



0253

Framing a Learning-Based Approach to Interactive System Design

J. Choi, K. Sato

Institute of Design, Illinois Institute of Technology, Chicago, IL, United States

jungmin@id.iit.edu

Introduction

When interacting with an interactive system to achieve a goal, a user utilizes his or her existing knowledge and constructs new knowledge consciously or unconsciously. Throughout the active process of knowledge exchange, accumulation and generation, the user's mental models of the target system are built and constantly modified over time in order to obtain a desirable result. According to Driscoll (2005), "*knowledge is constructed by learners as they attempt to make sense of their experiences. Learners therefore are not empty vessels waiting to be filled, but rather active organisms seeking meaning*" (p. 387). In other words, learning is a consequence of the learner's experience and interaction with the world. According to this approach, learners are encouraged to actively construct their own knowledge in complex learning environments. Because the nature of knowledge-engaging process in user-system interaction involves the learning process, this paper considers that interaction corresponds to the user's learning process. By doing so, it intends to improve the experience of the user by supporting his or her learning process in the use of an interactive system.

Figure 1 depicts the preliminary research assumption on how the user's knowledge and mental models of the system could change as he or she constantly interacts with the same system. The evolutionary process could be considered as a learning process over time; that is, from t_0 to t_n . The basic notation to represent the different types of mental models was modified from Norman's (1983) four types of representation models that affect user-system interaction: S, the system that the user is using, C(S), the conceptual model that is created to provide an appropriate representation of the system held by designers, U(S), the user's mental model of the system, and R(U(S)), the researcher's model that describes the user's mental model. Before using the system, the user may do or do not have initial mental models of the system, U(S) t_0 , based on his or her prior knowledge and experiences. Having a goal to achieve through the interaction, the user starts to use his or her knowledge to interact with the system.

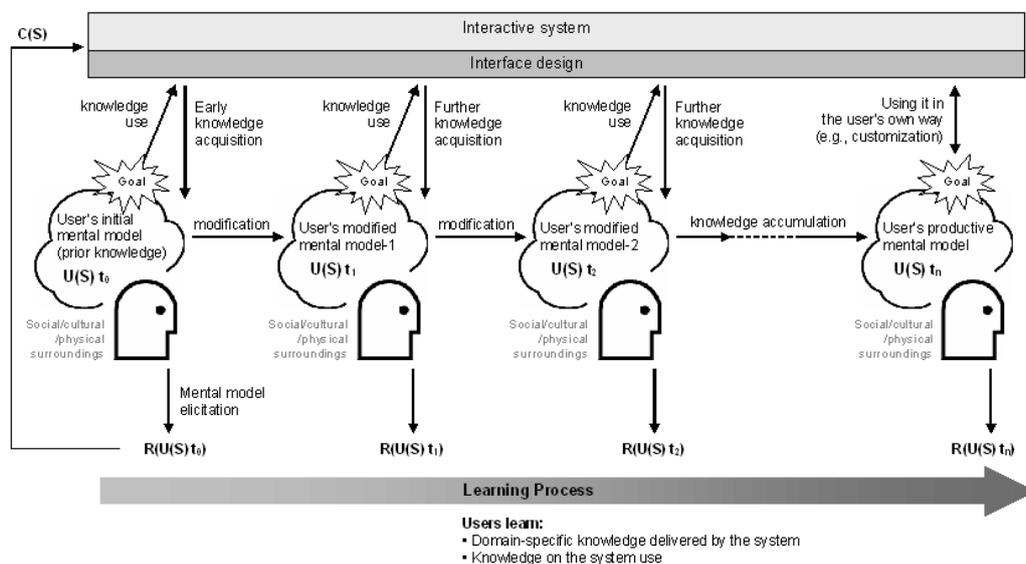


Figure 1. Changes of user's knowledge and mental models in user-system interaction

Through interaction with the system, the user may modify his or her mental models of the system by acquiring new knowledge from the system and/or from the user's social, cultural, or physical surroundings. The modified mental model, $U(S) t_1$, is utilized when the user has another goal. Throughout the iterative process, the user's knowledge of the system as well as the domain is accumulated. Finally, the user might have more productive mental models, $U(S) t_n$, that could enable him or her to have some insights on how the system might work and what additional functions might be available. On the system design-side, these changes should be explicitly captured by the researcher using mental model elicitation methods, and would be described in the researcher's model, $R(U(S))$. Eventually, the model of a user's learning process would be inputted into the designer's model, $C(S)$.

The need for these kinds of research could be fortified by recent technological trends in designing interactive systems, such as the ubiquitous computing. In ubiquitous computing environments, the computing technologies embedded into the systems as environmental artifacts and as everyday objects seek to allow people to more naturally interact with the information delivered by the system. In order to allow people to efficiently and actively manipulate the complex information from pervasive systems and to obtain more appropriate information, researchers and designers need not only to understand the changes in their knowledge structures - that is, learning process - but also to provide appropriate information and interface design corresponding to their identified knowledge levels. Moreover, the main concern of this study is to help users actively manipulate their interaction with a system. As user-adaptiveness should be part of the technological characteristics of the ubiquitous environment, users tend to be understood as passive interactants in the adaptive computing era. The users need to have enough chance to construct their own mental models of the system, which can help them fully utilize the potential values offered by the system. From this viewpoint,



when designing adaptive computing systems, it is necessary to understand and encourage the users' mental model formation and the use of the system.

Research Positioning and Contributions

This paper tries to frame an approach to identify users' learning processes within interactive systems as well as to provide system designers with the knowledge regarding these processes so that they can employ this knowledge into the design process attempting to enhance the user-centeredness of the system. The expected contributions of this research to the interactive system design field could include the following:

- (1) It would be possible to improve the ease-of-use of an interactive system by adopting this approach. The system that can provide adjusted interfaces corresponding to the user's knowledge and mental models could help the user utilize the system more easily and learn it more quickly.
- (2) The system designed to predict and facilitate the users' learning could ultimately enrich their experience through the process of interacting with the system. By helping the users to expand their knowledge and to build accurate mental models of the system, the system may encourage the users not only to actively control the system but also to find new ways of use, which could lead to new experiences of the system.
- (3) From the application perspective, this new approach could be helpful for designers to develop learning tools, including learning-supporting tools embedded in interactive systems (for example, tutorials and help systems) and independent learning systems (for example, training systems for professionals).

To achieve the goals of this research, this paper investigates the relevant literature in order to form a viewpoint. Figure 2 illustrates the different research disciplines that could have significant theoretical influence on this study: Cognitive Science, Human-Computer Interaction (HCI), and Artificial Intelligence (AI). Cognitive Science provides the foundation of the basic concepts in the human cognitive process that can be essential for learning. Then, the theories of mental models and the applications in the HCI and system design fields are investigated. Last, the methods of knowledge representation are introduced, which is a major concern of AI but is studied by other research areas as well. The knowledge gained from those disciplines would be applied for this research to frame its own approach and theoretical base.

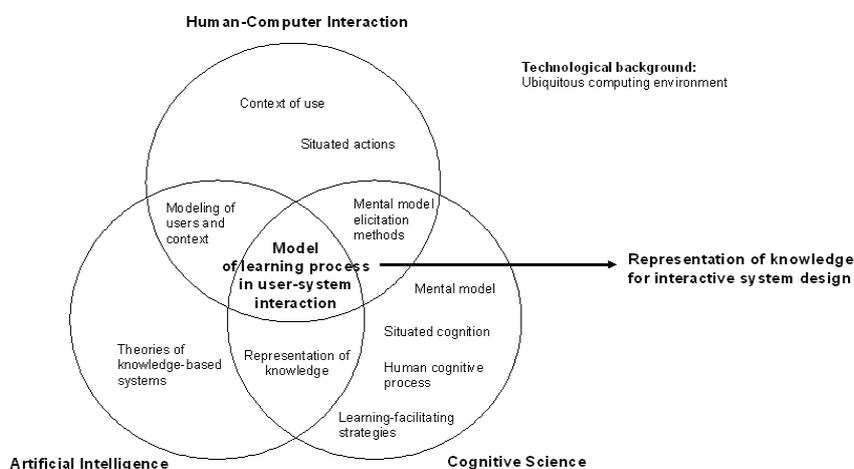


Figure 2. Interdisciplinary approach to form the viewpoint

Literature Survey

Fundamental Concepts based on Cognitive Science Theories

Since user-system interaction is defined as a learning process in this study, it is necessary to understand what learning is and how the learning process occurs in general. This study adopts the Cognitive Science viewpoint that emphasizes learning as a process and a learner as a mediator. From this point of view, this section encompasses some fundamental concepts of human cognitive process and the relevant learning-facilitating, that is, cognitive process-supporting, strategies.

Human cognitive process

Cognitive Science is concerned with the structure and processes of the mind and cognition (Driscoll, 2005). They conceive a human learner to be an information processor in the same way a computer is. According to the cognitive information processing theory, learning is considered to be the process of receiving information and storing it in memory. Also, the learner is assumed to process incoming information, relating it to the existing knowledge in memory. In the context of this study, a user can be substituted for a learner, and the knowledge processing through the user-system interaction can be substituted for the information processing. Consequently, the strategies to enhance the interaction could be substituted for those to facilitate information processing. Some theories of Cognitive Science and Learning Science provide learning-facilitating strategies from the viewpoint of how to help a learner effectively perceive, memorize, and retrieve the received information.

Schema and mental model

In terms of the memory structure, schema theory is thought to give more concrete ideas to cognitive studies. According to Rumelhart's (1980) definition, a schema is "a data structure for representing the generic concepts stored in



memory,” and schemata refer to “*packets of knowledge*.” Schema theory tries to explain how the knowledge packets are represented and how the representation helps the use of knowledge in particular ways. To describe the changes of existing schemata through learning, three different processes have been proposed: accretion, tuning, and restructuring (Driscoll, 2005). Accretion involves adding new information without conflicts to previous knowledge. When new information is not consistent with previous knowledge, minor schema modifications (tuning) occur, or entirely new schemata that replace or incorporate old ones are created (restructuring). For this study, the further knowledge on the acquisition and modification of schemata would be applied to explain a user’s knowledge process in learning an interactive system.

Schemata actively influence how people interpret events and solve problems, leading to the concept of mental models. Driscoll (2005) states that mental models are “*schemata that not only represent one’s knowledge about specific subject matter, but also include perceptions of task demands and task performances*” (p. 130). In other words, mental models are “*schemata that guide and govern performance as one undertakes some task or attempts to solve some problem*” (p. 130). Unlike Driscoll’s viewpoint where he considers mental models as a kind of schemata, Preece et al. (1994) argue that because schema-based theories are too inflexible, they cannot be used to explain flexible everyday situations such as going to restaurant and meeting people. They insist, therefore, that mental models, which are appropriate to account for those dynamic aspects of cognitive activity, could be considered as an alternative. From this viewpoint, mental models are thought to be constructed by activating schemata. Even though the two viewpoints hold quite different positions in the understanding of schemata, it seems that they have a similar idea of the dynamic nature of mental models. The HCI and system design fields have been interested in people’s mental models regarding the use of target systems. The theories and issues related to mental models discussed in these fields will be addressed in the latter part of this paper.

Motivation

Motivation is an important factor to encourage people to learn and keep learning certain contents or objects. It refers to “*the process whereby goal-directed behavior is instigated and sustained*” (Schunk, 1990). While behaviorists claim that physiological needs motivate organisms to do certain behavior, cognitive theorists have regarded cognitive processes as important mediators of motivation (Driscoll, 2005). Based on a number of theories and concepts on psychological motivation, Keller (1983) proposes four strategic components to help a learner to be intrinsically motivated to learn:

- Attention: strategies for arousing and sustaining curiosity and interest
- Relevance: strategies that link to learners’ needs, interests, and motives
- Confidence: strategies that help learners develop a positive expectation for successful achievement
- Satisfaction: strategies that provide extrinsic and intrinsic reinforcement for effort

In this research, these kinds of strategies to support more engaging learning could be applied to encourage a user to keep learning a system through user-system interaction. While the basic concepts and the supporting strategies for a cognitive process have been introduced based on the traditional human information processor model, one recent alternative view to human cognition provides a more epistemological background for this



study that assumes a user's knowledge construction through interaction with an artifact (a system); that is situated cognition.

Situated cognition and actions

One of the recent influential movements in studying human cognitive process is to emphasize the situated nature of cognition. Researchers with this view understand cognition not just as a psychological, but rather a social phenomenon, which is "*stretched across mind, body, activity and setting*" (Lave, 1988, p. 18). According to Seel (2001), the aim of situated cognition theory is to account for how people learn in the external world to be understood through their interactions with it, using their perceptions and internal representations of the world. From this viewpoint, a learning process is conceived as "*the individual's ability to construct meaning by extracting and organizing information from a given environment* (Seel, 2001)."

Along the same line with situated cognition, but with more focus on human action, Suchman (1987) tries to explicate "*the relationship between structures of action and the resources and constraints offered by physical and social circumstances*" (p. 179). The author argues that "*the organization of situated action is an emergent property of moment-by-moment interactions between actors, and between actors and the environments of their action*" (p. 179). The unit of analysis of situated actions, therefore, should be the relationship between the individual and the environment, neither the individual nor the environment (Lave, 1988). Situated cognition theory, which incorporates the interaction between people and their environment (including artifacts) into the consideration of human cognitive process, could be used for this study to build its epistemological base.

Existing approaches to research on learning in interactive system design fields

Some researchers in the field of system design have been interested in the learning curve and learnability issues. Some of the researchers have studied how to minimize users' learning curves during the system use or how to make the system interface or contents more learnable. Haramundanis's (2001) study reviews the definitions of learnability from different disciplines and provides the guidelines to enhance the learnability of information materials; this study emphasizes on the five key attributes of learnable materials: memorable, logical, reconstructible, consistent, and visual.

In addition, several research efforts have addressed the issues of learning in the area of learning system design. For example, Brown and Duguid (1996) insist on the importance of the situated nature of learning, and provide some ideas for interactive learning systems in which situated theories could be operationalized. In addition, by considering the learning mechanism as embodied through the system structure that could functionally support the learning, Chang et al. (2005) propose a mathematics e-learning system that encourages more interactive learning through a series of mechanisms, allowing intimate and frequent interaction among students and teachers.

Some researchers are more concerned with the embedded learning tools that help the users perform tasks more efficiently, such as tutorial and help systems. For example, Carroll (1992) developed several tools to support novice users' computer skill learning, including minimalist instruction which reduces the amount of



information that a user need to read, and the Training Wheels interfaces which limits the novice users to simple functions so as to protect them from potential errors. Also, the Scenario Machine accommodates similar interfaces as the Training Wheels, but provides the explanations as to why they are blocked from the unavailable functions.

Importantly, Anderson (1996) describes the three-stage skill acquisition process from a more fundamental viewpoint: cognitive, associative, and autonomous. The author explains how a skill can be learned with respect to the transition from declarative to procedural knowledge. In the first cognitive stage of learning, declarative knowledge is acquired and the learner rehearses the information needed to perform the skill. Then, the associative stage involves knowledge compilation through which procedural knowledge develops. Errors are gradually detected and eliminated during this process as well. In the final autonomous stage in which the skill is gradually improved, there are fortifying processes that can speed up the performance. Because learning to use an interactive system may be conceived as a kind of skill-acquisition process, the processes and problems that users may experience in the learning process could be understood through the lens of Anderson's skill learning process framework.

Although considerable research efforts have been made on the various aspects of learning in user-system interaction, little research is available providing applicable methodologies to involve the human learning process in the design of the system or to enhance the users' learning of the system, through the control of the learning mechanisms. Also, in order to apply users' learning processes into system design, researchers must first explicitly disclose what kinds of knowledge have been accumulated by the users and what types of mental models the users have constructed. To provide some ideas on the externalized representation of knowledge processes, theories and applications of users' mental models and the elicitation methods will be addressed in the next section.

Studies on Mental Models and the Elicitation

According to Norman (1983), *"in interacting with the environment, with others, and with the artifacts of technology, people form internal, mental models of themselves and of the things with which they are interacting. These models provide predictive and explanatory power for understanding the interaction"* (p. 7). Mental models are thought to guide and regulate all human perceptions of the world and to be constructed in specific environmental contexts according to the needs of the users (Seel, 2001).

Mental representations and models in Cognitive Science

Mental representations have been considered as analogous with physical representations. That is, descriptions and classifications developed for physical representations have been applied to mental representations (Paivio, 1986). In Cognitive Science, the term *"mental models"* was used by Johnson-Laird (1983), who argues that three types of mental representations of a device or idea can be found: *"propositional representations which are strings of symbols that correspond to natural language, mental models which are structural analogues of the world, and (mental) images which are the perceptual correlates of models from a particular point of view"* (p. 165). That is, a mental model analogically



represents the relative position of objects that corresponds to the structural state of the real world objects. He assumes that propositional representations are initially built in expressions in mental language, and then the semantics of the mental language map the propositional representations into mental models. On the other hand, Seel (2001) focuses more on domain-specificity of mental models. According to the referred author, in cognitive and educational psychology, mental models are considered as qualitative mental representations that are developed to solve problems or to acquire ability in a specific domain, based on the subject's knowledge of the world.

Mental Models in HCI and Design

In the context of HCI and system design, the role of mental models is to enable people to describe systems and to predict future events (Preece et al., 1994). Sasse (1997) states that while a designer would create a conceptual model of a system that he or she is developing, the users would create a mental model through interaction and/or formal or informal instruction which may be different from the designer's. Even though the different models may be not a problem, the problem could potentially occur when a user's model of the system is inaccurate. Norman (1983) insists that "*mental models are naturally evolving models*" (p. 7). That is, through interaction with a system, users create mental models of the system and continue to modify them over time. By doing so, the user's mental models become more adequate, and eventually help him or her obtain goals.

Considering that there have been many interests in mental models in HCI and design fields, it could be asked why studying mental models is so critical in those fields. Johnson-Laird (1983) argues that users' ability to interact with a computer system depends on whether or not they have an accurate mental model of the system. The author emphasizes that information must be presented to a user in the proper way through which the cueing and construction of the model can be supported. From a similar viewpoint, Norman (1983) insists that if the designer obtains the appropriate design model and communicates this model effectively through the interface design of the system, the user could make an accurate mental model, which could enable them to use the system successfully. Preece et al., (1994) also state that interface must be designed to enable users to establish productive mental models of relevant aspects of the system.

There are two main types of mental models that people use when interacting with systems, structural and functional, as Table 1 describes (Preece et al., 1994). For the purpose of reducing human error in the control of complex systems, Rasmussen (1990) developed a theoretical framework of mental models, concerned with what types of knowledge processing are involved to control such systems. The three levels of knowledge processing include skill-based level which consists of automated routines, rule-based level which is about problems that are familiar to the users and that can be solved through learned routines, and knowledge-based levels which is related to the users' novel and unexpected situations where they have to evaluate the situations through their mental models. A user's learning process involving mental model constructions could be better described by indicating the different roles and formation patterns between the two types of mental models according to the different knowledge processing levels.



Structural models	Functional models
<ul style="list-style-type: none"> • describe how the device or system works • allow users to predict the behavior of the system • imply the internal mechanics of a system in terms of its components parts • Largely, context-free 	<ul style="list-style-type: none"> • describe how to use the device or system • structured around a set of tasks • imply procedural knowledge • Context-dependent

Table 1. Types of mental models

Modeling of mental models

Since this study aims to externalize the process of how users' mental models of a system are formed and changed, the existing approaches to the formalization of mental models need to be examined. Nielsen (1990) proposed a meta-model to classify the models of user-system interaction. The 7 elements of models are (1) U, the user; (2) D, the designer; (3) C, the computer system; (4) M, manuals and other documentation of C; (5) T, the task performed by the user; (6) W, the surrounding world in which U performs T; and (7) R, the researcher looking at any of the above. By modifying the basic elements, Sasse (1997) attempts to map how users' mental models are constructed, based on the each type of various mental models that have been proposed through the prior studies. Using the notations in the Table 2 that are derived from the concept of who has a model of what target, Sasse proposes the logical format to explain what processes are involved in building each type of mental models. Through this representation, the author emphasizes the importance of sufficient procedural support to model users' mental models, which could be in the form of guidelines or examples so that designers can immediately apply them to their design practice.

Who has model of	User	Designer	Researcher
System	UC User's Model of a computer system	DC Design Model	R(UC) R(DC) Conceptualization of User's Model Conceptualization of Design Model
User		DU Designer's Model of the User	RU Researcher's Model of the User
Task	UT User's Model of Task	D(UT) Designer's Model of User's Task User's Task	R(UT) Researcher's Conceptualization of User's Task
World	UW User's Knowledge and Experience	D(UW) Designer's Model of User's Knowledge	R(UW) Researcher's Conceptualization of User's Knowledge

Table 2. Terminology of the models by user, designer, and researcher (Sasse, 1997)



Types of user's models	Mapping: how users' models are constructed
Conceptual Model (Norman, 1986)	$D(U^I)+D(UW)+R(U) > DC > C+MC^* > UC$
Analogy (Wozny, 1989)	$D(UC1) > DC > C+MC > UC2$ (new model)
Metaphor (Tognazzini, 1991)	$D(UW^{**}) > DC > C+MC > UC$ (model on new system)
Surrogate Model (DiSessa, 1986)	$DC > C+MC > UC$
Task-action mapping (Young, 1983)	$UT > DC > C+MC > UC$
Formal task-based mapping (Tauber, 1988)	$R(UT)+R(U) > DC > C+MC > UC$
Semantic mappings (Payne et al., 1990)	$R(U(WI)^{***}) > U(CI) > UC$

* system image: computer system accompanying materials and documentation

** users' existing knowledge

*** users' model of real-world task

Table 3. Mappings for user's models (Sasse, 1997)

Once a user model is developed, it is necessary to evaluate whether it works well for its intended purpose. Different types of criteria to examine the validity of models have been proposed. Table 4 indicates several categories of these criteria. Since the future works in this research include the validation of the proposed user's learning process model, model validation methods and criteria need to be further investigated.

Researcher	Young (1983)	Teeravarunyou (2002)	Shanks et al. (2003)
Criteria	<ul style="list-style-type: none"> ● Performance: choice of method, details of performance, locus and nature of errors ● Learning: generalizations and over-generalizations, what retained and what forgotten over long term, long-term memory distortions ● Reasoning: predicting the response of the system, inventing a method, explaining the system's behavior ● Design: providing guidelines for a good design 	<ul style="list-style-type: none"> ● Knowledge transformation: Identify a means that transforms user knowledge into viable products ● Generalization of design solutions: Designers should be able to generate design solutions utilizing patterns of user knowledge ● Expert reviews of design concepts: Design solutions are interpreted by an observer and then are reviewed by design experts 	<ul style="list-style-type: none"> ● Accuracy: Accurately represent the semantics of the focal domain as perceived by the focal stakeholder(s) ● Completeness: Completely represent the semantics of the focal domain as perceived by the focal stakeholder(s) ● Conflict-free: The semantics represented in different parts of the model should not contradict one another ● No redundancy: The model should not contain redundant semantics

Table 4. Criteria for model validation

Elicitation of Mental Models

How can we know whether users have particular knowledge or not? Particularly, how do we know what types of mental models users possess of a certain system? To answer those questions, considerable research has proposed various types of methods for eliciting users' internal mental models. Table 5 summarizes some of the



methods, providing the potential weak points in some methods. Because users will create unpredictable situations in the course of the user-system interaction even when the researcher tightly structures the interaction, Sasse (1992) argues that a less artificial and restricted setting might result in more reliable observations.

Methods	Descriptions
Think-aloud observation	<ul style="list-style-type: none"> asks participants to provide verbal accounts of their reasoning during user-system interaction highly artificial behavior - a user's model construction is mainly a subconscious process (Sasse, 1997)
Constructive interaction	<ul style="list-style-type: none"> observes a pair of participants working together to complete given tasks, encouraging them to verbalize their thoughts (Miyake, 1986) difficult to structure user-system interaction because users determine the direction of activity (Sasse, 1997)
Teach-back	<ul style="list-style-type: none"> after training, asks participant(s) to teach a new user about the product one of constructive interaction approaches (Sasse, 1997) can yield more insights with experienced users than with novice users requires a lot of time and effort in analyzing the data
Joint exploration	<ul style="list-style-type: none"> pairs two users and asks them to explore the system together (Sasse, 1997) one of constructive interaction approaches may involve the danger of one user taking charge and dominating the interaction
Ratings	<ul style="list-style-type: none"> asks participants to evaluate and rank the concepts or ideas by given criteria (Radvansky et al., 1990)
Laddering	<ul style="list-style-type: none"> used to reveal superordinate and subordinate relations between concepts (Shadbolt & Burton, 1990)
Sorting	<ul style="list-style-type: none"> asks participants to divide a list of concepts into groups and subgroups (Chi et al., 1981) in another example, asks subjects to re-arrange the cards containing labels and to draw connections between the components (Westerink et. al., 2000)
Drawings	<ul style="list-style-type: none"> requests users to draw their model of the system and to give verbal interpretations of the model (Westerink et. al., 2000; Gray, 1990) Recognition is often not described very well in pictorial representations
Object-mediated method	<ul style="list-style-type: none"> provides subjects with a collection of photographic images and keywords involved in a task and asks them to compose collages to describe their process (Teeravarunyou, 2002) may stimulate users to remind related experiences by using a more concrete representation of artifacts

Table 5. Methods for eliciting mental models

Based on the empirical examination of different methods, Sasse (1997) concludes that which mental model elicitation method is best depends on the goals of the study. Because most methods seem to have trade-offs, it is necessary to carefully examine existing methods to decide the method for the purpose of this study. Sasse (1997) also points out that one of the methodological problems emerging from the analysis of the empirical studies is that many authors do not offer clear descriptions of the process of deriving models from the collected verbal data or protocols as well as any indication of the analysis methods of verbal protocols. Therefore, it is necessary to investigate the more systematic and objective approach to the data-analysis and model-identification process.



In terms of applicable methodologies, Sasse's (1997) representation method for modeling users' mental models seems useful for describing various ways in which users' models would be constructed, reflecting some contextual knowledge such as users' prior knowledge and usable knowledge sources. However, that type of mental model and knowledge representation does not provide a sufficiently applicable way to develop interactive systems that could be adapted to and facilitate users' mental model construction. The knowledge representation, mainly studied in the AI field to develop intelligent systems, could be considered as the alternative approach. The following section introduces some of the basic ideas and goals of knowledge representation.

Knowledge Representation

Knowledge

Although there are many different viewpoints to define knowledge, from the viewpoint of intelligent systems design, such as AI, knowledge is a relation between a knower (an agent) and a proposition expressed by a simple declarative sentence (Brachman & Levesque, 2004). According to the authors, an important characteristic of propositions is that they are abstract entities that can be true or false. In other words, to say that an agent knows something is to say that the agent has formed a judgment of that. There are various categorizations of knowledge that need to be represented in intelligent systems. Table 6 summarizes some of the existing categorizations. Even though different researchers use different terms, they seem to have consensus regarding the facts that there is knowledge about certain facts and knowledge about how to use the factual knowledge.

Researcher	Anderson (1996)	Woods (1986)	Chandrasekaran et al. (1998)
Types of knowledge	<ul style="list-style-type: none"> ● Declarative that includes facts about the world which can be put into words ● Procedural which is about how we do a certain thing. 	<ul style="list-style-type: none"> ● Facts about what is or has been true (the known world state) ● Rules for predicting changes over time 	<ul style="list-style-type: none"> ● Domain factual which is about the objective realities (objects, relations, events, states, causal relations, etc.) in the domain of interest ● Problem-solving which is about how to use the domain knowledge to achieve various goals.

Table 6. Types of knowledge

Knowledge representation

Knowledge representation is not concerned with modeling the phenomena in the world, but concerned with modeling the knowledge that people have of the world (Johnson, 1992). The way that knowledge is structured in memory is assumed to be highly structured (Preece, 1996). According to Johnson (1992), representation typically comprises two parts: the data structure that are stored in a particular format, and the processes that operate on the data structure. Based on the many theories and models of human knowledge structuring, Johnson defines three representational groups: propositional, analogical, and procedural. Table 7 describes the types of representations and some examples of particular forms in each group.



Types of representations		Representative formats
Propositional representations	represent knowledge as a set of discrete symbols or propositions, concepts, objects and features, and relations	<ul style="list-style-type: none"> • Semantic networks: represent the associations that exist between conceptual knowledge, in the form of directed labeled graph with nodes interrelated by relations • Frames: provide variable slots which can take the specific fillers for an instantiated frame. A frame is initiated when it is provided with the particular details for a given context • Scripts (Schank and Abelson (1977)) represent a structure for the temporal order of the elements of an activity, and sufficient information to match the script to the instance of the activity
Analogical representations	maintain a close correspondence between the representing and represented world, assuming the variable parameters of the representation are continuous in the same way as voltages, maps, and so on.	
Procedural representation	represent the knowledge that people use for executing actions, which can be directly interpreted by a system	<ul style="list-style-type: none"> • Production rules: consist of “If → then” statements, used to build production systems that are modular in format

Table 7. Types of knowledge representations

The field of AI has mainly studied the methodologies for representing knowledge with the concern how an intelligent agent would use its knowledge in deciding its actions (Brachman & Levesque, 2004). Since this study is intended to provide knowledge that can be applicable to system design, the identified users’ learning process must be externalized and structured in a certain format. In terms of the representation format, Anderson (1996) argues that what could or could not be represented easily in a format is important. That is, different representations are needed not for different systems but rather, for different aspects of the same system.

Roles of knowledge representation in intelligent systems

Focused on the field of AI, knowledge representation can be used to develop knowledge-based systems in which symbolic representations are involved as their knowledge bases. Using the knowledge bases represented in a certain symbolic form, knowledge-based systems can deal with open-ended tasks that are not determined in advance (Brachman & Levesque, 2004). Davis et al. (1993) identified five fundamental roles of knowledge representation in intelligent systems in a more broad scope:

- (1) As a surrogate: Representations substitute for direct interaction with the real things in the world. Inappropriate surrogates inevitably cause incorrect inferences.
- (2) As a set of ontological commitments: To select a representation is to decide how to see the world, which could mean making a set of ontological commitments.
- (3) As a fragmentary theory of intelligent reasoning: The representation usually accommodates only part of the complex phenomenon of intelligent reasoning.



- (4) As a medium for efficient computation: Since reasoning in machines is a computational process, computational efficiency issues must be involved.
- (5) As a medium of human expression: The important questions are how well the representation functions as a medium of expression and how well it functions as a medium of communication. That is, a representation should be easy to talk or think in the language of the domain.

As Davis et al. (1993) mention above, since a representation can address only part of the complex phenomenon of reasoning, it is needed to carefully combine the existing methods to develop the most appropriate representation methodology for this research. In addition, the method for representing knowledge should support interactive system designers to efficiently communicate with each other while using it.

Conclusions and Perspectives

The purpose of this research is to identify users' learning processes during interaction with interactive systems, as well as to provide system designers with the knowledge on their learning processes so that they can incorporate the knowledge into the design process. In order to form a viewpoint and theoretical foundation for the overall research, this paper reviews the relevant literature from three different, but strongly inter-related research fields: Cognitive Science, HCI, and AI. Cognitive Science provides not only the basic concepts involved in the human cognitive process but also the epistemological background for this research, that is, the situatedness of cognition and learning. The theories of mental models and the applications in the HCI and system design fields offer more usable knowledge in relation to the modeling of users' learning process, including the elicitation methods of mental models. The methods to employ the learning process into system design are brought from the research areas related to knowledge representation, mainly AI. Even though the previous works provide useful insights on the learning through the interaction with systems, they do not give sufficiently applicable knowledge that can be used in the design process.

The learning-based approach pursued by this research involves the conceptualization of users' learning processes, the implementation through knowledge representation, and the validation of the proposed methodology. Figure 3 depicts the overall conceptual structure of this research that would be supported by the theoretical reviews in this paper. In order to allow designers to use the model of users' learning process and the learning-facilitating strategies in the system design, guidelines for the application must be presented. The implementation of system design is enabled by representing the knowledge in a certain controllable way. Finally, the validity of the proposed methodology has to be verified to examine whether or not the methodology works properly to achieve the goal. There would be possibly two ways in which this learning-based approach can contribute to system design: (1) embedding richer interaction in the system by incorporating learning mechanism and (2) enabling learning systems to provide more engaging learning by incorporating learner-adaptive interaction. By employing this approach, this research aims to provide users with easier and richer experiences in the system use.

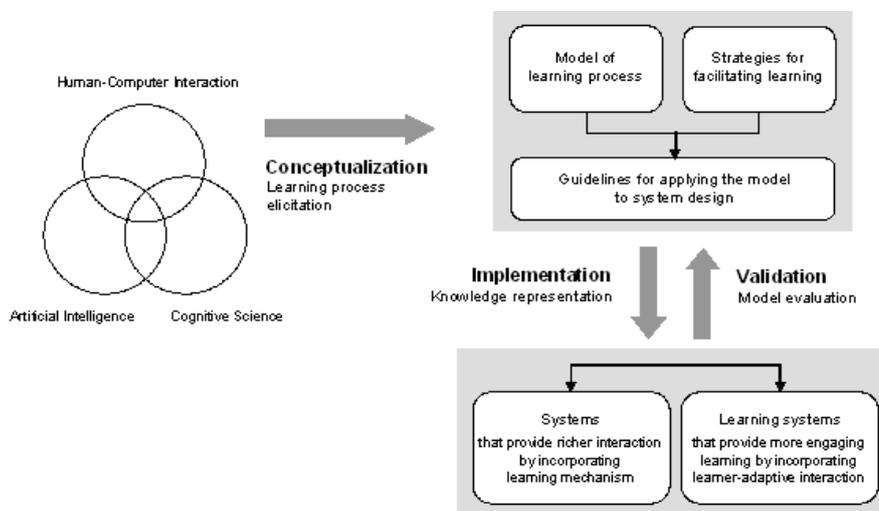


Figure 3. Conceptual structure of the research

References

- Anderson, J. R. (1996). *The Architecture of Cognition*. Mahwah, NJ: Lawrence Erlbaum Associates.
- Brachman R. J. & Levesque H. J. (2004). *Knowledge Representation and Reasoning*. Morgan Kaufman/Elsevier: San Francisco.
- Brown, J. S. & Duguid, P. (1996). Stolen Knowledge. In H. McLellan (Ed.), *Situated Learning Perspectives*. NJ: Educational Technology Publications.
- Carroll, J. M. (1992). *The Nurnberg Funnel: Designing Minimalist Instruction for Practical Computer Skill*. Boston, MA: MIT Press.
- Chandrasekaran, B., Josephson, J., & Benjamins, R. (1998). Ontology of Tasks and Methods. Proceedings of the 11th Workshop on Knowledge Acquisition, Modeling and Management (KAW'98); Banff, Canada, April 18th - 23rd, 1998.
- Chang, P., Pai, T., & Wang L. (2005). Grouping and Interactive Learning Mechanism for Mathematics Learning Programs. Proceedings of the 5th IEEE International Conference on Advanced Learning Technologies; Kaohsiung, Taiwan, July 5-8, 2005.
- Chi, M. T. H., Feltovich, P. J., & Glaser, R. (1981). Categorization and Representation of Physics Problems by Experts and Novices. *Cognitive Science*, 5(2), 121-152.
- Davis, R., Shrobe, H., & Szolovits, P. (1993). What is a Knowledge Representation? *AI Magazine*, 14(1), 17-33.
- Driscoll, M. P. (2005). *Psychology of Learning for Instruction* (3rd ed.). Boston, MA: Allyn and Bacon.
- Gray, S. H. (1990). Using protocol analyses and drawings to study mental model construction during hypertext navigation. *International Journal of Human-Computer Interaction*, 2(4), 359-377.
- Johnson-Laird, P. N. (1983). *Mental Models*. Cambridge: Cambridge University Press.
- Johnson, P. (1992). *Human-Computer Interaction: Psychology, Task Analysis and Software Engineering*. London, UK: McGraw Hill.
- Keller, J. M. (1983). Motivational Design of Instruction. In C. M. Reigeluth (Ed.), *Instructional Design Theories and Models*. Hillsdale, NJ: Erlbaum.
- Lave, J. (1988). *Cognition in Practice: Mind, mathematics, and culture in everyday life*. Cambridge, UK: Cambridge University Press.
- Miyake, N. (1986). Constructive Interaction and the Iterative Process of Understanding. *Cognitive Science*, 10(2), 151-177.
- Nielsen, J. (1990). A Meta-Model for Interacting with Computers. *Interacting with Computers*, 2, 147-160.
- Norman, D. A. (1983). Some Observations on Mental Models. In D. A. Gentner & A. A. Stevens (Eds.), *Mental models*. Hillsdale, NJ: Erlbaum.
- Paivio, A. (1986). *Mental Representations: a Dual Coding Approach*. New York, NY: Oxford University Press.
- Preece, J., RogersSharp, H., Benyon, D., Holland, S., & Carey, T. (1994). *Human Computer Interaction*. Boston, MA: Addison-Wesley.
- Radvansky, G. A., Gerard, L. D., Zacks, R. T., & Hasher, L. (1990). Younger and Older Adults' Use of Mental Models as Representations for Text Materials. *Psychology and Aging*, 5(2), 209-214.
- Rasmussen, J. (1990). Mental models and the control of action in complex environments. In D. Ackermann, & M. J. Tauber (Eds.), *Mental Models and Human-Computer Interaction*. NY: Elsevier Science Publishers.



- Rumelhart, D. E. (1980). Schemata: the building blocks of cognition. In Rand J. Spiro, Bertram C. Bruce, & William F. Brewer. (Eds.), *Theoretical issues in reading comprehension*. Hillsdale, NJ: Erlbaum.
- Sasse, M. A. (1992). User's models of computer systems. In Y. Rodgers et al. (Eds.), *Models in the mind: Theory, perspective, and application*. London, UK: Academic Press.
- Sasse, M. A. (1997). *Eliciting and Describing Users' Models of Computer Systems*. Ph.D dissertation, School of Computer Science, University of Birmingham; England.
- Schunk, D. H. (1990). Introduction to the special section on motivation and efficacy. *Journal of Educational Psychology*, 82, 3-6.
- Seel N. M. (2001). Epistemology, situated cognition, and mental models: 'Like a bridge over troubled water.' *Instructional Science*, 29, 4-5.
- Shadbolt, N. & Burton, M. (1990). Knowledge elicitation. In J. R. Wilson & E. N. Corlett (Eds.), *Evaluation of Human Work: A practical ergonomics methodology*. London, UK: Taylor and Francis.
- Shanks, G. G., Tansley, E., & Weber, R. (2003). Using ontology to validate conceptual models. *Communications of the ACM*, 46(10), 85-89.
- Teeravarunyou, S. (2002). *An approach to user knowledge and product architecture for knowledge lifecycle*. Ph.D dissertation, Institute of Design, Illinois Institute of Technology; Chicago, IL.
- Westerink, Joyce H. D. M., Majoor, Betty G. M. M., & Rama, Mili Docampo (2000). Interacting with Infotainment Applications: Navigation Patterns and Mental Models. *Behaviour and Information Technology*, 19 (2), 97-106.
- Woods, W. A. (1986). Important issues in knowledge representation. *Proceedings of the IEEE*. 74(10), 1322-1334.
- Young, R. M. (1983). Surrogates and Mappings: two Kinds of Conceptual Models for Interactive Devices. In D. Gentner & A. L. Stevens (Eds.), *Mental models*. Hillsdale, NJ: Erlbaum.