing of the perceived image as well as the neurophysical optical processing of light waves reflected off retinas. For example, the analysis of a shadowy, linear, curving figure on the ground by an individual who lived in a country void of snakes would not even consider the possibility of a snake. Instead, this individual would perceive the shape in terms of what he/she already knows and believes it to truly be. As in this example, it is clear that perception involves semantic-level principles, such as inference, deduction, interpretations, judgments, and rules.

Another example of cognitive penetration is where an individual fears the IRS and upon receiving a call from an IRS official, finds his/her palms sweating and heart rate increasing. Here, the individual's belief that the IRS jails delinquent tax payers penetrates into his/her
physical, biological system. An understanding of the penetrable effect of knowledge can help in recognizing the specific internal cues that set certain behaviors into motion, and this understanding can teach individuals how to control undesirable behaviors.

In addition to beliefs, attitudes, and values affecting an individual's cognitive system, noncognitive influences, such as feelings and moods, also can affect the cognitive process and resulting behavior. For example, a fear of heights could certainly affect the way an individual decides which highway route to take, knowing that one of the routes could go through mountainous terrain. In desperately trying to find an immediate solution to this problem in addition to driving a car, it would not be unusual to find the individual behaving in a paranoid, nervous, and restless manner and making quick, illogical verbal commentary.

Cognition involves more than simple information processing; it also involves feelings, attitudes, beliefs, values, and other influences that affect the resulting behavior.

Perception Influenced by Culture

Perception involves the objective, neurophysical, biological data, in addition to the beliefs, attitudes, and values that constitute perceived reality. Perception is not a constant view from individual to individual, it varies depending on the perceived reality held by a particular
cultural group. Certain groups of people who share similar attitudes, values, and beliefs, such as the Brazilian Yanamamos have views about life, religion, and survival which would be significantly different than for example, American Jewish children. These culturally determined values, attitudes, and beliefs influence one's perception.

In computing a cognitive process like perception, these pervasive, qualitative components need to be considered as major factors in developing the computational model. If the beliefs change, then the cognitive processing and results may subsequently change. Pylyshyn noted, "beliefs about an imminent threat cause the heart rate to increase and an entire set of physiological reflexes to occur" (p. 138). It is clear in this example that a noncognitive or nonsemantic process, such as heart rate can be affected by a cognitive process and set of beliefs. In this instance, cognition alters a noncognitive process that may not be consciously acknowledged. This activity occurs at a taken-for-granted level, which automatically occurs without having to justify, rationalize, or explain the entire process. Because past experiences have dealt repeatedly with this same subject, an individual knows how to respond automatically without having to objectify the numerous steps in between, which took into account beliefs, attitudes, and values about the phenomena. The pervasive beliefs, attitudes, and values influencing responses are taken for granted. Obviously, as society
changes and grows, the set of beliefs, attitudes, and values also change to accommodate more knowledge and experience. Thus, our cognitive processing and response to a particular phenomena may change as our perceived reality consisting of beliefs, attitudes, and values changes.

In other instances, noncognitive processes can be influenced consciously and deliberately, as in the control of one's heart rate through biofeedback or other training methods. In a very intentional, objective manner, an individual can learn to control a response to a particular phenomena. In addition, cognitive and noncognitive processes can be altered by external influences, such as surgery or brainwashing. As is obvious, feelings about a particular phenomena, such as a boss, spouse, or minister, can affect an individual's thoughts about the phenomena and the resulting behavior. Certain emotions, such as fear, anger, and anxiety, can penetrate cognition, in addition to altering the cognitive process.

A.I. models need to take into consideration cognitive data, such as attitudes, values, and beliefs, which are derived and determined by the individual's culture. By doing this, the A.I. system will be able to replicate more closely how individuals from various cultures perform certain cognitive tasks, such as perception, appreciation, and preference. Trying to reduce all of humankind's thinking into one universal representation does not fairly
account for the unique differences among individuals, groups of individuals, and varying cultural groups, and the possible differences found when various individuals perform the same cognitive task but end up doing it with a different manner or technique or come up with different conclusions and results. Individual and cultural differences affecting cognitive processing can be observed easily in a college art class, where students given the same problem, media, and criteria return with different acceptable solutions to the same problem.

A Linguistic Sentential Model

Pylyshyn emphasized the role of linguistics and sentential formulas in the symbolic and semantic levels of his model. His model was derived from formal systems as those used in logic and math where linguistics can be formally defined, using strict rules and formal notation. His system was formal in that rational concepts can be described linguistically, using symbolic notation, cognitive representations, and semantics. For these reasons, it seems probable that Pylyshyn chose a rational, formal means for representing his cognitive model because there is a tradition of formal, linguistic systems present in the A.I. literature (see chapter II for a detailed description of A.I. programming techniques).
Although Pylyshyn emphasized the role of linguistics, he still was aware of the significance of emotions, even though the model did not explicitly incorporate them.

A growing number of people, while not disputing the general view I have been outlining, feel it is only a very small part of the overall account of cognition. They feel that there are large and important areas of cognition that do not involve ratiocination and the manipulation of sentential formulas. Some plausible candidates for areas that do not involve reasoning-type processes are learning, conceptual change, ontogenetic development, emotions, and, most significantly from my point of view, the large area of nonlinguistic or apparently nonlogical reasoning, such as intuitive or imagistic reasoning. (pp. 196-197)

Pylyshyn was aware that cognition could involve more than the cognitive information processing of sentences, it also could involve processing of pictorial representations, emotions, intuition, and other kinds of noncognitive processes. Pylyshyn's model was based on a symbolic, sentential format that is related most closely to the formal systems used in logic and math. The notations used in a formal system, such as math, must abide by certain rules, such as those outlined in Goodman's taxonomy (1968): (a) syntactic disjointness, the requirement that each symbol be a part of a single type symbols (i.e., letters, numbers,
musical notes); and (b) syntactic finite differentiation, the requirement that each symbol be sufficiently different from all other symbols of that type to avoid ambiguity (Pylyshyn, pp. 198-199). By this, symbols have to be unique and specific to the relations that they are involved with, and it is desirable that symbols be highly constrained to avoid replication.

Accounting for Emotions

Pylyshyn recognized that there were processes involving cognitive influences that have not been addressed by his model, such as imagination, emotions, and creativity. To address these areas would mean finding a way to convert a process like emotion into discrete, finite, symbolic terms recognizable by a computer. This would prove to be a difficult task because these areas are nonempirical; that is, they cannot be entirely explained from explicit observation. Therefore, emotions would be difficult to program, test, and model because they are unobservable; only the end behavior, stimuli, and neurophysiological aspects could be recorded empirically.

Another concern to consider when computing for emotions is the qualitative magnitude and duration of the emotion. How long does it last? How intense or strong is it? Whereas, a thought or a word is a discrete cognitive-level term or sentence, an emotion is continuous in nature interweaving with the cognitive and physical states. An
emotional experience is not finite, it is in continuous evolution and motion.

Physical systems that are continuous and ongoing are thermometers, speedometers, thermostats, barometers, and oscilloscopes. Systems such as these are thought of as analog devices because they measure continuous, ongoing phenomena and convert these readings into discrete digital formats, such as a temperature measurement is expressed in Fahrenheit degrees, as 80°F, for easy interpretation. Since computers use a digital format, it makes sense that Pylyshyn’s model conforms to the accepted standard—utilizing a symbolic, digital, discrete, and formal system. Perhaps, a physical model, similar in functioning and conversion to a thermometer, could be used as a basis for incorporating emotions into a cognitive, computing system.

Digital and Analog Systems

Digital computers have been designed specifically for the formal, logical system; that is, they compute symbols in a step-by-step manner where each discrete language-like symbol is processed individually and the result is the sum of the parts. A digital system is not capable of processing a whole idea, math problem, or image all at once. The big problem must be broken down into smaller, discrete, individual subproblems, which are then processed logically in a sequential manner.
The opposite of a digital system is an analog system, which involves a continuous form of representation. Where a thermometer is generally thought of as an analog device, the actual temperature reading is converted into a single, discrete digital number for interpretation. Another example of an analog system is an electrical charge, which is continuous but is stated as a static unit of frequency, such as 400 Hz. Pylyshyn designed his model to take advantage of how a digital computer works and he emphasized this intent in stating,

Recall that characterizing digital computation involves specifying what I call an "instantiation function," which assigns sets of physical states to distinct computational states, as well as a "semantic interpretation function," which provides a regular scheme for pairing computational states and interpretations in the domain of the computation.

(p. 201)

Pylyshyn pointed out, however, that his cognitive model is capable of modelling an analog process:

it seems to me that the essential idea behind the use of the term analogue by most psychologists is captured precisely by what I have been calling functional architecture, inasmuch as both the notion of analogue and that of a function instantiated in the functional architecture are intended to emphasize that certain
regularities must be explained by appearing to natural, intrinsic constraints, as opposed to semantic or extrinsic ones. (p. 209)

Therefore, if an analog process can be stated as a generalized formal notation recognizable by the computer, then it can be accounted for by Pylyshyn's model in much the same way that an electrical frequency can be converted into megahertz for simple readability.

Pylyshyn drew a strong distinction between what he identified as cognitive and noncognitive processes in emphasizing the role of semantics. For example, replicating an analog process, such as imaging, does not automatically lend itself to semantic properties without some translation. Images have to be translated from a visual representation to a semantic, linguistic one with transducers. A process, such as imagining, is not semantically oriented and thus is considered noncognitive. Normally, an image is not thought of as a set of numbers representing the horizontal, vertical, and depth axes points of the image in a three-dimensional space. To have a cognitive model redraw the visual image in a similar way that a human being performs this cognitive activity would require that the model go through a process of perceiving, analyzing, and interpreting the shape, location, and perspective of the image before putting a mark on paper. The translation from the
biological perception to the symbolic, computational code would be performed by transducers.

Correlations with Emotional Theories

Traditional cognitive-psychological theories of emotion, as presented in chapter III could be implemented in Pylyshyn's model. The cognitive theories of emotion emphasize the role of cognitive processes, such as thoughts, inferences, and evaluations, in producing an emotional response. One such cognitive theory, Leeper's in 1960, viewed emotion as an organizer for behavior where the emotion determines the resulting behavior (Strongman, 1973). For example, an angry man may stomp his fist down on his desk. The emotional state of anger causes the physical expression of stomping his fist. A more complex example would be where an individual has conflicting thoughts, such as about the honesty of an employee, yet his resulting behavior demonstrates acceptance of the individual based on his feelings of trust. In Leeper's view, emotions are tied to beliefs in controlling behavior. Leeper viewed emotions as controlling behavior by organizing and motivating it, rather than having a disorganizing effect on it. Leeper maintained that emotion involves motivation and perception and it is actively organizing, sustaining and directing behavior (Strongman, 1973, p. 30).

Besides Leeper's theory, other cognitive-psychological theories of emotion emphasize the role of cognition in
determining the resulting emotional behavior. For example, Arnold in 1960 defined emotion as the behavioral response resulting from cognitive appraisal of a situation (Strongman, p. 81). Depending on how the situation is perceived and inferences are drawn up, in turn, affects the emotional state. For example a disorganized, messy, dirty room could produce feelings of anxiousness and frustration. According to Arnold an individual to whom the evaluation of the stimulus is negative will react accordingly. Her theory is a mixture of cognitive and physiological approaches; that is, a combination of perceptual and inferential influences on emotional well being. Her theory involving the biological, perceptual, and representational inferential components corresponded closely to Pylyshyn’s use of three levels: a biological-physiological level, a computational-symbolic level, and a semantic-cognitive level. Arnold’s theory demonstrated how the cognitive penetrability of a conceptual process, such as appraisal, has an affect on the neurophysiological processes of the individual. Such a theory could be incorporated for use on a computer using Pylyshyn’s model because of its formalistic nature.

Valins’ theory of 1970 attempted to distinguish between the roles of internal and external cues and their influence on the resulting emotional response (Strongman, 1973, p. 75). According to Valins, external cues are those obtained directly from the stimulus itself, whereas internal cues are
the inferences derived from the cognitive analysis of the situation as related to prior experiences and past knowledge. Valins investigated the role of internal cues as they biased the emotional output. Even though, as Valins pointed out, it is difficult to determine which cue occurs first, the argument can still be made that cognition plays a significant role in determining emotional behavior. Valins' terminology of external and internal cues could be equated with Pylyshyn's concept of cognitive penetrability, in which one's neurophysiological level is influenced by the cognitive level.

Conclusion

In this chapter, I have outlined a relatively modern approach for synthesizing human intelligence on a computer. Pylyshyn's model (1985) replicated three levels of human processing that can be reproduced by a digital computer system: (1) a physical-biological, machine level, (2) a symbolic-functional, computational level, and (3) a representational-semantic, inferential, cognitive level. This model resembles cognitive operations occurring in humans.

Pylyshyn's model of three levels can be adapted to account for the process of emotions. The transference of emotional data between the physical level and the computational cognitive level would be managed by the transduction function. Emotions would have to be converted
by the transducer function into a symbolic form, such as a notation representing anger or happiness that is recognizable by a digital computer. According to Pylyshyn, a transducer acts as an intermediary operation converting physical information into a computational form. Transduction is action-oriented, receiving physical information and sending converted information to the symbolic, computational level.

In addition, transduction could serve as a means of communicating feelings. In order for emotions to be recognized by a digital system, they would have to be converted in a fashion similar to that done by a thermometer, speedometer, barometer, or oscilloscope, which present the reading in a finite, numerical notation. This conversion would be handled by the transduction function, which would convert the neurophysiological sensual aspects of the emotion to a symbolic, computational format.

Pylyshyn pointed out that his model could be used for analog processes and he noted that such processes would be captured in the functional architecture, where certain regularities or patterns are explained using "natural, intrinsic constraints, as opposed to semantic or extrinsic ones" (p. 209). Thus, if an emotion can be stated as a generalized, highly constrained formalism recognizable by the computer system, then emotions can be computed.
The transferral of emotive information from the biological level to the cognitive levels would be carried out by the transducer function. To do this, the act of transduction would be the initial place for translating the analog process into a discrete, physical format. Such a notation could represent anger, happiness, joy, ecstasy, sadness, and loneliness as an algorithmic formalism.

Through cognitive penetrability, it is conceivable that certain mentalistic concepts and representations could be tagged to certain emotions invoked by reception of certain physical input. Physical changes at the biological level could be tagged to emotions that would affect the cognitive process. For example, one's overall mood, disposition, and thoughts can be greatly affected by one's physical health. Having the flu can cause one to feel depressed, irritated, frustrated, and perhaps confused and even angry when thinking about the effect of the illness on one's job. The neurophysical illness and subsequent emotions will be reflected in the general cognitive outlook of the person, that is, the person will tend to think negatively when sick.

In fact, emotions could have a generalized effect on the entire system simultaneously affecting all three levels: biological, functional, and representational. The pervasive nature of an emotion influencing all other aspects and processes of the system is referred to as a generalizing effect. To account for the generalizing effect of emotion
influencing the overall makeup, well being, and cognitive processes requires that the computing model be self-adapting and -modifying in order to be able to alter subsequent actions and thoughts due to the omnipresent nature of the emotional state. The human equivalent to this would be how a person's mood, such as feeling happy or depressed, has an overall impact on all subsequent processes. A depressed person would tend to think more negatively, drawing upon more negative thoughts, resulting in a general negative outlook and a generalized feeling of depression, than if the person felt ecstatically joyful. In this example, it is important to recognize that emotions can affect not only cognition and behavior but also have an effect on all processes following it. The computational system would have to be flexible and adaptive using both front-chaining and backtracking methods.

Tagging emotions to the neurophysiological and cognitive processes could be accomplished using an indexing method. Indexing is quite an acceptable programming method in A.I. Programs typically have used indexing to correlate empirical data, such as input and output, to the significance of the cognitive task being performed. It is conceivable that emotions could be matched to specific cognitive representations and activated when a certain set of criteria or constraints was met. Through the indexing process, emotions could be tagged to both cognitive and
biological process. A traditional example of indexing would be where reaction time is viewed as a correlate measure of the computational complexity for the processing of a cognitive task on a computer. The measurement of time in this example is tagged to the complexity of the problem solving task. The longer the computer takes in solving the problem, the more complex is the problem and the more difficult the task. Emotions would be invoked through an indexing scheme built into the computer program. Indexing would call upon certain emotional qualities when a particular neurophysiological or semantic content was addressed. Concepts and biological processes would be matched to specific emotions. The various physical and semantic operations would be ranked according to their correlations with emotional attributes. The emotions themselves would be characterized in terms of their magnitude: indicating the exact strength, intensity, and duration of the emotion. The varying degrees of emotional quality are referred to as weighting mechanisms. The strength of the emotion in terms of conditioning subsequent processes would depend on the strength shown by the weighting mechanism and reoccurrence of the same emotion. Pylyshyn elaborated on the role of a weighting mechanism, noting that it could explain why certain cognitive processes characterized by a certain mood or feeling would occur more frequently in certain situations than other concepts. The
weighting mechanism causes the beliefs tagged to negative affects to be called upon more frequently when confronted with a particular situation because they are more heavily weighted and appear at the top of the priority list. Pylyshyn commented on the roles of weighting mechanisms and their roles in the cognitive process.

Such a hypothesis could explain why inferences and other cognitive processes characterized by a particular affective quality occur more frequently in certain situations (as happens in the case of happy or sad moods): the weighting mechanism in the control structure of the functional architecture simply results in the beliefs with negative affect being more readily available (that is, being the unmarked case or being the first beliefs encountered by a selection process).

(p. 270)

The moods or emotions would affect the resulting behavior, as well as cause changes in the neurophysical, biological, and chemical processes of the system. Indirectly, emotions also could influence cognition by altering the biological, physical architecture and the symbol-computational level principles of the system, thereby resulting in "generalized effects on subsequent cognitive processes" (Pylyshyn, p. 269).

An emotion measured as strongly influential, as for example depression, and occurring in frequent repetition
would have a strongly pervasive quality, affecting all subsequent processes, until another emotion took its place. Repetition of a certain pervasive overriding emotion in a restricted period of time would tend to increase the magnitude, strength, and duration of the emotion. On the other hand, an emotion not reoccurring and quickly replaced by another emotion, would be weighted lower in strength, duration, and magnitude. The weighting mechanism and indexing scheme would have to change in order to account for changing emotional influences.

The system would be in a constant state of change—modifying itself in response to external stimuli. For example, the strength of the incoming stimulus transduced from the physical-biological level to the representational-symbolic level would rank the priority of the indexing process and what weighting mechanisms come into play (for a description of the programming techniques of indexing and prioritizing, see "matching" and "agendas" in chapter II). The priority of an affect valence could change based on new biological physical experiences and new cognitive representations, inferences, and learning.

The specific description for emotions and their respective qualities would have to be expressed in formalistic terms in order to be recognizable by a digital computer, as is done by other continuous analog systems, such as thermometers, speedometers, barometers
oscilloscopes, and thermostats. Emotions would be symbolically coded as an algorithmic program in a manner similar to analog devices that translate their readings into digital formats using approximation techniques.

If Pylyshyn's model was adapted to accommodate these recommendations, it could be used to test the strength of equivalence between modelling traditional cognitive theories of emotion (as described in chapter III) and the actual cognitive processes being modelled. Such tests would ultimately display the strengths and weaknesses of a cognitive model as observed in the machine's processing of input and creation of output. Factors such as correlating the input and output functions of the model to the cognitive task can be used to empirically measure the strength of equivalence. Such observable aspects would also provide insights for understanding unobservable processes such as cognition.

In chapter V, I will consider the implications of applying a computational model to account for arbitrary yet formal phenomena, such as emotions. Speculations about the general relationships between A.I. and art also will be made.
CHAPTER V
SUMMARY AND CONCLUSIONS

Statement of the Problem

This dissertation was an epistemological study to analyze cognitive theories found in artificial intelligence and psychology in order to identify what role, if any, emotions play in the cognitive or intellectual process. Understanding the relationship of emotions to processes of intellectual development or processes of intelligence, has implications for constructing theories of art explaining emotions and aesthetic response in the creative process.

Review of A.I. Research Related to Programming and Processing of Knowledge

A.I. research was examined to identify significant principles of A.I. with major techniques involved in the programming and processing of knowledge. This review indicated that the A.I. research focused primarily on logical, formalistic, and semantic factors in cognition to the exclusion of qualitative processes.

Various formalistic means for acquiring and representing knowledge were presented in the research, such as logic, frames, scripts, and semantic networks.
Basically, knowledge was observed to be a way of representing information that was necessary in solving problems. Finding a solution to a problem was directly correlated to the quantity and quality of the information; therefore, knowledge acquisition and representation was a significant component in the A.I. systems analyzed. Traditional ways of representing knowledge centered on logical, linguistic, syntactic, and semantic kinds of information using finite and discrete symbols such as words and numbers.

In addition to finding an appropriate technique for knowledge representation, a finely designed A.I. system required a strategy for using the knowledge at the appropriate times. Knowledge itself doesn't analyze or solve a problem. A problem is solved by calling on the most appropriate knowledge at the most desirable time in an efficient and direct manner. This strategy for solving the problem determines the flow of control, that is, the paths to take in exploring various alternatives. These alternatives are explored through the use of rules referred to as heuristics. Heuristic search examines all the possible directions in determining the solution. General purpose heuristic search techniques can be described independently of domain-specific knowledge. They are generic rather than linked to a specific problem and domain of knowledge. Understanding search and techniques that
determine the selection, order, and application of rules
heuristics is fundamental to understanding how programming
and processing of knowledge is accomplished in A.I.

Cognitive-Emotive Theories

Chapter III provided an overview of basic cognitive-
emotive theories, drawn from psychology and emphasizing
neurophysiological factors, behavioristic views, and
cognitive-behavioristic theories.

How cognitive appraisal of the stimulus affects
emotional and behavioral response was studied and analyzed.
Researchers differentiated between moods, feelings, and
emotions, based on duration and reoccurrence of the emotion.
Other studies observed that emotions occurred prior to
cognition and analyzed the effects of the emotions on the
learning process. Some researchers viewed emotions as a
disorganizing force causing a behavioral response, while
others regarded emotion as a motivating and organizing
force. Still other studies considered emotion as interwoven
with the cognitive and physiological processes.

Earlier studies differentiated among the processes--
emotion, cognition, behavior, and neurophysiology--and
observed them as separate sequential events, such as
cognitive appraisal occurring before, and therefore
influencing, emotional response. Studies emphasizing the
interwoven relationship between cognition and emotion
postulated a changing sequence of influences. Depending on the
situation, emotion affected cognition and vice versa; neither process was viewed as an independent activity. Emotion and cognition were seen as continuous processes, occurring at the same time. In certain instances, one of the processes could dominate. Many early researchers, however, failed to recognize the continuous, synergetic quality of emotion. Emotion is similar to other human processes, such as breathing; in that they are continuous processes. It can, at times, appear more intense and explicit.

Neurophysical and behaviorist studies dominated the history of emotional research. Very little effort had been directed towards studying cultural influences on emotion and cognition. Incorporating emotions into A.I. systems was advocated by some researchers, who recognized the role and significance of emotion on cognition.

Emotion was shown to deepen one’s understanding of art, while, in turn, understanding of art can provide insights about feelings.

An A.I. Model Related to Emotions

In chapter IV, a cognitive model for A.I. was presented and adapted to account for emotions. In developing A.I. models, it is important to acknowledge the capabilities and limitations of the computer that will be used to implement the A.I. model. A computer is an information-processing mechanism that receives information in a digital format.
Input must be converted to a digital format recognizable by the machine. One way to do this is to use an analog device that converts continuous processes, such as emotions, into digital format, in much the same way that abstract concepts, such as thoughts and ideas, are made tangible through the use of a symbol system called language. Traditionally, emotions have been conceptually oriented using words or labels. A first step towards incorporating emotions into an A.I. model must be the cognitive labelling of emotions. Through cognitive labelling of emotions, words can represent emotions in the same way that they are used in poetry to express feelings and thoughts.

For use in an A.I. model emotions have to be first expressed in physical terms and then converted into a format recognizable to a computer. This activity is similar to how an analog temperature measurement is converted to a digital format, or the way Beethoven's Fifth Symphony can be captured by a recording instrument, which, in turn, converts the music to a digital format for a compact disc. Obviously, the same problems with translating abstract concepts such as infinity, volume, gravity, and crescendo into mathematical, chemical, or musical notation, also exist in converting emotions to digital data.

The strength, duration, and reoccurrence of an emotion could be indicated through weighting mechanisms, similar to the way the Dewey decimal system differentiates between
books with similar content by forming classifications. Such a system provides the precision and quantification required by a computer. The magnitude of the emotion, as specified by a system of weighted mechanisms or valences, would be passed through transduction from the physical-biological level of the system to the symbolic-functional level. Once the emotion is transferred to the symbolic-functional level, the emotion would be treated symbolically like the notes of a musical score, the mathematical symbols used in an algebra equation, the chemical notation representing physical properties, the alpha-numeric characters used in human language, or the symbols and syntax used in a programming language like C.

By indexing, emotions can be matched to concepts. When a particular concept is in use, associated emotions come into play. Concepts would be associated with keywords, which would call upon a group of selected emotions related to the particular concepts. Individual emotions in a grouping would be prioritized according to the magnitudes of the emotions. Emotions that are insignificant would be placed at the bottom of the list. Emotions judged significant as a result of repeated use, duration, and intensity would be placed at the top of the list. The order of emotions would constantly change due to changes in the frequency, duration, and intensity.
Emotions influence cognition in such areas as negative or positive thinking, paranoia, skepticism, and open-mindedness. Reoccurrence of a particular emotion influences thinking, which, in turn, is continually reinforced through rationalization of the emotion and reexperiencing of the emotion as a behavioral response. An emotion is considered pervasive when it has affected one's overall nature, that is, one's thinking, disposition, mood, and behavior. A particular emotional response can be triggered by either a neurophysiological or cognitive factor. A neurophysiological factor such as a bad stomachache certainly affects a person's general outlook and feelings. One's appraisal of a situation influences feelings about the event. Emotions stimulate neurophysiological, cognitive, and behavioral processes as all those who have been in love can attest.

Suggestions for Future Research

Computer models such as the one described above could be used to explain the relationship between cognition and emotion. The input and output functions could be empirically observed to obtain descriptive and quantitative data that could be used to compare operations and data structures of the cognitive process and the computational model. Performances at the symbolic level could also be compared to determine the number of steps, sequence of operations, and the time involved for a human and a machine.
to perform. The model should also explain its method of problem solving, the flow of control, selection, and sequence of rules that were applied, the paths taken, and nodes explored and ignored. The model should be self-explanatory in describing how it arrived at its solution to the problem. It should be able to explain how certain emotions influenced the decision-making process and the resulting decision or behavior.

The study of how emotions influence cognition requires analysis from behavioral, neurophysiological, cognitive, and cultural perspectives. Empirical methods focusing on quantitative methods could be used to gather data about the neurophysiological and behavioral processes. In addition, qualitative methods, such as interviews and autobiographies, could be used to obtain information from individuals about how their emotions related to their thinking and processing of knowledge. Ethnographic research methods could be employed to study patterns of behavior and cognitive processes in individuals in the same cultural group. Associations could be made from comparing and contrasting the evidence obtained from using the various ethnographic methods. Studies could be replicated with the same or similar cultural groups to further define unique characteristics of the cognitive-emotive process in question. Cross-cultural studies could be conducted to differentiate unique characteristics of a cognitive-emotive
process as experienced by varying cultural groups. Different cultural groups present different quantitative evidence about varying behavioral responses and neurophysiological processes and different qualitative data regarding emotions and cognition when performing the same cognitive task. These studies might help to identify those aspects in emotion and cognition that are culturally determined and those that are universally-present.

It should be recognized that cognition and emotion are not completely universal processes experienced in the same consistent manner by all people. They vary depending on the particular attitudes, values, and beliefs of the particular cultural group. Explanations for cognitive-emotive processes depend upon cognitive, emotive and cultural data obtained through both qualitative and quantitative methods of research.

An A.I. model needs to consider both the influence of emotion on cognition as well as the pervasive power of culture on emotion and cognition. In doing this, the A.I. model will more closely replicate how an individual from a particular culture performs a specific cognitive task, such as art appreciation, preference, and visual perception. A.I. models that include both cultural and emotional factors would be better able to provide unique solutions to problems specific to particular cultural contexts. A Japanese A.I. system would produce a different painting than a U.S. system
when given the same problem, criteria, and media because of varying cultural attitudes, values, and beliefs.

Issues Related to the Need for Further Research

Logical and Universal Emphasis

The A.I. theories presented in this dissertation and Pylyshyn's model are all based on a logical linguistic foundation. One reason for this was to maintain the role of the computer as an efficient, consistent, accurate, and functional processing machine. It would be considered anti-industrial and nonproductive in a technocratic society to have a computer modelling other kinds of human behaviors and processes such as daydreaming, feeling, and imagining. Pylyshyn’s model has limited coverage of sensory activities that are also part of cognition, such as hearing music in one’s mind when no music is playing. Cognitive processes involve more qualitative sensory aspects than what is described by a semantic A.I. model. Although all those processes are involved and necessary in inventing new ideas or in flexible, creative problem solving, the programming methods or formalisms illustrated in chapter II emphasized the productive, accurate, and efficient nature of A.I. systems. These theories therefore presented a one-dimensional, limited view of human processes rather than providing more inclusive aspects of human qualities involving mental smells, imagery, and sounds. Creative feelings have been ignored or given fleeting consideration
thereby limiting the creative aspects or problem-solving potential in the A.I. models.

Very rarely is there one absolute answer to an art problem or one universal way of responding to a work of art. Individuals from various cultural groups will provide different, but acceptable, solutions to a given problem. Creativity involves making decisions about a problem to arrive at a unique solution. Although creative problem solving involves the use of formal and constant knowledge such as color theory and elements of design, it also involves the use of knowledge and emotion which are not constant or predictable, such as randomness, unpredictability, and surprise. The artist's intent, influenced by culture, directs his/her creative problem solving. A.I. models should provide unique and creative solutions for problems influenced by culture and emotion (i.e., the way people actually solve problems), instead of providing only a universally consistent solution that ignores unique and varying qualitative differences.

**Functional Architecture Emphasis**

Another reason that A.I. is rooted in a tradition of logic is the functional nature of the digital computer, which uses a two-valued system—on and off. Because words are finite and syntactically oriented, it makes sense that the first A.I. systems performed tasks that took advantage of the machine's inherent functional architecture.
Significant technical strides were made because of the researcher's attitude and respect for the logical operations of the digital machine. Unfortunately, correlations emerged suggesting that humans actually did think like machines, as in the information processing theory of Minsky (1982), who believed that all thinking is the same, even creative thinking, except that it is done better than ordinary thinking due to practice. Minsky didn't account for qualitative influences affecting cognition. He emphasized the semantic, sentiential, formalistic role of the model.

In fact, it seemed that some cognitive scientists intended to prove that their models were universally correct and that all cognitive processes could be forced into their models, rather than acknowledging the existence and influence of qualitative and cultural factors.

Pylyshyn's model was deeply concerned with the operations and functions of the machine itself. His philosophy stemmed from the view that if a cognitive model can't be computed then it's not worthwhile to consider. Unfortunately, this view narrowed the concept of cognition into what could be performed by a machine, rather than acknowledging what might actually exist but can't be presently replicated on a machine. Models like Pylyshyn's equated machine intelligence with human intelligence: any cognitive process that could be computed was human intelligence. The computer was replicating human cognition
in performing information processing tasks. Thus, human cognitive processes were considered the same as the computer's. Based on this theory, it could be inferred, unfortunately, that the computer model and human intelligence share the same cognitive fundamentals.

A.I. researchers have shown correlations and similarities between the computational model and cognition. They have done this in an effort to demonstrate the validity of the model by showing how equivalent the two are. In the future, cognitive scientific research should also clearly define the differences between the two. Understanding of the differences in addition to the similarities will provide new directions for research in A.I.

The digital functioning of the machine, based in two-valued formalisms, has directed the efforts of cognitive scientists. Thus, the A.I. research has been overwhelmed with cognitive models that were based in logic and semantics. The fields of logic and semantics investigate relations that are quantitatively and logically written as discrete and finite formalisms.

Traditional A.I. models emphasized the significance of cognition while excluding factors influencing cognition, such as emotions, moods, attitudes, and beliefs.

The Use of Fuzzy Logic

As discussed earlier, emotions are continuous processes, varying in magnitude with crescendos and
decrescendos of intensity and duration. Emotions, like other qualitative processes, are referred to as analog because they are continuous and have magnitude. Even though analog processes are not finite and discrete, they can still be converted into a two-valued logical format recognizable by the digital computer in much the same way that a computer can read external temperatures with a peripheral device like a thermometer. Current research in A.I. is beginning to acknowledge the existence and influence of qualitative factors in cognition. The fuzzy logic work by Zadeh (1984) explored the gray areas of language and understanding that are considered imprecise, yet immediately understood by others. Zadeh employed approximation techniques in his A.I. systems to account for terms like very warm, very likely, few, many, and several. Further research on approximate reasoning is recommended for an understanding of how individuals make guesses and estimates and to account for behaviors that are more intuitive and culturally influenced, and that cannot be explained logically.

Fuzzy logic is much different from the traditional Aristotelian two-valued logic, where results are either true or false. Two-valued logic suits some situations in which the meaning is distinct and discrete, as in male or female, dead or alive, white or black, and on or off. But two-valued logic does not account for the reasoning used to summarize a story or describe the unity in a painting.
Fuzzy descriptors aren't precise truths; they are meaningful generalizations that most people understand. Fuzzy descriptions can be converted to approximations for use on a computer.

Zadeh was interested in the potential role of fuzzy logic in expanding A.I. He didn't suggest that fuzzy logic was a panacea for A.I., but rather that it addressed problems that were complex, complicated, and more general than the traditional kinds of problems.

Before Zadeh's research on fuzzy logic will significantly impact the field of A.I., a change of attitudes will be required by those doing A.I. research. Qualitative research methods dealing with aspects of human experience, such as emotions, feelings, and attitudes, which are generally not expressed as finite numbers, will have to be accepted. The results of these methods will be expressed in fuzzy terminology, words like very likely or unlikely. Fuzzy logic, according to Zadeh, will be a retreat from the unrealistically precise expectations of the imprecise real world.

The incorporation of fuzzy logic into A.I. will be a step towards enabling the artistic computer system to work with both arbitrary types of experience, such as the artist's spontaneous problem solving with a work of art in progress, as well as with nonarbitrary domains of artistic experience, such as a painter working exclusively with cool
Colors. Nonarbitrary can be defined as any behavior or process that is not random and has a definitive purpose, goal, or reason. A nonarbitrary process, such as balancing one's checkbook, is methodological and formalistic because it can be described precisely and written as a logical procedure following specific rules in a set order. A nonarbitrary formalism, such as rules of arithmetic, follows precise rules in the correct order in achieving the correct result(s). Currently, many of the cognitive processes that have been artificially simulated employ computational models that are formalistic and nonarbitrary, like the steps taken in solving an algebraic linear equation.

Replicating Human Experience

A.I. will never be able to fully replicate human cognitive processes. Humans are endowed with qualities, such as feelings and intentionality, that do not exist in a computer. People are motivated, driven, frustrated, and excited in solving problems, and these qualities are certainly a mixture of cognition and affect. Because a machine doesn't possess these qualities, it will never be able to experience the solution of a problem in the same way that a human does. Often, humans' problem-solving abilities are reinforced with positive feelings resulting from the accomplishment of a goal. Humans feel throughout the problem-solving process, and their feelings change. Feelings, intentionality, attitudes, cultural values, and
beliefs steer people towards inventive solutions to problems that they wouldn’t have thought of logically. They are also the driving force behind an artist’s creative problem solving, and they direct his/her style, manipulation of media, and use of the elements of design. Research in art education from psychological, idiosyncratic, and cultural perspectives could contribute greatly to the understanding of the artist’s creative process.

Sentential and Semantic Emphasis

Pylyshyn’s model overemphasized the role of language in A.I. He equated thoughts, ideas, and cognitive processes with a symbol system recognizable by the computer. Even though the computer can process these symbols and perform cognitive tasks, such as solving a linear equation, using symbols, this information-processing activity doesn’t imply that the A.I. system comprehends the meanings of these symbols or the relations amongst them. Equating the functioning of the human mind to the processing of symbols is invalid because a computer doesn’t understand the symbols anymore than a book understands the meanings of the words printed in it. Cognition involves much more than information processing; it involves processes like feelings, attitudes, values, beliefs, intentionality, and comprehension of symbols.
Creative Problem Solving

In creative problem solving, an artist solves qualitative problems such as the selection and use of the appropriate media and elements of design to express ideas and feelings. Eventually, the artist becomes better at representing problems and in controlling the qualities, as noted by Ecker (1966). The qualities guide the artist in achieving the desired results preconceived in his/her mind. The creative process is motivated by this premeditated goals.

Creativity is a form of intelligence in which the art-making process is a deliberately controlled affair. The process is intentionally defined by the artist's idea of what the end result should be. Although this process cannot be explained as a logically sequenced procedure, it is not unlawful or illogical.

The artistic thinking involved in making a work of art is also qualitative. As the artist works, his/her thoughts are focused on the qualities of the work of art. These qualities include the nature of the media, the subject matter, expression of feeling, and style.

Creative thinking is an intentional process in which the means of producing the work of art are deliberately conducted by the pervasive quality, that is, the directive criterion, purpose, or artistic intention. This theory of creativity emphasizes a working correspondence between the
means of production and the end product. The end product cannot be isolated and analyzed in terms of creativity without examining what occurred during the art-making activity.

The artist is guided by rules which govern his/her way of working to achieve a particular style, such as cubism. The rules are not as exact and definitive as the explicitly stated rules of a scientific method. Yet, they are understandable enough for the artist to work with and talk about. The rules or pervasive qualities are flexible in that a series of paintings can be created which are not identical yet in the same style. For example, if an artist wants to produce a cubist painting, there are certain rules that govern the way the artist works; two examples of such a rule are reducing three-dimensional objects to flat planes and showing various viewpoints of an object simultaneously. If the artist isn't guided by the pervasive qualities found in cubism, then he/she won't produce a cubist painting. The cubist artists Picasso and Braque found the pervasive qualities open and liberal enough that many different themes and subjects could be pursued within the same cubist style: still lifes, portraits, group studies, etc. Creative problem solving is a special kind of thinking that attempts to grasp the qualitative essence of a particular style by ordering the parts towards the whole. Certain elements are
rejected, others are emphasized. Artistic thinking is formal and orderly, it is not random or uncontrollable.

There are some nonarbitrary aspects of artistic thinking that could potentially be structured into a computer program. Artistic problem solving is not often an obscure, random experience, even though the artist may not appear to be following any set rules in a logical order. The artist may gradually become aware of what he/she wishes to achieve and how to achieve it. Although the creative process involves forms of exploration and appears spontaneous it is a highly goal-oriented activity.

Creative thinking in art also involves sequences and procedures. Even though the pervasive qualities are not explicitly stated in finite, logical terms, they are discernible. The pervasive qualities are a method controlling the way the artist works. This theory of creative thinking could be adapted to an A.I. system in which the program would use and process knowledge about a particular style of art, such as Gothic architecture would be inputted into the computer, describing basic characteristics of the building, such as the floor plan, types of windows, and the exterior facade. To use this program, the artist would input the building requirements, such as total square footage and the various necessary functions. From this information, several design alternatives would be presented by randomizing different
elements. Each design would represent the pervasive essence of Gothic architecture. The alternatives would range in size, cost, and materials. From the alternatives the artist would decide which plan or plans best suited his/her client. If no one plan was suitable, the artist would indicate and rate the various factors considered most and least desirable. The program would then compare the specified changes and would approximate a new design based on this information. The final plan chosen by the artist would be printed out as a blueprint with all the necessary measurements and elevation drawings.

An artistic A.I. system strictly following the pervasive quality of style would be problem solving as it compared the different requirements of cost, size, function, etc. Are the humane qualities of the environment most important, or should the cost effectiveness and function of the space be given priority? Should the authenticity of the style be the single most important factor, or is it to be a partial concern shared with a regard for energy efficiency? In deciding, the computer program would order the various qualitative parts with the inputted preferences to achieve the end result. Randomization could alter the significance of certain design elements and relationships, thereby allowing for a multitude of designs to be generated within the same style. In the end, however, the artist would still make the final decisions.
Cultural components, attitudes, and beliefs, such as the period and place that he/she lived, that influence the artist should be accounted for in the A.I. system. There is a significant relationship between one's culture and the pervasive qualities of art that extend beyond the formal concerns of line, shape, color, and medium. Picasso's Guernica, for example, is not only an authentic example of the cubist style, but also a political statement. What were the pervasive qualities controlling Picasso as he worked? How did he use his personal experiences, values, and attitudes to grasp the essence of cubism as he painted Guernica? Picasso considered certain factors from his life experiences to be more important than others, and he chose the significant ones for his art forms.

Research in A.I. would have much to gain by looking at areas of creative problem solving, since the rules for the artistic procedure appear to be approximate and fuzzy. The way an artist works in ordering the pervasive qualities can be correlated to Zadeh's research on approximate reasoning. Although artistic problem-solving procedures tend to be fuzzy, they are clear enough that artists can talk about their works in progress with a certainty about the works' directions. It would appear that these artistic processes, at least in part, lend themselves to a type of structure that could eventually be programmed as an artistic A.I. system.
Research in A.I. focused on technology and cognition can contribute to a clearer understanding of intelligence in general, which encompasses artistic thinking. Art education that includes the arts and humanities can contribute to the research in A.I. by incorporating research with an emphasis on creative processes and qualitative problem solving.

A suggested A.I. system for a creative art process.

Research on the creative process has relevance for A.I. research, particularly in the following area: 1) Thought is embodied in the art object; 2) The artist thinks as he/she works. It is a spontaneous, interactive process; and 3) The artist thinks about and through qualitative media that he/she works in. Although the artistic process is a continuous progression from the means of production to the desired end result, Ecker (1966) was able to delineate and explain specific thinking processes involved in qualitative artistic problem solving as the artist interacted with both media and concepts.

A similar method could be used in an A.I. art system for developing "sketches" or concepts for three-dimensional computer graphics or scenes. Below are stages that could be conceived or imagined in such an interactive A.I. system.

1) The artist would slip on a pair of electronic gloves, which would be hooked up to the computer like a peripheral device. The artist would select the type and amount of material that he/she was going to work with from
the assortment of media icons appearing on the screen. For example, a plastic or additive type of media would appear on the screen. The visual display on the computer screen would then show the medium being manipulated according to specific directions projected through movements of the artist's hands. The material could be "pinched," "pulled," "torn off," or "lumps could be added" to the basic form. Other media could be selected that would respond to subtractive approaches in art. From the assortment of media of varying plasticity from steely to spongy, the artist could then select a medium and an assortment of tools to create a three-dimensional computer graphic image.

2) The A.I. system would invent new relationships for the artist to consider. For example, all the positive shapes in the design could completely change into the reverse, into negative shapes, or, conversely, the negative areas could become positive.

3) The system could identify or diagnose a pattern describing and analyzing the artist's way of working in a particular style. This would be related to the pervasive quality of the work of art guiding the creative process.

4) The system could then conjecture alternative rules or other pervasive qualities. There would be a refinement of existing rules and additions of new rules.

5) The system would then continually check the artist's input for consistency according to the identified patterns
or change in qualitative directions, thus updating itself based on new input and information.

6) Alternative forms or solutions would be displayed on the screen for the artist to select from. The artist could select an individual form or several forms, which could then be combined and refined. The same system could be applied to different tasks, such as using different styles for the same subject matter or exploring various themes and forms in one particular style.

Other types of A.I. systems could be developed where computers would be used to see and attempt to identify an artist's style, as projected in a series of artworks by the same artist. Factors related to the artist's style, such as patterns observed within and between paintings, could be used to identify works attributed to the same artist. When the A.I. model was presented with the problem of recognizing an unfamiliar work of art by an artist that it was already familiar with, the model would be able to analyze the style and state who the artist was, based on clues found in the new work that related to patterns in the artist's style. Presently, computers recognize patterns in pictures by comparing the information seen in the picture with information stored in the program's database. A pattern is identified when a match occurs between the two sets of information.
The alphanumeric symbol system used by people provides a means of communication that is full of meanings. Words, sentences, paragraphs, and so on, represent ideas that are generally understood by the particular cultural group using the language. Another kind of symbol system is the elements of design used in artwork. Through introductory levels of aesthetic criticism dealing with description and analysis, viewers are able to verbalize about the symbols and relationships among them. In this sense, then, levels of artistic appreciation can be formalized in a step-by-step, goal-oriented algorithm for use by computers. Higher levels of aesthetic criticism, such as interpretation and evaluation, tend to be too arbitrary in that different critics will have varied responses to the same art. Yet, a computer could be programmed with a random component yielding a different interpretation each time. The problem that some people would have with this model is that there would be no one reliable answer to a problem, because of the variety of acceptable responses. But, it wouldn't be a problem for a computer to replicate the role of an art critic evaluating a work of art, providing the A.I. system was endowed with specific knowledge and rules for art criticism.

Emotion and Aesthetic Experience

The aesthetic experience is equally dependent on both cognitive and affective processes that occur together rather
than as separate stages of the experiences. Ideas are affected by the emotions experienced regarding the work of art being thought about. Thinking about and experiencing a work of art requires feelings and emotive qualities. An aesthetic experience integrates one's intellect and emotions.

An emotion does not exist in a vacuum. It's experienced in relation to something. The expressive properties of a work of art, referred to as the qualitative features, are those that trigger an emotional response. The viewer interprets the art in terms of these expressive properties that include cultural, historical, psychological and other qualities. Art gives form to feelings by making them objective. Through art, feelings like joy, sadness, and anger can be given apparent form and meaning. An artist's perception of subjective life experiences can be objectified and shared by others through art.

Emotions change in intensity and develop through time. They are not brief, finite, and discrete. Emotions like love and sorrow are complex and can't be compressed as simple behavioral responses like jump or push. An artist expresses ideas and feelings through a work of art. While art presents feelings, it is not the actual feeling, nor is it a copy. It is the appearance of feelings in an articulated form.
An individual's interaction with the world is neither completely emotional nor completely cognitive. An aesthetic experience with a work of art involves both thinking and feeling. Aesthetic response to art involves cultural influences, such as attitudes, values, and beliefs. The viewer's response to art is not a simple behavioral response to a stimulus.

Historically, the research in A.I. has taken a behavioristic approach in formalizing cognitive processes as algorithms. Frequently, the research in developing A.I. systems has been directed towards the application of physical activities and motor skills, e.g., robotic research and the performance of formal mental operations like solving an arithmetic equation by a computer. Formalistic procedures as such are limiting in that they cannot be used to describe the human qualities inherent in creative expression and response to art. A.I. doesn't take into account feelings and attitudes prominent in qualitative problem solving and decision making. Human choices do not always follow logical rules. Our choices are influenced by our attitudes and values. Further research in A.I. needs to investigate the integrated, relational process of feeling and thinking; these studies could then be associated with the aesthetic process. Research on qualitative problem solving would also provide insight into philosophic speculation and scientific inquiry. A.I. research in visual
perception, Gestalt principles of visual organization and aesthetics could help delineate concepts of creativity and response to art. There is much to be learned about creativity and the aesthetic experience. The use of computers and A.I. in these areas would provide another perspective for understanding mental processes involved in the creation of and response to art.

An area significant to the research in qualitative problem solving and A.I. is the study of aesthetic response and feelings in relation to computers. Computer systems at this time are knowledge-based and disregard the realm of emotion. Pain, fear, and joy are significant factors in one's experience and comprehension of the world. Generally, the artist's function is to express his/her ideas and feelings in artwork. How we perceive and interpret such emotion is an area needing investigation.

The Role of Culture in Aesthetic Experience

The emotions a viewer experiences through a work of art are derived both from associations with prior experiences, as well as from the forms projected in the art. The viewer brings to the work his/her attitudes, values, and beliefs, which have been obtained through living in a particular culture.

The psychological theories presented in chapter III, the A.I. programming techniques described in chapter II, as well as Pylyshyn's model in chapter IV, emphasized a
logical, rational approach to cognition rather than a cultural emphasis on values and beliefs. Culture was defined as the shared values, attitudes and beliefs of a specific group of people. Enculturation is an ongoing, life-long process in which these specific cultural values, attitudes, and beliefs are learned by individuals in that cultural group and reinforced. Few studies examined the pervasive influence of culture on one's emotions and cognition. Perhaps research directed towards observable cultural factors affecting behavior and cognition could be performed in which external factors are indexed to certain cultural elements. Through repetitive experiments, correlations demonstrating the significance of culture on cognition, emotion, and behavior could be studied.

Other qualitative research methodologies, such as ethnographies in which ritualistic behavioral patterns displayed by individuals in cultural groups are examined in relation to the group's beliefs, values, and attitudes, need to be developed and used. Accounting for varying cultural backgrounds could help us understand differences and commonalities between the human processes of thinking and feeling. To recognize culture as a significant influence on cognition places value on shared group behavior, as well as the uniqueness of the individual. The A.I. models and theories presented universal approaches to cognition that disregard the unique characteristics of the individual and
cultural factors. Recognition of cultural influences can help researchers understand these influences on cognition and emotion.

Implications for Art Education

Research conducted by aestheticians and computer scientists on learning and thinking in art may provide new directions for art education researchers working on similar problems. The research in A.I. on both the creation of and response to art are central to issues in the field of art education.

A.I. research is the study of thought and intelligence as possessed by a computer. Controversy exists about whether computers can replicate the thinking processes of the human mind. Presently, computers are adept at following tasks written logically within a program. If thinking processes can be analyzed and then converted into computer programs, computers should be able to perform cognitive processes. Analyzing and converting thinking processes to programs would be a major contribution to art education research concerned with perception, memory, and the various stages of the art-learning process. A.I. research could provide art education with theoretical models of intelligence. To A.I. research, art education could contribute toward shaping concepts in artistic perception, appreciation, and stages of artistic problem solving.
There are nonarbitrary aspects of artistic thinking that have the potential for being structured into a computer program. Artistic problem solving is not an obscure, random experience, even though the artist may appear not to be following any set rules in a logical order.

Research in the visual perception of artworks that deals with qualities ambiguously related could help the pattern recognition work in A.I. The goal of pattern recognition research is to enable a computer to scan, recognize, and identify imagery and potentially an artist's style. Research could also be directed at qualitative problem solving, in which the computer invents artistic problems based on inquiry made from the patterns recognized in a series of artworks. Once the computer has formulated a problem, it should then develop and help solve the artistic problem in the making of art. The knowledge gained through the problem-solving process could be applied to new problems and different situations, using a flexible and context-free methodology. Research into the use of computers for purposes beyond logical formalisms will need to be pioneered before applications using creative thinking can be envisioned. A philosophy of intelligence for A.I. is needed that encompasses qualitative thought as well as formalistic thinking.

Educational research describing the processes in artistic thinking and learning could provide a more
comprehensive research base in A.I. Educators have used computers to delineate and examine research in intelligence. In explaining theories of intelligence, educational researchers have made analogies between the information-processing capabilities of the computer and the ways that people process information.

Studies that investigate patterns of artistic thinking could add knowledge to the research in A.I. that relates to problem solving in creative fields of study. The research findings in pattern recognition have some similarities with solving problems in art, in which the end result is not a precisely predetermined solution from the beginning. In order to obtain the desired result, the artist is directed by the pervasive qualities, such as the style, theme, or emotion, he/she wants to express in the artwork. These qualities act like rules guiding the working artist. How the artist approaches the problem and masters the qualities are learned though a series of trial and errors, perhaps over a lifetime of work. Understanding how the artist learns to represent, organize, and solve an artistic problem is significant to understanding the creative process.

Research problems in aesthetics, related to such areas as perception, art criticism, and learning in art, provide a common ground for research in both A.I. and art education. Scholars across fields bring different perspectives to the studies.
A.I. models will require the development and implementation of natural, expressive computer languages and voice recognition techniques, that enable the artist to communicate with the computer in a comfortable and unrestricted way. The A.I. system will need to be capable of interpreting the responses of the artist. To help bridge the communication gap between artist and machine, artists will need to objectify their creative problem-solving processes and be able to talk about their procedures precisely and meaningfully. An artistic communicative language would be more familiar with the artist's way of working and employ artistic terminology than having the artist input a program to generate an image.

The A.I. system would be capable of making artistic decisions by evaluating different alternatives, based on a set of criteria. An artistic A.I. system could learn as the artist manipulates the medium. It could also learn by analyzing which suggestions the artist has selected to use and how the artist has used them. Studies on how artists approach and respond to artistic problems would help to direct the research from a limited perspective of intelligence into more qualitative areas of creative thinking and learning.

In art, rules such as the elements and principles of design, may be applied in a strict fashion by the beginning art student. As the student masters the techniques and
media, he/she will experiment with these rules to produce more personalized creative work. It is by exploring that an artist invents new ideas. A restructuring of knowledge occurs as the artist modifies his/her concepts about art to encompass ideas. An intelligent computer system would be able to distinguish the relevant aspects of its information in the acquisition and problem solving stages.

An A.I. model could also critique works of art. This system would be devised from a combination of processes, such as the evaluating and interpreting of artwork, and the solving of technical problems. With this system, different artistic processes would act in unison as an interrelated whole rather than as separate operations. A combined aesthetic system could interpret a work of art, as well as describe the interpretive conventions used in the description, that is, the system would be able to provide a self-analysis of how it arrived at interpretations and conclusions.

In developing artistic A.I. systems, researchers need to learn how artists manipulate materials and develop design ideas. This understanding of the creative problem-solving activity would be used in designing the artistic A.I. system. This system would have to be capable of identifying and correcting errors in the artist's design. It should be able to check the design against the artist's criteria to see if the former is consistent with the latter. If not, it
would make the necessary changes. This system on its own would be able to recognize and label objects within the design, such as chairs, houses, and trees, as well as nonrepresentational shapes, such as squares, circles, and triangles. It would be a completely interactive system, providing real-time guidance to the artist by critiquing, interpreting, and modifying the artwork in progress. The A.I. system would be an essential component in the artist's creative process. In this sense, the computer will continue as only an artistic aid; it will not replace the artist in the creative process. The artist brings to the work of art intention, cultural attitudes, values, beliefs, imagination, and feelings. An A.I. system has the potential to motivate artistic thinking and suggest myriad alternative concepts; this work would be very time-consuming and wearing if manually executed.

In researching A.I., art educators need to collaborate with researchers outside of art education, or, at least be aware of the research in nonarbitrary thinking in other areas, to define differences and similarities between qualitative and quantitative processes in intelligence. Research in A.I. has been limited to quantitative and logical structures of thinking, excluding such humanistic endeavors as art and literature. Inclusion of research related to qualitative problem solving in art provides a
more comprehensive base of study for examining the area of intelligence in computers.

Collaborations among researchers from various fields who are investigating areas like cognition, emotion, A.I., aesthetic response, and creative problem solving could impact the future research directions of A.I. as new insights about human processes are discovered.
REFERENCES


