A Critical Review of Development of Intelligent Tutoring Systems: Retrospect, Present and Prospect

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ABSTRACT:

This paper introduces, Intelligent Tutoring Systems along with their typical architecture, developmental history, past and present systems and concludes with a broad discussion on wide-spanning focus areas for future developmental research. A critical analysis of the developmental history highlighting the theme behind the developed systems, their purpose and the key ITS concept, have been presented. A closer look revealed that, development of a certain concept proved to become a turning point for all future developments of that era. All such key concepts and subsequent developments have been examined. The paper provides recommendations and pointers, to the areas that need to be probed further and drilled down to establish ITS success for generations to come.

KEY WORDS:
Intelligent Tutoring Systems (ITS), Computer Assisted Instruction(CAI), Case Based reasoning(CBR), Affective Tutoring Systems(ATS), Expert Systems, Expert Systems Development.

1. INTRODUCTION

The amalgamation of Artificial Intelligence techniques into education, producing educationally useful computer artifacts dates back to early 1970s. Over a large spectrum of incremental developments, they have taken various forms, one amongst which is Intelligent Tutoring Systems (ITSs). It is a computer-based program not only to emulate a 'human tutor', but to personalize the instructions based on the background and progress of each individual learner. There has been evolution from a very primitive form of computer-assisted instruction, ranging through various forms of e-learning systems, progressing to form learner adaptive systems, to modern day ITS, with significant development in their user interface as well, highlighting and facilitating a smooth cognitive interaction of man and machine. The systems have transformed to become a true intersection of computer science, cognitive psychology and educational research. They have offered various focus points in system development across various time periods highlighting research areas, on and off being addressed by researchers from time to time.

1.1. Architecture of a Typical ITS System

A typical ITS, has the following four basic components **[1]**. The section below lists them with their functionality, individually and then by way of their integration.

1.1.1. The Domain model

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1.1.2. The Student model

1.1.3. The Tutoring model, and

1.1.4. The User interface model

1.1.1. Domain Model: The domain model (also known as the cognitive model/expert knowledge model) consists of the concepts, facts, rules, and problem-solving strategies of the domain in context. It serves as a source of expert knowledge, a standard for evaluation of the student's performance and diagnosis of errors.

1.1.2. Student Model: The student model is an overlay on the domain model. It emphasizes cognitive and affective states of the student in relation to their evolution as the learning process advances. As the student works step-by-step through their problem solving process, the system engages itself in model tracing process. Anytime there is any deviation from the predefined model, the system flags it as an error.

1.1.3. Tutoring Model: The tutor model (also called teaching strategy or pedagogic module) accepts information from the domain and student models and devices tutoring strategies with actions. This model regulates instructional interactions with student. It is closely linked to the student model, makes use of knowledge about the student and its own tutorial goal structure, to devise the pedagogic activity to be presented. It tracks the learner's progress, builds a profile of strengths and weaknesses relative to the production rules (termed as 'knowledge-tracing').

1.1.4. User Interface Model: This is the interacting front-end of the ITS. It integrates all types of information needed to interact with learner, through graphics, text, multi-media, key-board, mouse-driven menus, etc. **[2]**. Prime factors for user-acceptance are user-friendliness and presentation. The Figure 1 presents a typical ITS architecture.

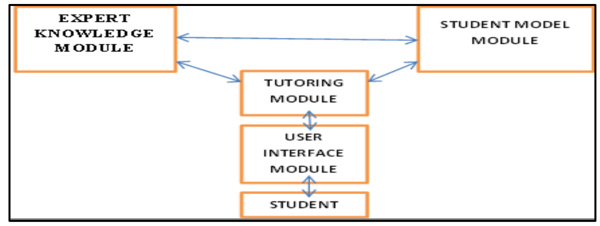

FIG 1: Typical Architecture of an ITS

2. CHRONOLOGICAL REVIEW OF ITS DEVELOPMENT

This section of the paper presents ITS development across past (1970s-1999) and present (2000-2013).

In the past decade, there has been tremendous growth in the field of expert systems and ITS with student modeling as a research area maturing sufficiently constituting a very promising technology for personalization and adaptivity of e-learning systems. Since 1960's to present, ITS have been heralded as one of the most promising approaches to deliver individualized instructions. In the early 1960, programmed instruction, enhancing learning for low aptitude individuals, was educationally fashionable, moving towards structured and goal oriented instruction **[1]**.

Dawn of 1970's saw a new era of ITS development with knowledge representation, student modeling, Socratic tutoring, skills and strategic knowledge, buggy library, expert systems and genetic graph. "Bug Library" is a collection of mistakes. In genetic graph, "Genetic" related to the notion of knowledge being evolutionary, and graph denoted the relationships between parts of knowledge expressed as links in a network. In 1980's, the emphasis in ITS development was case-based reasoning, more buggy based systems, discovery worlds, progression of mental models, simulation, natural language processing, authoring systems and systems based on model tracing. Model tracing Tutors contained a cognitive model or simulation of an expert's correct thinking in the domain **[3]**.

In 1990's focus shifted to learning theory that embodied concepts such as learner control, collaborative as against individual learning, information processing and virtual reality as against situated learning. Unlike individual learning, people engaged in collaborative learning capitalizing on one another's resources and skills. Both novice and master are active participants in the learning environment.

In the present years technological resources have been integrated with education. However, the integration of educational technology at early childhood education is a more recent trend compared to at other levels of education. From year 2000 to 2013, important issues related to ITS development concentrated on student modeling approach, learning through games, adaptation to emotional state of user, web based tutoring systems, knowledge modeling by fuzzy linguistic information, WIMP interfaces, summary assessment techniques, motion capture technology, interrelation between person's cognitive load and pupil's size and education data mining.

The section below represents a retrospective developmental account of ITS between the period 1970 and 1999.

Basic Instructional Program (1970) employed teaching procedural skills in learning programming language BASIC. Exercises were dynamically and individually selected per user using Curriculum Information Network (CIN) **[4]**. **Carbonell's SCHOLAR (1970)** used semantic net to represent domain knowledge as well as the student model.**[5]**. Collins in 1975 outlined set of tutorial rules for **Socratic tutoring**. One such system was **WHY**. It stores domain knowledge in script hierarchy containing stereotypical sequences of events **[6]**. **WEST [7]** helped students to improve arithmetic expression manipulation skills. It was called issue-based tutoring. **SOPHIE (Sophisticated Instructional Environment)** assisted learners in developing electronic troubleshooting skills. SOPHIE I, SOPHIE II, SOPHIE III have extended the environment of their predecessors. **[8]**. **BUGGY (1978)** employed buggy library approach for diagnosis of student errors (bugs). It was a framework for modeling misconceptions underlying procedural errors in addition and subtraction exercises offered to student for solving. **[8]. DEBUGGY [9]** was an offline version of a system based on BUGGY using the pattern of error. IDEBUGGY developed by Burton in 1982 was an on line version to diagnose student's procedure bit by bit while giving the learner a new problem to solve at each step. Limitation of buggy library was its inability to anticipate all possible misconceptions. **MYCIN [10]** was a rule-based expert system for diagnosing certain Infectious diseases such as meningitis. Using the learning of MYCIN, **GUIDON** was constructed by Clancey in 1979 to interface with MYCIN for tutoring, interactively presenting the rules in the knowledge base to a student **[11]**. **WUSOR** was the name of the on-line coach for the game WUMPUS, developed by Stansfield, Carr and Goldstein in 1976 **[12].** LISP Tutor by Anderson Boyle and Reiser and a Geometry Tutor by Anderson Boyle and Yost arrived in mid-1980 employed the approach of model tracing. **[13-14]**. **PROUST** by Johnson and Littman Soloway in 1984 diagnosed non-syntactic student errors in PASCAL **[15]**. **PIXIE** developed by Sleeman in 1987 is an online ITS based on Leeds Modeling System (LMS) having a diagnostic model for determining sources of errors in algebra due to incorrect (mal) rules that are inferred from basic principles and bugs at abstraction level **[16.]**

In late 1980 arrived the **Case-based Reasoning** (CBR) research by Schank and Kolodner which had a more adaptive learning environment, with the advantage of being suitable to domains where there are too many ways in which the rule can be applied (e.g., programming, game playing) and suggests approximate answers to complex problems. **[17-18]**.

The year 1990 brought the new trend of graphic simulations. Hauk Mack III was a system that expanded number of components and complexity of animations by orders of magnitude **[19]**.

The other areas of research and development that gained prominence were Natural Language Processing (NLP) and authoring shells. SOPHIE was built on a powerful and original NLP technique developed by Richard Burton; called Semantic Grammar. It represented a powerful combination of carefully selected keywords with algorithms that searched the context for meaningful variables and objects. Authoring shells are kind of e-learning systems that feature authoring environments for system users, simplify the software development life cycle. Domain knowledge in such systems can be represented by using different knowledge representation specifications. **[9][20][21].**

3. THE PRESENT SCENARIO OF ITS DEVELOPMENT

In recent years, progress has been towards providing adaptivity and personalization in computer based education through student modeling, mobile technologies, educational games and standalone educational applications.

An adaptive educational system has to provide personalization to the specific needs, knowledge and background of each individual student which is challenging since students not only have different learning needs, but also different learning characteristics. The section below lists each of these concepts with their applicability in present day ITS development. The major approaches introduced were overlay, perturbation, stereotypes, machine learning techniques, cognitive theories, constraint based model, fuzzy student modeling, Bayesian network, and ontology student modeling **[22].** Few of these have been briefly stated below. The overlay model was invented by Stansfield, Carr, and Goldstein in 1976 and has been used in many systems ever since **[23]**. The main assumption underlying it is that a student may have incomplete but correct knowledge of the domain. Overlay models are inadequate for sophisticated models because they do not take into account the way users make inferences, or integrate new and old knowledge, and change representational structures with learning. Stereotypes were introduced to user modeling by Rich in 1979 in the system called GRUNDY **[24]**. The main idea of stereotyping was to cluster all possible users of an adaptive system into several groups according to certain characteristics that they typically shared **[25]**. A perturbation student model is an extension of the overlay model that represents the student's knowledge as including possible misconceptions as well as a subset of the expert's knowledge **[26]**. It represents learners as the subset of expert's knowledge, like the overlay model, plus their mal-knowledge **[27].** This extension allows for better remediation of student mistakes, since the fact that a student believes something that is incorrect is pedagogically significant **[28].** The processes of observation of student's action and behavior in an adaptive and/or personalized tutoring system, and of induction, should be made automated by the system. A solution for this is machine learning, which is concerned with the formation of models from observations and has been extensively studied for automated induction. **[29].** The cognitive theory attempts to explain human behavior during the learning process by understanding human's processes of thinking and understanding [57]. The Constraint-Based Model (CBM) proposed by Ohlsson in 1996 is based on Ohlsson's theory of learning from errors, and proposes that a learner often makes mistakes when performing a task, even when he/she has been taught the correct way to do it. Fuzzy logic is able to handle uncertainty in everyday problems caused by imprecise and incomplete data as well as human subjectivity. Fuzzy Student Modeling was applied, by Stathacopoulou et al. in 2005 to a discovery-learning environment that aimed to help students to construct the concepts of vectors in physics and mathematics **[30]**. Several student models have been built based on ontologies. These support the representation of abstract concepts and properties so as to be easily reused and, if necessary, extended in different application contexts **[31]**. A glimpse of few significant systems of the era is presented below:

Adaptive Intelligent Web Based Education Systems (AIWBES) were developed as an alternative to traditional e-learning environments according to 'onesize-fits-all' approach **[32][58]. Affective tutoring systems (ATS) [33]**. The system utilizes a network of computer systems, prominently, embedded devices to detect student emotion and other significant bio-signals and adapt to the student's mood and display emotion via a life-like agent called Eve, whose tutoring adaptations are guided by a case-based method for adapting to student states - confused, frustrated or angry **[34]**. **Multi Criteria decision model** has been employed to integrate expert's knowledge modeled by fuzzy linguistic information, enhancing accuracy of diagnosis for adaptation of computerized test of the student competence level. **Pen-based tutoring system**s are based on WIMP (windows, icons, menu & pointer) interfaces. Newton's Pen is a "statics tutor" implemented on a ''pen top computer,'' a writing instrument with an integrated digitizer and embedded processor. This project entailed the development of sketch understanding techniques and user interface principles for creating pedagogically sound instructional tools for pen top computers. Development on the pen top platform presented novel challenges because of limited memory and computational power resources **[34]**.

Automatic Summary Assessment has been a widely used mechanism. Several techniques such as latent semantic analysis (LSA), n-gram co-occurrence and BLEU have been proposed to support automatic evaluation of summaries **[35]**. Landauer et al in 1998 first developed latent semantic analysis (LSA) in the late'80s with the purpose of indexing documents and information retrieval **[36]**. LSA works by using a matrix to capture words and frequency of the words appearing in a context that is transformed using Singular Value Decomposition (SVD). Based on the result of Landauer's experiment, LSA is capable of producing acceptable results. However, LSA does not make use of word order as Landauer claims that word order is not the most important factor in collecting the sense of a passage. Pérez et al. in 2004 modified the BLEU algorithm, which was originally developed for ranking machine translation systems, into one that is capable of marking students' essay. **[37]**. Lin and Hovy in 2003 conducted a study on using the two machine translation evaluation techniques, BLEU and NIST's n-gram co-occurrence scoring procedures, on the evaluation of summaries to measure the closeness of the candidate to the reference summary **[38]**. With the recent success of e-learning and advances in other areas such as Information Extraction (IE) and NLP, automatic assessment of summary writings has become possible.

Handwriting Based Intelligent Tutors use handwriting input offering several affordances for students that traditional typing-based interactions do not **[39]**.

Educational Data Mining (EDM) is concerned with developing, researching, and applying computerized methods to detect student access patterns in large collections of educational data that would otherwise be hard or impossible to analyze due to the enormous volume of data within which they exist **[40]**.

Motion Capture Technology is being used in automated lesson generation systems for example one such system is 'Dance Learning from Bottom-Up Structure (DL-BUS)' for guiding beginners to learn basic dance movement, analyzing the dance to generate a two-phase lesson (phase-1 to divide dance into small segments and phase -2 to combine patterns in temporal order) providing suitable cognitive load thus offering an efficient learning experience.**[41].**

A level ahead is an **Intelligent Pupil Eye Analysis System,** involving the interrelation between person's cognitive load and pupil size. This sensitivity of the pupil can provide exhaustive data about the cognitive loads. Different works such as by Klingner et al., in 2008; Partala and Surakka, in 2003; Valverde et al., in 2010; Klingner, in 2010; Just and Carpenter, in 1993; Backs and Walrath, in 1992; and Porter et al., in 2007 demonstrate that task-induced dilations can serve as reliable proxies for cognitive load, and the sizes of blink pupil dilations reliably reflect a diverse scale of the difficulty of different activities thus validating pupillary dilations**. [42-49]**.

Non-crisp learner responses that are uncertain usually belong to completely understanding or not understanding case for the content of learned courseware. One of the Response Theory was Personalized Learning Item Response Theory (PEL-IRT), which including the fuzzy aspects, transformed into **Fuzzy Item Response Theory (FIRT)**, proposed by Chih-Ming Chen and Ling-Jiun Duh correctly estimated learner ability via the fuzzy inference mechanism **[50-51]**.

UZWEBMAT: (Turkish abbreviation of Adaptive and Intelligent WEB based Mathematics teaching–learning system) -teaches secondary school level permutation, combination, binomial expansion and probability. **[52]**

4. FUTURE ASPECTS AND RECOMMENDATION:

The section outlines the areas where considerable amount of development is needed and awaited to make ITS systems live up to their objective. The expectations raised by these systems during initial days have made it more essential for a fool-proof system to evolve in the current century. A few such areas needing serious thought and contemplation by engineers/ research scientists are stated below.

Computer Assisted Assessment is a long standing problem that has attracted interest from research community since sixties and has not fully been resolved yet. The **ASSISTment** software provided hints and scaffolding in response to students' problem solving errors. The students performed better on a post-test than peers who completed their homework in traditional paper-and-pencil form, meaning that they did not receive immediate feedback and assistance on the problems. The results were encouraging, although limited by the relatively brief nature of the intervention. Previously, many researchers put efforts into e-learning systems with personalized learning mechanism to aid on-line learning. However, most systems focused on using learner's behavior, interests, and habits to provide personalized e-learning services, but neglected the match between learner's ability and the difficulty level of the recommended courseware. Frequently, unsuitable courseware caused learner's cognitive overload or disorientation during learning. This area needs significant intervention by research community.

Adaptive abilities of ITS, are still not high enough, particularly regarding modes of practical problem-solving and support to learner in this process. Enriched adaptation techniques are required with focus on student's behavior. From the early years of systematic use of instructional design, educational scientists desired to use the results of artificial intelligence to support authors, developers and researchers, in their pedagogical work to create 'automatic' course designing machines. The objective was to make the built-in process more and more responsive and adaptive to the tuition circumstances, resulting in the design of a more intelligent training material. The last thirty year development in this discipline is still in an emerging phase.

The evaluation of ITS is an important though often neglected development stage. There are many evaluation methods available but literature does not provide clear guidelines for the selection of evaluation method(s) to be used in a particular context. Conventional computer programs are sometimes verified and validated through formal proofs of correctness. However, this technique is unsuitable for AI programs which deal with analytically intractable problems, represented as incompletely specified functions.

Extensively validated research in cognition, perception, and learning as indicated by Jay, in 1983; Jonassen & Hannum, in 1987; Larsen, in 1985 suggests ways to design and improve educational programs, particularly the interface and user-related features. The area of human computer interaction holds potential that needs to be explored for channelized and focused development **[53-55].**

An expert's knowledge/inspection (called evaluation) is used as an explicit standard for judging a program. Due to ITS complex and dynamic behavior it is not as easy. Moreover there are known bottlenecks in extracting expert knowledge such as limited number of experts, their varied degrees of expression, difficulty in converting the knowledge gained from experience into a documented form etc. This is an area to further introspect.

The use of machine learning techniques can greatly improve the dynamic construction and updating of student models. There is hardly any research done for developing ITS for blind students, although there are systems developed for hearing impaired participants **[56].** There are other set of disabilities, where there is a need for ITS to train. Training/exploring potential in creative art in creative arts is an area which has limited intervention as of now.

The main limitation of model tracing with respect to ill-defined domains is that, for some domains there are no clear strategies for finding solutions and it can therefore be difficult to define an explicit task model. Moreover, for complex domains, one would need to determine a large number of rules and solution paths, and designing a set of rules or a state space for each task would be very time consuming.

ITS does not appreciate or fails to offer encouragement at the time of student need. It fails to provide help in context of confusion causing to perceive negative emotions for her/his own actions. The shift has been made towards the methodologies instead of the much needed attention towards the student or the domain. Social learning/collaborative learning is an area where a number of users come-together, collaborate, discuss and enhance their degree of understanding about a topic. There is a need for ITS researchers to explore the possibility and develop a framework for integrating social networking agents. There is a need to drill down and analyze emotional states of the learner and accordingly align the focus as well as learning/teaching strategies of ITS. There is immense future research direction embedded in it. With an increased demand for portable devices, various hand-held intelligent tutoring systems promise rich dividend.

5. CONCLUSION

The paper chronologically presents the development of ITS. It presents the retrospect present and the prospect of ITS. Over the period, they have gradually moved closer to the individual student learning need. Adaptability and user-friendliness have been the key concepts. Further, the prospective areas for future ITS development have been outlined for recommended research work. Human computer interaction has emerged as an area offering definite potential and demanding intervention by research scientists.

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