Association for Information Systems

AIS Electronic Library (AISeL)

ICEB 2004 Proceedings

International Conference on Electronic Business (ICEB)

Winter 12-5-2004

Adaptive User Interfaces for Intelligent E-Learning: Issues and Trends

Abdul-Rahim Ahmad

Otman Basir

Khaled Hassanein

Follow this and additional works at: https://aisel.aisnet.org/iceb2004

Adaptive User Interfaces for Intelligent E-Learning: Issues and Trends

Abdul-Rahim Ahmad[1], Otman Basir[1], Khaled Hassanein[2]

[1] Systems Design Engineering, University of Waterloo, Waterloo, ON, Canada
[2] DeGroote School of Business, McMaster University, Hamilton, ON, Canada
arahim@uwaterloo.ca; obasir@uwaterloo.ca; hassank@mcmaster.ca

ABSTRACT

Adaptive User Interfaces have a long history rooted in the emergence of such eminent technologies as Artificial Intelligence, Soft Computing, Graphical User Interface, JAVA, Internet, and Mobile Services. More specifically, the advent and advancement of the Web and Mobile Learning Services has brought forward adaptivity as an immensely important issue for both efficacy and acceptability of such services. The success of such a learning process depends on the intelligent context-oriented presentation of the domain knowledge and its adaptivity in terms of complexity and granularity consistent to the learner's cognitive level/progress. Researchers have always deemed adaptive user interfaces as a promising solution in this regard. However, the richness in the human behavior, technological opportunities, and contextual nature of information offers daunting challenges. These require creativity, cross-domain synergy, cross-cultural and cross-demographic understanding, and an adequate representation of mission and conception of the task. This paper provides a review of state-of-the-art in adaptive user interface research in Intelligent Multimedia Educational Systems and related areas with an emphasis on core issues and future directions.

Keywords: Adaptivity, Adaptive User Interface, E-Learning, Preference Modeling, User Modeling, Multimedia, HCI

1. INTRODUCTION

The emergence of such revolutionary technologies as Graphical User Interface (GUI), Artificial Intelligence (AI), Soft Computing, Multimedia, Hypermedia, Internet, etc. has created an intense interest in computerized and ubiquitous educational systems like Intelligent Multimedia Educational Systems (IMES) with adaptivity at its core [12], [21], [28]. Indeed, individualized teaching is the most favored practice of instruction and different teaching strategies work best in different contexts. Consequently, the ability to adapt to an individual learner's needs as well as context could significantly stimulate both the learning process and the user engagement [13], [21], [26]. As such, an IMES can contribute to the success of learning if it adequately represents the domain tasks, concepts, and learning goals and intelligently adapt its presentation in terms of complexity and granularity according to the cognitive level/progress of the learner [21], [27].

The development of such pervasive enablers as the Web and Mobile Technologies has further highlighted the research in Adaptive User Interfaces (AUI) offering tremendous educational opportunities by removing temporal and spatial constraints as well as providing personalization and interactivity [10], [12]. However, it is the Web and Mobile Learning Services where the problem of 'being lost in hyperspace"' becomes especially critical [13]. As such, the 'information overload' is no more a trite buzzword but a frequently encountered reality for many. Consequently, an adequate educational framework for IMES should focus on cognitive development and knowledge acquisition, through creative, efficient, efficacious, and intelligent tutoring strategies for presentation of the domain knowledge. An AUI in IMES is geared towards seeking superior outcomes in the spatial and temporal separation as well as presentation of domain knowledge based on user's explicit and implicit preferences, constraints, cognitive progress, decision styles, learning objectives, and access modes.

The AUI has been an object of attention since long and has a significant role in IMES from cognitive, pedagogical, psychological, and social aspects. Adaptivity in IMES could come in terms of adaptation of multimedia content, presentation, navigational options, teaching strategies, etc. to user's needs [45]. In addition, the dynamics of today's society underscore the need for adaptive interfaces accessible by different user groups, including disabled and elderly [1]. However, the potentially diverse scope and heterogeneity of the target population pose greater challenges [27].

In view of diversity, subjectivity, and tedium involved in pertinent concepts and issues, we provide only a brief overview of such concepts. Furthermore, a few capabilities and caveats in the design and deployment of such systems are highlighted. Various promising and synergistic technological options for design and implementation of an AUI are presented for reference purposes, as well.

2. INTELLIGENT INTERFACE PARADIGMS

Research in intelligent user interfaces has been built on such notions as natural language understanding, explanation systems, intelligent tutoring systems, intelligent help systems, computer-aided instruction, multi-modal systems, model-based development, intelligent presentation systems, and agent-based interaction. As a result, several paradigms have been established. The most prevalent paradigms include

user-based interactions, model-based interaction and agent-based interaction [5], [16]. An IUI may facilitate the learner's selection through either *adaptive ordering* of options (based on frequency of use data), *adaptive prompting* (based on contextual information resulting from a model), or *guidance* (with the help of an agent). The boundaries of different paradigms and technologies are quite fuzzy. Nevertheless, here we provide a brief overview of the most popular paradigms.

2.1 User-based Interaction

One frequently cited indication of intelligence in UIs is the ability to adapt the output to the level of understanding and interests of individual users, typically served by adaptivity, adaptability, or dynamicity of the aspects of interaction [34]. An *adaptive* UI changes dynamically in response to its experience with learners [24]. Such an effect is typically achieved by using dedicated software tools responsible for acquiring and maintaining user models and reasoning towards suitable interface adaptations. In contrast, an *adaptable* UI provides tools that allow the user to tailor certain aspects of the interaction in using a system [13], [34]. Such systems allow the user to modify certain aspects of the interactive behavior. Whereas, in a *dynamic* UI the user's behavior is monitored just like with *adaptive* UI. However, instead of changing (adapting) a predefined presentation, dynamic hypermedia systems generate a presentation from "atomic" information items. The research in user-based interaction design is built upon advances in intelligent tutoring systems, learner modeling, explanation systems, and knowledge representation.

2.2 Model-based Interaction

Model-based Interaction development involves the use and articulation of reusable models and knowledge repositories encapsulating the wide variety of details pertaining to the UI development. It promises to decrease both the time and expertise required to create interfaces, through reusable models, automation, decision, and design support mechanisms. It enables design support such as critiquing, design refinements, and incremental updates. However, the current generation of model-based interface development tools has not appropriated the full range of the aforementioned potentialities [5].

2.3 Agent-based Interaction

This paradigm involves the use of software agents to delegate tasks concerning various facets of interaction [5], [15]. Although there is no agreed upon definition of intelligent agents, most intelligent agents are characterized by autonomy, adaptivity, pro-activity, and sociability [15], [31]. They usually contain a representation/model of belief in the state of the environment and have facilities to discover from

patterns of behaviour from user(s) and agent(s). There are three major types of agents involved in agent-based interaction: *interface agents* tie closely to an individual's goals, *task/tutor agents* involve processes associated with arbitrary problem-solving tasks, and *information/domain agents* connect to source(s) of information. An interface agent learns from user's actions working as an intelligent assistant. Whereas, tutor agent provides scaffolding (or envelope) to the learner and progressively removing it as the learner internalizes the knowledge. As such, these agents also require models of the learner, tutor, as well as domain in order to perform their tasks.

3. ADAPTATION TECHNIQUES

As already mentioned, adaptation in a UI can be served by adaptivity, adaptability, or dynamicity in the aspects of interaction. In IMES perspective, adaptation to both user and context are needed. Adaptation to user/learner requires a learner model containing attributes of the learner to which adaptations are sought. At the same time, adaptation to context requires such knowledge models as teacher model, domain model, and interaction model. The adaptation effect may be realized through adaptivity in content selection, presentation, recommendation, etc. [11]. Adaptation may also furnish navigational support [13]. Indeed, different adaptation techniques work most efficiently in different context and require meticulous selection of the most relevant technique as well as the need for adaptation in the adaptation technique(s), or meta-adaptation, during the cognitive progress of the learner [6], [13].

In IMES context, the adaptive navigation support is one of the simplest, earliest, and most extensively studied aspects of automatic adaptation. The underlying notion is to help users find their paths in hyperspace by adapting link presentation to the characteristics/model of the user. The popular means for incorporating adaptive navigation support are direct guidance, sorting, hiding, annotation, and generation of link structure suitable to the learner characteristics [13]. These techniques are used to achieve both global and local guidance/orientation support. Studies have demonstrated the effectiveness of various adaptive navigation support techniques in terms of browsing and learning efficiency [13]. Adaptive content selection is another aspect of adaptivity resulting from the varying interests and preferences of various users regarding available information. It allows information pieces relevant to learner's cognitive level and/or goals to be presented to the user. However, the selected content must be presented in a form appropriate to the user. Consequently, a natural extension to this would be the adaptive content presentation that exhibits different visual layout and/or media. Adaptive recommendations also form an important dimension in achieving effectiveness of an AUI by providing users suggestions about the future line of action.

An ideal scenario would be where the adaptive system has all or most of the adaptation techniques at its disposal. However, it requires a sound understanding of applicability and limitations of each adaptation technique as well as their combinations. Currently, there is a relative dearth of such complex and extensive studies because of obvious reasons.

4. CORE ISSUES IN AUI

Significant research has been done in developing AUIs for accommodating the heterogeneity and evolution of user characteristics. It draws from such diverse fields as psychology, cognitive science, ergonomics, human-computer interaction, AI, etc. However, here we focus on some core issues in AUI within the IMES context.

The goal of adaptivity in IMES is to promote efficient learning rather than simply accommodation of a learner's preferences highlighting the need for a sound understanding of both user and context. The general requirements for a system adaptive to the user include an underlying theory associating user behavior to interface needs, an access to behavioral cues, a variety of interface designs alternatives, and knowledge models accumulating behavioral cues and needs [34], [21], [39]. Nevertheless, the need to make adaptivity actually work in commercially deployable systems while meeting the usability and acceptability requirements poses notable constraints on the theory [34].

A universal problem in any hypermedia navigation is cognitive overload and disorientation [13]. However, the keyhole effect resulting from the contextual, spatial, and temporal separation of information in IMES provides an opportunity to reduce the learner's cognitive overload and distraction [27]. For instance, the amount of information and its context may be constrained in early stages of training with progression based on user's current cognitive and learning capabilities etc [27].

Some possible negative effects of AUI are related to usability, privacy, and trust issues that should be adequately addressed [12], [29]. Indeed, the very idea of adaptivity violates several well-defined and accepted usability principles largely developed for rigid direct manipulation interfaces [41], [42]. Moreover, frequent adaptations reduce consistency in the UI, a much sought for goal in HCI, hampering the learning rate [6], [42]. For instance, a sudden and automatic change in the interface may confuse, disrupt, and frustrate the user. Moreover, the notorious Production Paradox suggests that learners may not adopt/learn strategies that improve long-term efficiency and efficacy. Instead, a learner may adopt a strategy that helps in accomplishing desired task on an ad hoc basis and adapting to such 'quick and dirty' strategies could even prove counter-productive. Absolute, or near absolute, user control is another important usability consideration that is difficult to achieve in AUIs. It has been recommended that user

must get a 'sense of control' over automatic adaptations by making the system 'scrutable' [17]. However, studies in adaptive E-stores have indicated that, when adaptivity is based on implicit information, users want control of both the content and the context [6].

In contrast, AUIs serve many usability guidelines better than rigid interfaces such as reduced information and cognitive load, enhanced task support and visibility of relevant objects or actions, etc. Some researchers have even suggested that an AUI can be effective primarily when actions available to the user remain same.

Like any intelligent system, an AUI may make mistakes in determining the implicit intentions of the learner. The time needed to learn any user-controlled recovery mechanism hampers the system acceptance. Even the simplest of such recovery approaches may result in an increased cognitive load, confusion, and distraction of the user from the intended task. In addition, such user-controlled recovery mechanisms reduce the pedagogical efficacy of the system.

The foremost task in IEMS is to define such design goals as generalizability, scalability, portability, central data storage and ubiquitous access as well as higher responsiveness, learning rate, user engagement, user satisfaction, and reusability, etc. [15], [17], [10]. Nevertheless, the complexity, diversity, volatility, subjectivity, and multiplicity of considerations in designing an AUI mean that our expectations from such systems should be realistically limited.

The next important task in an AUI is the creation of knowledge model, as discussed later. Nevertheless, the richness of the human behavior, technological opportunities, contextual information, as well as multi-sensory nature of the IMES mean there is no panacea in such sensitive human-computer interaction area. Conceivably, the majority of adaptive systems in IMES context are research-level systems [12], [13]. Currently, Web courses present same static learning material to students with diverse cognitive and contextual goals, preferences, and capabilities [13]. Nevertheless, user-modeling experiments have confirmed the importance of a sound theoretical foundation operating in synergy of such practical issues as performance, reliability, and usability.

In IMES context, modeling the pedagogy and linking it to various user characteristics or learning styles is an important determinant of superior learning. Consequently, it is desirable to use the pedagogical strategy most suitable to the learner. As such, the pedagogy would also play an important role in determining the granularity and style of presentation.

5. KNOWLEDGE MODELS IN AUI

An AUI can adapt to either the user or the context of

user's work. However, an effective AUI requires an ability to adapt to both user and context. This requires extending the basis of adaptation by complementing the classic user models with models of context such as purpose, subject domain, pedagogy, interaction mode (platform, location, time, bandwidth) etc. [13]. It means learning theories, concepts, pedagogies, and their impact on the instruction design and practice are important [27]. Consequently, various knowledge models are required in achieving adaptivity in IMES.

Primary models include user/learner model, domain expertise model, pedagogical/tutor expertise model, and interface model. A Learner Model (LM) captures knowledge about the user for the system to respond to the needs of the user efficiently. A Domain Model (DM) represents the features of the particular domain that is of interest to the user. A Tutor Model (TM) holds the knowledge, capabilities, assumptions and limitations of the tutoring system itself. An Interface or Interaction Model (IM) possesses the dynamic representation of the dialogue between the user and the system. The defining boundaries of these models can be quite fuzzy and some other modules/models may also appear. Nevertheless, the separation of contents, instructional philosophies, and adaptation options or concept structures facilitates conceptualization as well as system maintenance.

5.1 Learner Model

The main objective of an AUI in IMES is to tailor the learner's information space by presenting learning material according to learner's cognitive level/progress, socio-cultural attributes, goals, plans, tasks, preferences, and beliefs [15]. This objective is highly dependent on the maintenance of adequate, efficient, and reliable LMs by explicitly representing and updating the user's characteristics, preferences, and behavior. This information is used by other components of the system for providing adaptivity. It has been frequently argued that an LM can result in improved interaction by removing the dissonance between learner's cognitive abilities and demands of interactions in IMES [8].

An LM tends to address three general purposes: inferring the user knowledge or general ability (Knowledge Assessment), recognizing the user plans or goals (Plan Recognition), and predicting the user inferences and future behavior (Action Prediction). It should be capable of representing a learner's multiple interests and misconceptions as well as flexible enough to adapt to changes in a user's cognitive level due to interaction with information. Consequently, an LM must deal with the uncertainty in making inferences about a user under incomplete and uncertain information, raising important issues discussed later. Nevertheless, studies have shown that adaptive student modeling can be remarkably robust and contribute to improved learning in IEMS environment [16], [34].

The initial LM could be generated by default values, a set of stereotype-based LMs, or querying learners. However, such stereotypical models lack coarse granularity. Furthermore, querying the users to build initial model increases cognitive and ergonomic load on users. Consequently, an effective LM needs to be constructed unobtrusively based on user behavior using both long-term and short-term information.

5.2 Domain Model

The Domain Model (DM) is the abstract representations of the target subject area. It deals with the link relationships between the concepts and the decomposition of concepts in a structured hierarchy of sub-concepts and atomic information such as texts, images, sounds, and videos [33]. Such conceptual representations should enable the system to analyze, understand, explain, communicate, or predict some aspects of the domain. Tasks, objects, and data form basic building blocks in various DM paradigms. The Task based approaches seek to represent the domain in terms of tasks. The Object-oriented paradigm represents the domain in terms of the objects, the relationships between objects, and exchange of information between objects. Data-Oriented approaches tend to abstract the structure of the domain as a network of entities and the functions of the domain by a network of dataflows and processes.

A DM mimics the expert system paradigm with an ability to generate multiple knowledge-based superior solutions instead of one ideal outcome, thereby endowing flexibility and robustness [3]. Such an approach would involve elaboration, articulation, enumeration, and ranking of competing design alternatives through propagation of design knowledge into the development cycle and embedding design recommendations into the interface implementation [5]

5.3 Tutoring Model

The Tutoring Model (TM) provides a model for the pedagogical philosophy allowing adaptation to different learning styles [37]. It should be able to dynamically incorporate individual differences among students. As such, it requires substantial efforts in knowledge acquisition and representation. TMs are primarily constructed around defined problem solving tasks and cognitive models, so they can interpret each student action (*model tracing*) and draw inferences about the student's knowledge state from each student action (*knowledge tracing*) such that the pedagogical decisions reflect the needs to each student [37].

5.4 Interface Model

The interface is the communication between the student and the aspects of the system. As such, an Interface Model (IM) is required for intelligently controlling the

dialogue, the screen layouts, and other interactions with the learner. Each interface element is linked to an internal representation of an instructional goal and the current state [16]. The two main aspects considered in IM are multimedia content and user exploration. The use of multimedia objects in IMES promises instructional efficacy. However, the complexity of the learning activity involving such a variety of tasks as information retrieval, navigation, and memorization means that just a naïve collection of multimedia objects does not promise improved, or even proper, learning [37]. Various tasks in AUI have different requirements and consequently need different multimedia objects for efficient and efficant interaction. Consequently, learners need to be provided with diverse forms of interactivity that match the pedagogical objectives of the IMES.

6. UNCERTAINTY MANAGEMENT

In any human modeling, making inferences about the beliefs, abilities, motives, and future actions of people require a good deal of uncertainty management that may manifest as incomplete, inconsistent, imprecise, or uncertain information [4], [8]. Incompleteness suggests the unavailability of some of the information. Inconsistency refers to the difference or conflict in the knowledge elicited from implicit or explicit information. Imprecision refers to values that are vaguely defined or measured inaccurately. Uncertain information points to the subjectivity in estimate about the value/rule.

The information available for inferencing in AUIs is inherently imprecise, vague, ambiguous, and incomplete with greater gap between the available evidence and drawn conclusions using fairly meager and haphazardly collected data [46]. The knowledge-intensive nature of various models in AUI implies that a little uncertainty in information may translate mischievously into the system response [47]. Consequently, any AUI decision mechanism requires robust ways of coping with such uncertainties. Unfortunately, the majority of theories and tools devised to handle subjectivities and uncertainties in information are quantitative in nature relying on crisp data. Such tools, in general, cannot handle the subjectivity and uncertainty emanating from all aforementioned sources [3], [35]. Thus, formulating effective ways of analysis and revision of knowledge models in AUI under uncertainty is an important research direction. Early solutions to this problem were based on heuristics or ad hoc techniques. Other approaches opted to constrain learners follow a predetermined line of reasoning, making it explicit. Nonetheless, such approaches could result in inflexible and overly constrained interface.

However, certain numerical uncertainty management tools have gained prominence. These methods for tackling uncertain knowledge are generally referred to as Soft Computing (SC). The role model for SC is the human mind and differs from conventional or hard computing in its tolerance of imprecision, uncertainty and partial truth. As such these hold immense promise for AUI.

6.1 Deterministic Approaches

Deterministic approaches work under the simplifying assumption that all the required information required can be quantified a priori and made available in need [3]. Such approaches usually make use of arbitrary default, user-defined, or expected values that are possibly refined by the user during the course of interaction with IMES. Conceivably, these myopic approaches are not effective in such complex and mercurial environments as IMES. In addition, there are user-based approaches that rely on ad hoc methods such as getting weights, preferences, and properties through user inputs. The usefulness of such approaches is severely limited by cognitive, informational, and functional capabilities of the user. It also distracts the user from her main objective, i.e. learning the subject at hand. Furthermore, personalization based on user inputs cannot accommodate changes in learner's interests or cognitive progress [23].

6.2 Algorithmic Approaches

An extension of deterministic approach is the assumption that some prudently devised algorithms could encompass all plans and corresponding actions. Indeed, it has been shown that plan recognition could be treated as deduction under a particular set of assumptions about the possible causes of actions [25]. Various algorithmic approaches work by determining a learner's plan from a library of possible plan schemas [9]. Such content-based algorithms may perform well at determining the general context. However, these cannot easily evaluate qualitative attributes like user's decision style, perceived usefulness, timeliness of presentation, etc. Consequently, even a good user-modeling algorithm alone does not form a truly useful system [10]. Furthermore, such algorithms require all plans to be identified to explain the learner's behavior and result in combinatorial intractability of the search task. Some probabilistic, heuristic, or soft computing approaches may reduce the search space and make plan recognition more tractable. Nevertheless, the problem in adaptive IMES is more complicated in the sense that not only we have to predict the learner's intentions but also predict learner's cognitive progress based on which system should provide higher learning opportunities.

6.3 Probabilistic Approaches

The majority of uncertainty management methodologies quantify uncertainties in form of some probabilistic measures that are propagated during reasoning [35]. Examples include the Bayesian Belief Networks, Certainty Factors, Dempster-Shafer, etc. Such approaches are based on the premise that assigning a

certain value to a plan hypothesis reflects the likelihood of its being pursued by the user [23]. Thus, it lends itself to some probability-like measure for representing information about user's individual preferences [46]. The key issue in using probabilistic approaches is accurate representation of the probabilistic dependencies in the task domain. However, student modeling using probabilistic approaches is problematic due to dynamism in student's knowledge resulting from interaction with information.

Among such traditional uncertainty modeling tools, Bayesian Networks (BN) are a popular formalism approach in user modeling and establishing sensible policies for handling uncertainty in knowledge assessment and plan recognition. BN is based on Bayes' theorem where the evidence is encoded in a directed acyclical graph with nodes corresponding to single/multi-valued variables and links corresponding to probabilistic influence relationships.

However, representing various cognitive and pedagogical aspects using BN requires assigning probabilities to such events. As such, extensive empirical experimentations are needed to establish such probabilities. Alternatively, such conditional probabilities could be estimated by domain experts or based on a more general theory about the relationships among variables of these types. However, the estimation of such probabilities by human experts is often inconsistent and biased. Past studies involving such probabilistic approaches highlight the need for highly extensive usability studies of the system involving determination of probabilities for BNs by users and experts.

Another problem with BN is that it is valid only under the simplifying assumption that the presence of evidence also affects the negation of conclusion, which is not valid in most instances. In addition, BN is not well suited for providing explanation facilities. Furthermore, the computational complexity of BN is sometimes prohibitive and representing a realistic problem solution could be quite large. In fact, it has been shown that the exact application of the Bayesian inference technique has an NP-hard nature [24]. Under dynamic conditions, the size and topology of the networks may hamper updating BN in real time. Moreover, if even a small change in the knowledge representation is required, it can affect a large number of sub-networks. Approximation techniques for applying Bayesian can be useful; however, such techniques are effective only under specified conditions.

In Certainty Factors (CF) approach, the knowledge is expressed in the form of rules and a confidence factor associated with each rule. It does not require statistical basis for supplying beliefs in events and allows simultaneous rule representation and quantification of uncertainty making it simpler and efficient compared to BN. However, CF approach is not built on a solid theoretical foundation and results in many weaknesses such as the implicit assumption of independence among hypotheses [35].

The Dempster-Shafer (DS) theory of evidence addresses some of the weaknesses of the probabilistic approach including the representation of ignorance, the unnecessary requirement that the sum of beliefs in an event and its negation be 1 etc. [40]. DS formalism has been applied to the quantitative modeling of preferences in situations with partially or even completely missing statistical data and to compute the impact of new observations on the resulting assessment. However, it does not specify how the probabilities are to be computed or how the results are to be interpreted. Furthermore, in certain instances, obviously incorrect conclusions can be reached [2]. Moreover, the exponential nature of evidence and hypothesis spaces means application of DS is in the NP. The only way to dodge this problem is to use some heuristics to compute approximate solutions [24].

In short, such assessment of the user's action history can be helpful in establishing a numerical estimation of user's future behavior, similar to a priori probabilities over the set of all plans [15]. However, the implicit assumption of continuity in a user's attitude is clearly debatable as user behavior might change completely. Consequently, the underlying uncertainties and dynamics of the problem dictate the need for a methodology pertinent to incomplete, imprecise, inconsistent, and uncertain preferences and rules [4]. Most existing probabilistic techniques fail to deliver in uncertain environments falling in more than one of the aforementioned categories. This shortcoming is more evident and imperative when the available information is incomplete.

6.4 Machine Learning

The traditional user modeling systems have disadvantages that can be overcome with ML techniques for adaptive learning [20]. For instance, an AUI in IMES requires an ability to continuously extend the system's knowledge about the applicability and efficacy of different adaptation techniques by observing the success of such techniques in different users/contexts. The ML techniques are capable of expressing a rich variety of non-linear decision surfaces [47]. Such techniques, in general, process training/input data and attempt to make decision or classification based on this input. Furthermore, one frequently used underlying assumption in ML is the improved predictive performance by using more training data [47].

ML-based user-adaptive systems work differently from traditional Knowledge Representation (KR) based approaches. Instead of a knowledge base, observations of user behavior and history of interactions are treated

as training examples used by Learning components. The knowledge acquisition is automatic and incremental. As such, learning results are revised steadily without any special revision mechanisms [32]. Some examples of ML techniques used as alternatives for enabling adaptivity are Artificial Neural Networks, Case-Based Reasoning, Memory-based Learning, Decision Tree Induction, and Learning Automata. Multi-strategy ML approaches have also been used to engender hybrid LMs. For instance, short-term and long-term interests of user can be incorporated in a hybrid model using techniques most suitable for the specific task [10].

Although the knowledge acquisition in ML is automatic and incremental, considering the dynamic nature of user's interests, cognitive skills, and goals, the ML approaches seem inappropriate in IMES. Furthermore, the KR is implicit and formats of learning results (probabilities, decision trees, etc.) are specific to the learning algorithm. Consequently, due to lack of generalized representation formalism, ML techniques are not easily amenable to reusing of learned results for other purposes such as explanation facilities [32]. Consequently, the eventual goal of constructing a learning system that requires no intervention from the designer other than a list of potentially useful features is still elusive in realistic applications. Nevertheless, the use of ML algorithms for user modeling purposes has attracted much attention.

6.5 Fuzzy Logic

A natural way to characterize the relationship between attributes in the LM and concepts in the DM is the use of fuzzy linguistic labels [32], [33]. People often reason in terms of vague and context dependent concepts in dealing with situations where they encounter uncertainty [43]. FL techniques are used for representing and reasoning with vague concepts to mimic human style of reasoning. This reasoning may be that of the user, whose inferences or evaluations are being anticipated, or it may be that of an expert whose knowledge constitutes the basis for the system's reasoning. A user modeling system based on FL renders reasoning easy for designers and users to understand and to modify [24], [26], [33].

Furthermore, explicit information gathered from students about cognitive understanding and interests are inherently vague and subjective because they themselves might not have precise knowledge or they might not be motivated or competent to express their knowledge precisely [26]. Moreover, such information is usually incomplete. As such, the values of the attributes can be expressed in terms of linguistic labels that are handled as fuzzy numbers. Such circumstances render FL a logical choice as the membership functions of FL are in general well-suited to the representation of such input, even if the subsequent processing does not use FL techniques.

FL claims a certain degree of human-likeness because of the way in which it captures human reasoning with vague concepts [2], [3], [43]. Consequently, it seems to be a good choice for both initialization and refinement of LM as well as DM by using linguistic labels for domain concepts selected by users and/or classifying user as one belonging to various stereotypical categories. Furthermore, it sanctions tuning of the parameters of a user modeling system based on feedback from system performance, a common approach used in the field of rule-based expert systems [3], [26]. Fuzzy adaptation rules may also facilitate automated detection of conflicts and inconsistencies in the set of rules and provide robust performance in such conflicting scenarios [33].

On the flip side, it has been argued that FL was not developed for the purpose of cognitive simulation. As such, it cannot be taken for granted that an FL treatment of a given problem corresponds to the way people would deal with it [24]. Furthermore, the task of determining the appropriate representations may still require considerable empirical testing and knowledge engineering [26]. Nevertheless, the same is true with any other uncertainty management technique. Indeed, FL has been shown to be effective and robust technique in a variety of fields involving reasoning with incomplete, inconsistent, imprecise, and uncertain information [2], [4], [35]. Moreover, FL is superior to other uncertainty management techniques in terms of the computational complexity. Consequently, we believe, FL has a significant role to play in cost-effective and robust knowledge modeling under uncertain conditions as well as reasoning with such knowledge in AUI/IMES.

7. FUTURE DIRECTION IN AUI

It is not easy to predict future of AUI in IMES due to fast changing computing technology and computer users. However, we believe AUI has a very promising as well as challenging future in IMES. Here we delineate few prolific research directions in this regard.

7.1 Logical Characterization

The Functional Representation of AUI in IMES is more prevalent and hinges on various knowledge models to capture knowledge for the system. However, it renders the analysis and comparison of IMES on technical level difficult as, by and large, most existing systems are designed for special purposes [18]. Consequently, there is a need for formulating a common language [22]. Recently, a logic-based definition of IMES has been proposed allowing an abstract generalized formalization [18], [22]. Standardization of educational formalism would also facilitate the specification of many instructional models [18]. The goal is to develop a standard meta-language to be used all over the world facilitating the reuse of adaptation techniques in different contexts by reasoning over facts described in

standardized metadata formats [18], [19], [22], [30], [38]. Furthermore, reasoning can be performed in wider context over distributed data. Consequently, such representation seems to fit well for facilitating explanation facilities.

7.2 Meta-Adaptivity

As already mentioned, different adaptation techniques work most efficiently in different contexts underscoring the need for adaptation in the adaptation techniques, or meta-adaptation, during the cognitive progress of the learner. However, most empirical studies in adaptation techniques are done in simplistic and well-defined 'with or without' scenario by varying only a specific adaptation aspect and there is need for more extensive testing.

7.3 Explanation Facilities

An Explanation Facility furnishes the ability to thoroughly explore the implications of knowledge models and bases of system's adaptations. Studies have shown that a significant amount of user's sense of control is attached to the ability to readily make sense of interaction with the system. Consequently, Explanation Facilities indicating to learners, if invoked, the reasoning behind actions seems to be a nice extension to existing AUI frameworks. Furthermore, it may provide users of an AUI a sense of control by making the system 'scrutable' [17]. Such functionality may also be complemented with a visible method for controlling the system's adaptations or the user profiles. In its simplest form, explanation facilities could show rules and their usage sequence in inferences regarding certain actions [17], [35]. However, decisions regarding the effective mode for presentation of explanations would be yet another interesting research direction. Some small-scale exploratory studies have highlighted value of, as well as the difficulty in, supporting explanation/control capability because of lack of visibility or novel nature of the notion [17]. It points towards the need for making the explanation/control capabilities both visible and comprehensible to the user. Once again, simple and linguistic format of FL brings power to provide explanation facilities in a simple, compact, efficacious, and comprehensible manner [4].

7.4 Novel Scenario Modeling

When users are inactive, existing models can detect these situations but do not know the cause. Some mechanism for inferring the cause of inaction, such as lack of motivation or understanding, and adapting the interface accordingly would be worth exploring. Moreover, an interesting and more complex situation would arise when a learner switches from one access device to another during the course of learning. As such, an apparent inaction of the user could also be a result of distraction to other interesting services as well as

multi-tasking. Modeling a multi-tasking user poses even more challenging problem. Nonetheless, such a user is quite common in today's Web and Mobile service users. Furthermore, a usual classroom-teaching scenario is group/collaborative work that facilitates rich interchange of information and ideas from one another as well as from teacher [15]. It requires sensitivity to cognitive, intellectual, social, and cultural diversity. Modeling for such scenarios in adaptive IMES would certainly become a major focus in this research area.

Similarly, exploring the role of emotions in user modeling and decision-making could be a purposeful exercise [46]. There is growing evidence that emotional states may affect performance by altering perception, cognition, selection, motor actuation, etc. and may influence attention, planning, learning, memory, and decision-making. Some preliminary research work in some simplistic situations can be found in literature [15]. However, extensive work is required for incorporating emotions in IMES in realistic terms. In this regard, various theoretical frameworks may provide useful tools, such as the OCC cognitive theory of emotion and Game/Drama Theory [46], [36]. Furthermore, an interesting direction could be knowledge representation that facilitates such soft knowledge as mental and conceptual models. Once again, we believe that FL could prove a powerful modeling tool in these scenarios.

7.5 Extensive and Comparative Evaluation

The real-world deployment of user modeling and user-adapted systems with a demonstrable effectiveness is a formidable task [16], [10]. Conceivably, a review of past AUI articles reveals insufficient empirical evaluations [14]. Nevertheless, empirical studies of actual users help reinforce, contradict, and refine designs to better accommodate and satisfy users in accomplishing their tasks. However, the upward trend is quite visible and bodes well for the future of AUI and several instances of successful real world deployment of AUI systems can be cited. Nevertheless, there are problems due to the relative inability to identify evaluation needs and insufficient mappings of such needs to available resources.

Various possible metrics for evaluating an interface are: subjective evaluation of interaction quality by the user, user-friendliness, effectiveness, degree of task simplification, generalizability, scalability, accessibility, acceptability, etc. [5], [34]. However, one of the objectives in AUIs is the higher interaction quality requiring absorption of such aspects as *usability, usefulnes*s, *suitability*, *tailorabilit*y, etc. that might not be measurable with currently available evaluation means and measures. Despite the difficulty in quantifying these aspects, user's rating could be useful for evaluating an AUI. Nonetheless, comprehensive evaluation instruments and techniques for guiding the

design of adaptations are largely missing. The primary reason for this is the contextual nature of adaptations that often does not facilitate objective assessments [5]. Incorporation of learner's misconceptions, beside knowledge and cognitive progress, is an important consideration for an effective AUI. Consequently, it has been argued that LM should also be validated using external tests and comparisons with actual user behavior [45]. Conceivably, all this is quite difficult to achieve.

As already mentioned, a more general description on adaptation functionality would allow easy and effective reuse of adaptation techniques in various domains or contexts. This can be achieved by making metadata about different resources explicit using standardized descriptions [18]. Consequently, empirical studies of AUIs with several dimensions of adaptivity would certainly assist in developing tools for meta-adaptation.

7.6 Generalizability, Scalability, Portability

In terms of generalization and scalability of the system, more experiments must be performed in order to determine how the system would scale up to deal with more parameters of the AUI. Knowledge representation facilitating soft knowledge, other than facts/procedures, such as mental and conceptual models is a largely unexplored direction. Furthermore, knowledge representation facilitating scaling up to larger/broader domains is an important issue. As already mentioned, this goal is significantly dependent on formalism in AUI/IMES frameworks. In addition, one of the most relevant requirements for acceptability and pervasiveness of AUI/IMES is the platform independence or portability. Such issues need to address the much-desired reusability a reality. Furthermore, in an organizational context, adaptive educational software is not only a teaching/learning resource and a carrier of instructional strategies but also a source of much touted organizational and strategic changes. Consequently, the research in AUI can be extended to incorporate organizational changes in the research framework.

7.7 Reduction in Development Time

The future research in AUI/IMES seems to be geared towards forms that are more complex and involve various multimedia embodiments. It would require articulation of abstract design patterns, elaboration and enumeration of different design alternatives, ranking of competing alternatives (based on experts' opinions and other subjective design criteria), and propagation of design knowledge into the development cycle [5]. Consequently, the need for reducing the developmental cycle time through some intelligent decision support mechanism cannot be ignored [2].

Recently, an expert system paradigm based framework has been proposed for intelligent decision support in layout design with an application to the adaptive Web page layout design [2], [3]. We believe that such knowledge-based decision support frameworks would be valuable in fast and easy generation, evaluation, and refinement of superior alternatives. Such efforts would reduce the cognitive overload and personal bias in building a system that is rich in alternatives for various users by making use of a combination of AUI/IMES techniques/technologies, philosophies/pedagogies, etc. Furthermore, some authoring application for analyzing the set of rules by expressing just properties, without having to be concerned with the methods and techniques of inferencing, is an interesting but challenging direction. Availability of an efficient, efficant and easy-to-use off-the-shelf tool towards this would certainly make designing and utilizing AUIs more attractive. Representing knowledge, skills and contexts at a meta-level in a standardized and easily interpretable graphic language might also facilitate reuse and adaptation of models from different sources.

10. SUMMARY

The purpose of this paper is to briefly introduce the issues, prospects, and difficulties associated with research in adaptive user interfaces within the IMES context. The success of the learning process in such an educational environment depends on the intelligent context-oriented presentation of the domain knowledge by the system and its adaptivity in terms of complexity and granularity consistent to the learner's cognitive skills and progress. The richness of the human behavior and technological opportunities mean there is no final solution in such sensitive human-computer interaction area. Nevertheless, we have tried to highlight the role of various paradigms, techniques, and technologies in creating efficant AUIs that may help in providing more flexible and enhanced IMES. Furthermore, a perfunctory review of future trends and research directions has been presented. We hope that this review of complexity as well as limitations of AUI and pertinent technologies would prove helpful in creating expectations that are more realistic. However, this is just a broad overview of AUI literature and by no means complete. An integrative and comparative review of various adaptation techniques, pertinent technologies, and knowledge models with specific consideration of Web and Mobile Learning would be a worthwhile effort

REFERENCES

[1] ACM, (2004) "ACM Code of Ethics and Professional Conduct", *ACM Computing and Public Policy: A Fair Society in Computing*, §1.4.
[2] Ahmad, A.R., Basir, O.A., Hassanein, K., (2003) "Fuzzy Inferencing in the Web Page Layout Design", *WSMAI'03*, April'03, 33-41.
[3] Ahmad, A.R., Basir, O.A., Hassanein, K., (2004a) "Intelligent Decision Support System for Layout Design", *Proc. of the 9th Asia-Pacific Decision Sciences Ins. Conf (APDSI'04)*, Korea, July 2004
[4] Ahmad, A.R., Basir, O.A., Hassanein, K., (2004b) "Decision Preferences, Constraints, and Evaluation Objectives

in Layout Design: A Review of Modeling Techniques", *Proc. of the 5th Int'l Conf. on Op. and Quan. Manag (ICOQM-V)*, Oct. 2004, Seoul, Korea, *to appear.*

[5] Akoumianakis, D., Savidis, A., et al., (2000) "Encapsulating intelligent interactive behaviour in unified user interface artefacts", *Interacting with Computer,* Vol. 12, 383–408.

[6] Alpert, S.R., Karat, J., Karat, et al. (2003) "User Attitudes Regarding a User-Adaptive eCommerce Web Site", *UMUAI*, Vol. 13, 373-96.

[7] Benyon, D.R. (1996) "Domain Models in User Interface Design", *Critical Issues in User Interface Systems Engineering*, Springer-Verlag.

[8] Bianchi-Berthouze, N., L. Berthouze, and T. Kato, (1999) "Understanding Subjectivity: An Interactionist View", *UM'99*, Springer, NY, 3-12.

[9] Bikel,D., Schwartz,R, Weischedel,R.,(1999) "An algorithm that learns what is in a name", *Machine Learning*, 34(1), 211-231.

[10] Billsus, D., Brunk, C.A., Evans, C., Gladish, B., Pazzani, M. (2002) "Adaptive interfaces for ubiquitous Web access", *Comm. of the ACM*, 45(5), 34-38

[11] Bontcheva, K., (2002) "Adaptivity, Adaptability, and Reading Behaviour: Some Results from the Evaluation of a Dynamic Hypertext System, *AH'2002*.

[12] Brusilovsky, P., (2001) "Adaptive hypermedia", *UMUAI*, 11(1), 87-110.

[13] Brusilovsky,P.(2003a) "Adaptive navigation support in educational hypermedia: the role of student knowledge level & case for meta-adaptation",*Brit.J.of Edu. Tech*,34(4), 487-97.

[14] Chin, D.N., Crosby, M.E., (2002) "Introduction to the Special Issue on Empirical Evaluation of User Models and User Modeling Systems", *UMUAI*, Vol. 12, 105-109.

[15] Conati C., Zhao X. (2004) "Building and Evaluating an Intelligent Pedagogical Agent to Improve the Effectiveness of an Educational Game", *IUI'04*, Jan. 13-16, Madeira, Portugal.

[16] Corbett,A.,McLaughlin,M.,Scarpinatto,K.,(2000) "Modeling Student Knowledge: Cognitive Tutors in High School & College", *UMUAI*, Vol. 10, 81-108.

[17] Czarkowski, M., Judy, K. (2003) "How to give user a sense of control over personalization", *AH'03*, 121-132.

[18] Dolog, P., Henze, N. (2003) "Personalization Services for Adaptive Educational Hypermedia", *ABIS 03 Workshop*, Oct. 6-8, Karlsruhe, Germany.

[19] Educational Modeling Language (EML) Group: htttp://eml.ou.nl/

[20] Goecks,J., Shavlik,J., (2000) "Learning Users Interests by Unobtrusively Observing Their Normal Behavior", *IUI'00*, New Orleans, LA.

[21] He S., Kinshuk, Hong H., Patel A. (2002), "Granular Approach to Adaptivity in Problem-based Learning Environment", *ICALT'02*, Palmerston North, NZ, 3-7.

[22] Henze, N., Nejdl, W., (2003) "Logically Characterizing Adaptive Educational Hypermedia Systems", *AH'03*, Budapest, Ungarn.

[23] Jameson,A. (2001) "Modelling both the context & user"*, Personal Technologies,* 5(1), 1-4.

[24] Jameson,A., (1996)"Numerical uncertainty manag. in user/student modeling: An overview of systems & issues", *UMUAI*, Vol.5, 193-251.

[25] Kautz,H.A., (1987) "A formal theory of plan recognition", *PhD thesis*,U.of Rochester, NY.

[26] Kavčič,A., Jiménez,R.P., et al. (2003) "Student Modelling Based on Fuzzy Inference Mechanisms", *Proc. of EUROCON'03: Computer as a Tool*, Ljubljana, Slovenia, Sep. 2003

[27] Kinshuk, and Patel, A. (2001) "Implementation issues in web-based training", *Web-Based Training,* Educational Technology Publ., NJ.

[28] Kinshuk & Lin T., (2003) "User Exploration Based Adaptation in Adaptive Learning Systems", *Int'l J. of Information Systems in Educatio*n, 1(1), 22-31.

[29] Kobsa, A., (2003) "Privacy through pseudonymity in user-adaptive systems", *ACM Trans. on Internet Technology*, 3(2), 149-183.

[30] Learning Object Metadata (LOM), http://ltsc.ieee.org/doc/wg12/LOM-WD3.html

[31] Maes, P., (1994) "Agents that reduce workload", *Comm. of the ACM*, 37(7), 31–40.

[32] Maleki-Dizaji, S., Othman, Z. A., et al. (2003) "Evolutionary Reinforcement of User Models in an Adaptive Search Engine", *WI'03,* 706-9.

[33] Martinovska, C., (2002) "A Fuzzy-Based Approach to User Model Refinement in Adaptive Hypermedia System", *AH'2002*, 411-414.

[34] McTear, M.F., (2000) "Intelligent Interface Technology: From Theory to Reality", *Interacting with Computers*, Vol.12, 323-336.

[35] Negnevitsky, M., (2002) *Artificial Intelligence: A Guide to Intelligent Systems*, Pearson.

[36] Obeidi, A., K.W. Hipel, D.M. Kilgour, (2003) "Emotion: The Missing Ingredient in Conflict Analysis", *Int'l Conf. on Systems, Man and Cybernetics*, Vol. 4, 3322 - 3329.

[37] Sampson D., Karagiannidis C., Kinshuk (2002), "Personalised Learning: Educational, Technological and Standardisation Perspective", *Interactive Edu. Multimedia*, Vol. 4, 24-39.

[38] SCORM: The Sharable Content Object Reference Model, http://www.adlnet.org/scorm/.

[39] Serafini,L., Bouquet,P. (2004) "formal theories of context in AI", *AI*, Vol. 155, 41-67.

[40] Shafer, G., (1976) *A Mathematical Theory of Evidenc*e. Princeton University Press, NJ.

[41] Shneiderman, B. (1997) "Direct manipulation for comprehensible, predictable and controllable user interfaces", *IUI'97*, Orlando, FL.

[42] Shneiderman, B. Maes, P. (1997) "Direct manipulation vs. interface agents", *Interactions,* 4(6), 42-61.

[43] Turban,E., Aronson,J.E., (2001) *Decision Support & Intelligent Systems*, PrenticeHall, NJ.

[44] Vomlel, J. (2004) "Bayesian Networks in Educational Testing", *IJUFKS*, 12(1), 83-100.

[45] Weibelzahl, S., Weber, G. (2003) "Evaluating the Inference Mechanism of Adaptive Learning Systems", *LNCS*, Vol. 2702, 154-162.

[46] Zhou X. and Conati C. (2003) "Inferring User Goals from Personality and Behavior in a Causal Model of User Affect", *IUI'03*,Miami,FL, 211-218.

[47] Zukerman, I., Albrecht, D., (2001) "Predictive Statistical Models for User Modeling", *UMUAI,* 11(1), 5-18..