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Intelligent tutoring systems: a systematic review of characteristics, applications, and evaluation methods

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ABSTRACT

With the rapid growth of technology, computer learning has become increasingly integrated with artificial intelligence techniques in order to develop more personalized educational systems. These systems are known as Intelligent Tutoring systems (ITSs). This paper focused on the variant characteristics of ITSs developed across different educational fields. The original studies from 2007 to 2017 were extracted from the PubMed, ProQuest, Scopus, Google scholar, Embase, Cochrane, and Web of Science databases. Finally, 53 papers were included in the study based on inclusion criteria. The educational fields in the ITSs were mainly computer sciences (37.73%). Action-condition rule-based reasoning, data mining, and Bayesian network with 33.96%, 22.64%, and 20.75% frequency respectively, were the most frequent artificial intelligent techniques applied in the ITSs. These techniques enable ITSs to deliver adaptive guidance and instruction, evaluate learners, define and update the learner's model, and classify or cluster learners. Specifically, the performance of the system, learner's performance, and experiences were used for evaluation of ITSs. Most ITSs were designed for web user interfaces. Although these systems could facilitate reasoning in the learning process, these systems have rarely been applied in experimental courses including problem-solving, decision-making in physics, chemistry, and clinical fields. Due to the important role of a cell phone in facilitating personalized learning and given the low rate of using mobile-based ITSs, this study has recommended the development and evaluation of mobile-based ITSs.

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Adaptive learning; artificial intelligent tutoring; intelligent learning; intelligent tutoring system; ITS

1. Introduction

The SCHOLAR tutor system was the earliest intelligent tutoring system (ITS) introduced by Jaime R. Carbonell in 1970 (Woolf, 2010). This program system was developed for reviewing the student's knowledge in the geography of South America. Indeed, by using the semantic network of concepts and facts of knowledge to evaluate their knowledge in the context of geography, the SCHOLAR began a two-way interaction with the students (Carbonell, 1970). In the last decades, the use of artificial intelligent (AI) methods especially machine learning has grown in the instructional systems. ITSs are adaptive instructional systems which incorporate AI techniques with educational methods. The important feature of these systems is the ability to customize the instructional

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activities and strategies based on the learner's characteristics and needs (Keleş, Ocak, Keleş, & Gülcü, 2009).

The ITSs have a classical architecture with four modules which are known by different names in studies. The first part is the expert module. This part includes the knowledge that the student wants to learn (domain knowledge) (Ma, Adesope, Nesbit, & Liu, 2014). Furthermore, the techniques of the problem-solving and analyzing the student's activities in the learning process are used in this module, similar to human experts (Carter, 2014). The second part is the student diagnosis module or student model, built by factors such as the level of knowledge, activities, responses, behaviors, learning styles, student's knowledge deficiency, and other information about learner gathered and updated in the process of learning in the system (Brown, 2009; Ma et al., 2014). The third part is known as instruction, tutor, or pedagogical module. It detects the knowledge deficiency in students and focuses on the strategies and methods of teaching for compensating the identified shortage of knowledge in a specific field (Polson & Richardson, 2013). Adaptive feedback, hint, and recommendation-generating, navigation of the learning path, and presenting adaptive educational content constitute the core of this module (Carter, 2014). The last module is the user interface which is communication part of ITS for controlling the interaction between user and system (Burns & Capps, 1989). There have been some reviews in e-learning systems which have been incorporated with AI techniques in order to improve the adaptive and customized learning (Drigas, Argyri, & Vrettaros, 2009; O'Donnell, Lawless, Sharp, & Wade, 2015). Further, other studies have reviewed the effectiveness and usability of these systems (Chughtai, Zhang, & Craig, 2015; Kulik & Fletcher, 2016). In addition, some papers examined the intelligent tutoring game system (Hooshyar, Yousefi, & Lim, 2017, 2018). After surveying the available review articles, we found that there are some questions left unanswered. Therefore, the aim of this study was reviewing the ITSs developed across all educational fields, in order to gather comprehensive information about their characteristics, applications, and evaluation methods.

2. Research questions

This systematic review responds to the following research questions:

RQ 1. For which educational fields ITSs have been designed?
RQ 2: Which AI techniques have been applied in the development of ITSs?
RQ 3: What are the main purposes of using the AI techniques in ITSs?
RQ 4: Which factors have been used for representing the adaptive or one-to-one instruction in ITSs?
RQ5: What types of user-interface have been used for development of ITSs?
RQ 6: Which methods have been employed for the evaluation of ITSs?

3. Method

This systematic review was conducted based on the preferred reporting items for systematic reviews and meta-analysis (PRISMA) proposed by Moher et al. (2015). Figure 1 displays the process of PRISMA for data collection and analysis.

3.1. Search strategy

The papers from PubMed, ProQuest, Scopus, Google scholar, Embase, Cochrane and Web of Science databases were searched within the period from 2007 to 2017 (10 October). The PICO criteria were used to define the search string: population (P), intervention (I), comparison (C), and outcome (O) (Stone, 2002). The population was ITSs, intelligent or intelligent adaptive educational systems, applications or software. Interventions included students' or staff education or training in any field. A comparison was excluded and the outcomes were the characteristics of developed ITSs and their

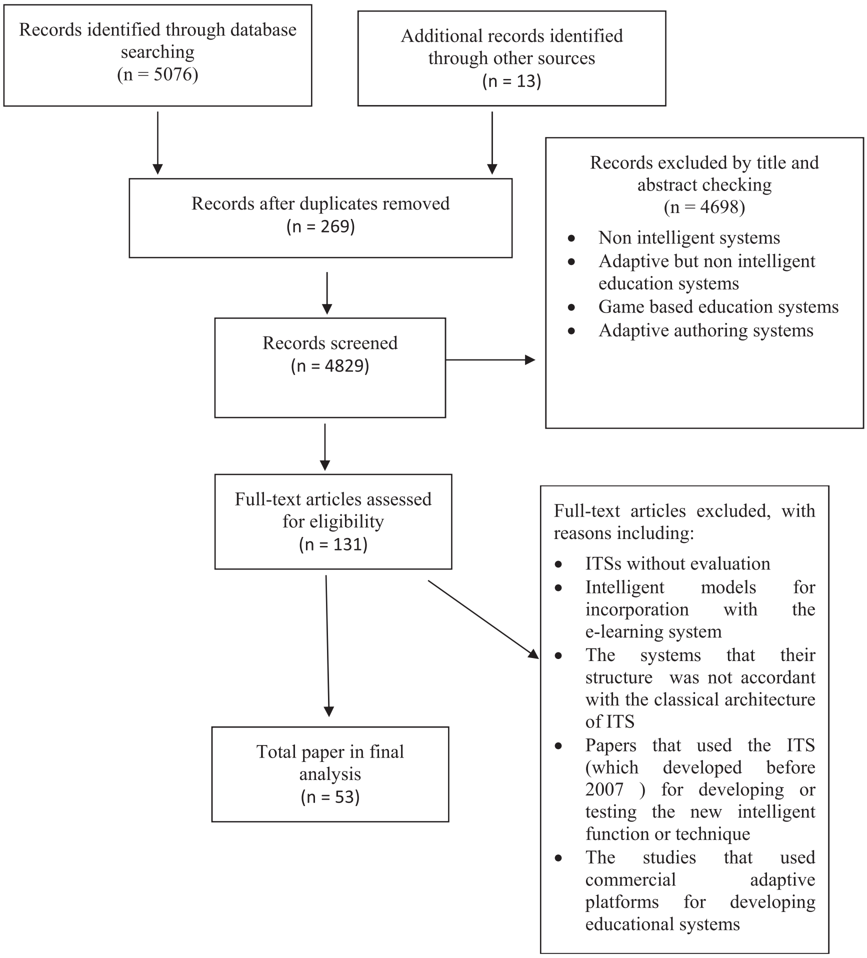

Figure 1. The process of PRISMA for data collection and analysis.

methods of evaluation. The search string was: (intelligent* OR adaptive OR customized) AND (learning OR instruction OR education OR tutoring OR mentoring) AND (system OR software OR application) AND (evaluation).

3.2. Inclusion criteria

Inclusion criteria were English language original papers evaluating the intelligent tutoring systems as training, education, or educational assistance tools for learners in any fields. We excluded the game-based education systems and non-intelligent adaptive education systems. Further, some educational systems were also excluded although they had been called ITS, as their structure was not consistent with the classical architecture of ITS or used commercial adaptive platforms for developing the educational systems.

3.3. Selection process

In the initial screening, the papers were screened based on the title and abstract by two separate reviewers based on the research and PICO questions. In this phase, the reviewers read the title and abstract of all the papers and categorized them into three groups. The first group was the papers which definitely had the inclusion criteria, which were assigned the number 1. The next group consisted of the papers that the reviewers were skeptical about their inclusion criteria, which were assigned the number 2. Finally, the last group was assigned the number 0 because it did not have inclusion criteria. Then, the papers were excluded if they receive the zero. The reviewers discussed the papers which did not receive the same number and decided about them. All the papers which receive the same number (one or two) were included for the next phase. Finally, the full-text of the included papers was obtained for the second-stage screening and then assessed by two reviewers.

3.4. Data extraction

In this phase, eight variables were extracted in order to answer the research questions. These variables included the name of the system, study population, AI techniques and their purposes, learner's characteristics, types of evaluation, system performance criteria, and field of education.

4. Results

The eight variables of the selected papers are presented in Table 1.

4.1. Educational fields

The educational fields employed in the ITSs were health/medical, computer science, mathematics, AI, physics, language, and others (Table 1). Figure 2 demonstrates the frequency of each field in the selected papers.

4.2. AI techniques

As presented in Table 1, various AI techniques were used in ITSs. The types of these techniques with their frequency (%) in the studies are reported in Figure 3. In 28.30% ($N = 15$) of studies, the combinations of these techniques have been used for developing ITSs.

4.3. Purpose of AI technique

According to the seventh column of Table 1, AI techniques were used in ITSs for different purposes, as summarized in Table 2.

4.4. Learners' characteristics

As represented in the eighth column of Table 1, an adaptive or customized learning was obtained in ITSs based on the several learners' characteristics, with Figure 4 revealing these characteristics with their frequency in the papers.

4.5. Evaluation of ITS

The results of the study indicated that seven approaches were applied for the evaluation of ITSs, as depicted in Figure 5.

According to the last column of Table 1, the criteria used for evaluating the system performance included accuracy, precision, sensitivity, adaptively, reliability, recognition rate, usability, and mean square error (MSE).

Table 1. The variables of systems in the selected papers.

Number	Title	Name of the system	Population	Educational field	AI techniques	Purposes of AI techniques	Learner's characteristics	Type of evaluation	System performance criteria
1	Harley, Bouchet, Hussain, Azevedo, and Calvo (2015)	–	University students	Human Circulatory	Intelligent Multi-agents	• adaptive feedback generation • adaptive recommendation generation • learner's knowledge evaluation	emotional measurement methods (automatic facial expression recognition, self-report, electro dermal activity)	Correlation between emotional measurement methods	–
2	Jeon (2010)	–	Medical personnel	Anesthesia machines	Bayesian technique (Bayesian decision rules(condition-action) with rule engine)	• Define, updating and evaluating the accuracy of the learners performance model • Presenting adaptive learning content	• Group learners profile • performance data • Previous learners data	Simulative evaluation the system for decision making, handling the missing data and adaptation actions	–
3	Costello (2012)	–	School Students	Computer programming	• Data mining technique (Intelligent clustering algorithms) • Condition action rule-based reasoning	• Presenting adaptive learning content • adaptive recommendation generation • defining and updating the learning style	• amalgamated learning style • Learner's preference • Learner's performance	Prototype evaluation: • System Performance measurement • User emotional responses measurement • System Analytical and Interactivity measurement • Effectiveness	Performance criteria: (precision/recall/ complexity of Algorithm measurements) Emotional criteria: (analytical/ interactivity measurements)
4	Grawemeyer et al. (2016)	As a part of Italk2learn platform	school students	Mathematics	Bayesian technique (Bayesian network classifying and reasoning)	• Classifying the learners affect states • Adaptive feedback generation	• Affect states • Reasoning stage • Learner Interaction with system	Case-control pre-post evaluation (affect-non affect conditions): • Student performance • Students' task behavior • student's learning experience • Feedback type	–
5	El Ghouch, El Mokhtar, and Seghroucheni (2017)	–	University students (bachelor of computer science)	Designed for variant courses (programming and the MERISE method)	Bayesian technique (Bayesian network classifying)	• Classifying the learners based on learning styles	• Learning style	• Student performance	–

(*Continued*)

Table 1. Continued.

Number	Title	Name of the system	Population	Educational field	AI techniques	Purposes of AI techniques	Learner's characteristics	Type of evaluation	System performance criteria
6	Hsieh and Cheng (2014)	–	School Students	Logic Programming	Case-based reasoning	• Learner's performance Evaluation • Learners evaluation (Matching learners errors patterns with existing errors in case-base)	• learner's preference • Learner's knowledge level • learner's behavior	• system performance • system adaptively • Student performance	System Accuracy of matching patterns System adaptively (relation between number of errors in case base with the accuracy of matching pattern)
7	Grivokostopoulou, Perikos, and Hatzilygeroudis (2017)	AITS	School students	AI curriculum	• Condition action rule-based reasoning (Rule-based expert system) • Data mining techniques (decision tree analysis)	• Presenting adaptive exercises • Learners evaluation (prediction the student performances)	• Learner's knowledge level • Learner's performance	• Student performance (pre-test/post-test and experimental/ control group) • Pearson correlations between the marks (scores) of the tutor and the automated marker • System performance	• average accuracy • precision • F-measure • Cohen's Kappa statistic
8	McDonald et al. (2013)	–	University Students	Health sciences (Cardiovascular physiology)	NLP based techniques (Statistical machine learning classifier based on NLP)	• Learners evaluation (evaluation the Student's responses to lecture questions) • Classification the learner's responses • Adaptive feedback generation	• Students responses to lecture questions	• Learners Performance (pretest-posttest) • User experiences	–
9	Grivokostopoulou, Perikos, and Hatzilygeroudis (2013)	FOL equivalence system	School Students	AI curriculum (first order logic)	Condition action rule-based reasoning (Rule-based reasoning)	• Learners evaluation (evaluation the learner's performance) • Adaptive feedback generation • Adaptive guidance generation	• Learner's knowledge level • Learner's actions	• Student performance (pre-test/post-test and experimental/ control group) • User experiences	–
10	Samarakou, Prentakis, Mitsoudis, Karolidis, and Athinaios (2017)	StuDiAsE	University students (engineering students)	Software design	Fuzzy based technique (Fuzzy rule-based system)	Defining learning styles	• Learning style • Learner's cognitive profile • Learner's behavior Learning ability	Testing the fuzzy classifier	–

11	Dzikovska, Steinhauser, Farrow, Moore, and Campbell (2014)	BEETLE II	School Students	Physic (basic electronics and electricity)	• NLP based technique • Condition –action rule-based reasoning	• Adaptive feedback generation (NLP based feedback) • Adaptive hint and recommendation generation • Learners evaluation (interpretation learner's answer correctness)	• Students responses to lecture questions	• Student performance (pre-test/post-test and experimental/ control group) • User experiences • System performance	• Overall Accuracy • Macro average F1 score • Accept-reject accuracy • Misinterpreted frequency • Non-interpretable frequency
12	Taele and Hammond (2015)	BopoNoto	University students (language student)	Language (the zhuyin phonetic script learning)	Data mining technique (Naïve and modified Euclidean distance classification)	• Language symbols classification • Learners evaluation (performance evaluation) • Adaptive feedback generation •	• Student performance	• System performance	Overall symbol recognition. Performance (classification accuracy) Comparison of recognition performance with another system
13	Gómez et al. (2014)	UoLmp	University students (language student)	English language	Condition –action rule-based reasoning (if-then rule-based reasoning)	• Adaptive learning content • Adaptive learning path	• learner's preference • current situation's properties •	• User experiences	–
14	Mohammed and Mohan (2015)	CRITS	University Students	Solve Computer Science programming problems	Fuzzy based technique (Fuzzy rule-based reasoning)	• Definition the membership of students in subcultural categories • Specification of the relevant subcultural to every student • Definitions of Cultural Formality for Text-based Content • Representing adaptive educational contents and feedbacks	• cultural contextualization (geographical, religious, ethnic, education levels) • familiar particular physical environment settings and terrains	• User experiences	–
15	Chrysafiadi and Virvou (2012)	–	University students (Informatics students)	Computer Programming	Fuzzy based technique (Fuzzy rule-based reasoning)	• Define and update students' knowledge level	• Learner's cognitive model • Learner's knowledge level	• Students performance (experimental/ control group) • User experiences • System performance	System reliability (variable consolidation reliability) Navigation efficacy (variable Measuring navigation efficiency)
16	Vinchurkar and Sasikumar (2015)	ITALIC	School Students	English language	Condition-action rule-based reasoning	• Generating the meaningful sentences	• Learner's responses to learning activities	• Students performance (experimental/ control group)	–

(*Continued*)

Table 1. Continued.

Number	Title	Name of the system	Population	Educational field	AI techniques	Purposes of AI techniques	Learner's characteristics	Type of evaluation	System performance criteria
17	Echeverría, Guamán, and Chiluiza (2015)	–	University students (Engineering students)	Slide presentation	• Data mining techniques (Feature extraction and Clustering) • Condition –action rule-based reasoning	• Determining the relevant features for evaluation the presentation files • Clustering the grading categories evaluated presentation files • adaptive feedback generation • adaptive recommendation generation	• Grading the presentation files	• User experiences	–
18	Dolenc and Aberšek (2015)	TECH8	school students	Gear unit	Intelligent agents	• adaptive learning content and path • adaptive feedback generation • adaptive recommendation generation	• Learner's knowledge • Learner's learning capacity	• Students performance (experimental/ control group)	–
19	El Saadawi et al. (2008)	Report Tutor	University students (Pathologist residents)	Derma pathology	NLP based technique	• parsing and evaluating the generated reports by learners • adaptive feedback generation	• Learner's responses to learning activities	• Students performance (pretest-posttest) • User experiences • System performance	• NLP Precision (PPV) • NLP sensitivity (recall)
20	Bulut Özek, Akpolat, and Orhan (2013)	–	University Students	Basic control system	Fuzzy based technique (Fuzzy rule-based reasoning)	• Generating adaptive learning content • Determining and updating the learning styles of learners	• Learning style • Learner's behavior	• Student performance (pre-test/post-test and experimental/ control group)	–
21	Alobaidi, Crockett, O'Shea, and Jarad (2013)	Abdullah CITS	School Students	Essential topics in Islam	• Condition-action rule-based reasoning • NLP based technique	• Classification of learners utterance • Generating adaptive learning content • Generation tutoring dialogues with Learners	• Learner's knowledge	• User experiences • Evaluating the tutoring dialogues	–
22	Myneni, Narayanan, Rebello, Rouinfar, and Pumtambekar (2013)	ViPS	School Students	Physic education	Bayesian technique (Bayesian network)	• Prediction adaptive learning content • adaptive feedback and hint generation	• Learner's knowledge • Learner's behavior • learner's performance	• User experiences • Student performance (pre-test/post-test and experimental/ control group)	–

23	Jugo, Kovačić, and Tijan (2015)	–	School Students	Ill-defined domains	Data mining techniques (Feature selection & K-mean clustering and Sequential pattern mining)	• adaptive recommendation • discovering high utility learning paths	• Learner's knowledge • Learner's behavior • learner's performance	• Clustering functionality test	• Cluster ordering evaluation
24	Jian-Min, Yu, and Min-Hua (2017)	–	School students	Remote Sensing	ANN-based technique (Forward propagation neural network)	• Classification the learner's performances	• Learner's knowledge • Learner's behavior • learner's performance	• User experiences • Student performance (pre-test/post-test)	–
25	Payne et al. (2009)	SlideTutor	University students (Pathology residents)	Derma pathology	Bayesian technique (Bayesian network)	• Prediction The learner's model	• Learner's behavior • learner's performance	• Student performance (pre-test/post-test)	–
26	Munoz, Ortiz, Gonzalez, Lopez, and Blobel (2010)	–	University students (Medical students)	Childhood disease management	Bayesian technique (Bayesian network)	• Define and update student's knowledge level	• Learner's knowledge • learner's performance	• Student performance (pre-test/post-test and experimental/ control group) • System performance	• System usability
27	Kacalak, Majewski, and Zurada (2010)	–	unknown	–	• NLP based technique • ANN-based technique (Hybrid neural network)	• Two-way communication between learner and system • Biometric learner's identification • Analysis of learner's knowledge • Classification of words and sentences • Identifying the meaning of words and sentences	• Learner's knowledge	Prototype testing	Recognition ability of Neural network the sensitivity of spoken word recognition the sensitivity of spoken sentence meaning recognition
28	Suebnukarn (2009)	–	University students (Dental students)	Clinical reasoning	Bayesian technique (Bayesian network)	• Define and update students' knowledge and activities • Modeling the clinical reasoning scenarios	• Learner's knowledge	• Student performance (pre-test/post-test and experimental/ control group)	–
29	Kose and Arslan (2017)	–	University students	Computer engineering	• ANN-based technique • Swarm intelligent algorithm (NOA)	• Determine Learner's intelligent level • Adaptive learning material	• Learner's intelligent level	• Student performance (experimental/ control group) • User experiences • System performance (comparison study)	Evaluation of the Training and evaluation performances of ANN (MSE)

(*Continued*)

Table 1. Continued.

Number	Title	Name of the system	Population	Educational field	AI techniques	Purposes of AI techniques	Learner's characteristics	Type of evaluation	System performance criteria
30	Almohammadi, Hagras, Alghazzawi, and Aldabbagh (2016)	IT2FLS	University students	As a part of e-learning platform to teach Microsoft word and PowerPoint	Fuzzy based technique (Type-2 fuzzy rule-based reasoning)	• adaptive learning content • determining learner's characteristics and instructional needs	• learner's preference • learner's behavior in the system • Learner's knowledge	• Student performance (comparison study) • System performance (comparison study)	• Average error of system output
31	Hao, Wang, and Zhao (2009)	SQL TUTOR	University students	Structured Query Language (computer programming)	Fuzzy based technique (Fuzzy clustering)	• Updating the student model • Adaptive learning content • Adaptive learning exercise	• Learner's knowledge • learner's performance	Student performance (experimental/ control group)	–
32	Jia-Ke, Xuan, Wei, Xian-Chun, and Chao-Fu (2008)	WITS	University students	Introduction to computer	Intelligent multi-agents	• Adaptive learning content	• learner's preferences • learner's performance • Learner's knowledge	• Prototype testing: • Learners experiences	–
33	Hafidi and Bensebaa (2013)	–	University students (Bachelor degree)	Mathematics and informatics	Condition-action rule-based reasoning	• Adaptive learning content • Updating the student model	• learner's preferences • learner's performance • Learner's knowledge • Learner's behavior	• Student performance (Pretest-posttest experimental/ control group) • Learners experiences	–
34	Smith, Min, Mott, and Lester (2015)	LEONARDO	School Students	Physic science	• Data mining technique (Clustering analysis) • ANN-based technique (Machine learning based on deep ANN)	• Prediction level of learner performance • Group the learners based on answers • Evaluation of the sequence of learners drawing actions • Inferring learners conceptual knowledge	• learner's performance • Learner's knowledge	• System performance (accuracy: Comparison study)	Model Accuracy rate Convergence rate and convergence point of models
35	Jeremic et al. (2009)	DEPTHS	university students	Software design pattern	Condition-action rule-based reasoning (rule-based expert system)	• Adaptive learning content • Adaptive learning navigation • Adaptive feedback and recommendation generation	• learner's performance • Learner's knowledge • learner's cognitive capacity	• Students performance (Pretest-posttest experimental/ control group) • Learners experiences • System performance	Accuracy rate of student model

36	Lanzilotti and Roselli (2007)	Logiocando	School students	Mathematics	Condition-action rule-based reasoning (rule-based expert system)	• Adaptive learning content • Calculate the level of difficulty of exercises • Adaptive learning navigation	• learner's performance • Learner's knowledge • Learner's behavior	• Student performance (Pretest-posttest experimental/ control group)	–
37	Carter (2014)	ITS-Debug	school students	Computer programming	CBR technique	• Diagnosis the learner's performance • Adaptive recommendation	• learner's preferences • Learner's behavior • Learner's knowledge	• Student performance (Pretest-posttest) • Students log evaluation	–
38	Fossati (2009)	iList	School Students	Computer science	Other techniques Machine learning / Procedural knowledge modeling	• Modeling the learner's knowledge • Adaptive recommendation generation	• Learner's behavior	• Student performance (Pretest-posttest/ comparison the five versions of iList) • Learners experiences	–
39	Yarandi (2013)	Rule-PAdel	School Students	Applicable to different domains (Mathematics)	Condition-action rule-based reasoning (Semantic rule-based reasoning)	• Adaptive learning content • Updating the student model • Adaptive learning navigation • Adaptive feedback and recommendation generation	• learner's performance • learner's learning style • learner's language • Learner's knowledge	• Learners experiences • Student performance	–
40	Bryfczynski (2012)	BeSocratic	University students	Chemistry, molecular biology, and computer science	• Condition-action rule-based reasoning (rule-based authoring system) • Data mining technique (Sequence clustering of learners action)	• Learners Evaluation and clustering • Clustering log files • Discover learners problem-solving strategy • Adaptive feedback	• learner's performance • Learner's behavior	• learners performance (Pretest-posttest experimental/ control group)	–
41	Khachatryan et al. (2014)	Reasoning Mind Genie 2	School Students	Mathematics	Condition-action rule-based reasoning	• Adaptive learning content • Updating the student model • Adaptive learning navigation	• learner's knowledge • learner's behavior	• learners performance (RCT) • Learners experiences • Teacher experiences • Prototype testing	Panel of expert
42	Weragama and Reye (2014)	PHP ITS	university students	Computer programming	Bayesian-based technique (Bayesian network)	• Determining and updating the student model	• Learner's responses to learning activities	• Students performance (Pretest-posttest experimental/ control group) • Learners experiences	–

(*Continued*)

Table 1. Continued.

Number	Title	Name of the system	Population	Educational field	AI techniques	Purposes of AI techniques	Learner's characteristics	Type of evaluation	System performance criteria
43	Walker, Rummel, and Koedinger (2014)	APTA	school students	Algebra	• Data mining technique (SVM Classifier) • Condition-action rule-based reasoning • Bayesian-based technique (Bayesian knowledge tracing)	• Classification of help types and conceptual content • skill mastery assessment • Prediction the probability of mastering in the skills • Adaptive feedback and hint generation	• learners performance in solving problems • Learner's performance in helping to his/her partner	• Students performance (Pretest-posttest) • Learners experiences	–
44	Mostafavi and Barnes (2017)	Deep thought 4	University students	Philosophy & Computer science (solving logic proof problems)	• Bayesian-based technique (Bayesian knowledge tracing) • Data mining technique (Cluster-based classification)	• Evaluation the learner's performance • Prediction learners performance • Classification the learners based on their performances	• Student performance • Leaner's knowledge	• Learners performance (experimental/ control group) • System performance (comparison study)	Prediction accuracy
45	Keleş et al. (2009)	ZOSMAT system	School students	Mathematics	Condition-action rule-based reasoning (Rule-based expert system)	• Adaptive learning content • Updating the student model • Adaptive learning navigation • Adaptive feedback and recommendation generation • Learners Evaluation	• learner's performance • Learner's knowledge	• Student performance (experimental/ control group)	–
46	Soh, Khandaker, and Jiang (2008)	I-MINDS	University students	Computer programming	• Intelligent multi-agent • Condition-action rule-based reasoning • Data mining technique (classification)	• Adaptive learning navigation • Adaptive feedback and recommendation generation • Updating the student model • Evaluation of learners (estimate its student user's competence) • Ranking and grouping the student's question • Adaptive learning content	• Learner's behavior • learner's performance • Learner's knowledge	• Student performance (Pretest-posttest experimental/ control group)	–

47	Latham, Crockett, McLean, and Edmonds (2012)	Oscar	–	Computer programming	Condition-action rule-based reasoning	• predicting learning style • Adaptive feedback and recommendation generation • Adaptive learning navigation	• Learner's knowledge • Learner's behavior	• Learner's performance (Pretest-posttest) • Systems performance • Learner's experiences	• Accuracy of prediction of learning style
48	Hooshyar, Ahmad, Yousefi, Yusop, and Horng (2015)	FITS	University students	Computer programming	• Intelligent multi-agent • Bayesian technique (Bayesian network) • NLP based technique (NLP algorithms)	• Adaptive feedback and recommendation generation • Adaptive learning navigation • Updating the student model • Estimating the learner's level of knowledge • Adaptive learning content	• Learner's knowledge • Learner's feedback	• learner's knowledge (Pretest-posttest experimental/ control group) • Leaner's performance	–
49	Kazi, Haddawy, and Suebnukarn (2012)	METEOR (successor of COMET)	University students	Clinical reasoning	Other technique (Heuristic methods for hint generation + Semantic similarity or distance calculation algorithms for to assess the correctness of learner's responses to questions)	• Adaptive feedback and recommendation generation • Evaluation of learners	• learners performance in solving problems	• System performance	• expert agreement with system generated hints students agreement with system generated hints
50	Chen and Li (2010)	PCULS	School students	English language	• Intelligent agents • ANN-based technique • Fuzzy based technique (classification and rule-based)	• Adaptive recommendation generation • Evaluation of learners • Adaptive learning content • Adaptive learning navigation • Determining and updating the student model	• current situation's properties • learners performance	• learner's knowledge (Pretest-posttest experimental/ control group) • Learner's experiences • System performance	• Accuracy of ANN-based locating system
51	Capuano et al. (2009)	LIA integrated with IWT	–	Applicable to different domains	• Other techniques (Machine learning)	• Adaptive learning navigation • Determining and updating the student model • Evaluation of learners	• Learner's responses to learning activities • Learner's knowledge • learner's preferences	• Learners performance (experimental/ control group) • Learner's experiences	–

(Continued)

Table 1. Continued.

Number	Title	Name of the system	Population	Educational field	AI techniques	Purposes of AI techniques	Learner's characteristics	Type of evaluation	System performance criteria
52	Wang et al. (2015)	iTutor	University students	Applicable to different domains (basic computer skills)	• Intelligent multi-agent	• Adaptive feedback and recommendation generation • Evaluation of learners • Adaptive learning content • Adaptive learning navigation • Determining and updating the student model	• Learner's knowledge • Learner's responses to learning activities • learners performance	• Learners performance (experimental/ control group) • learner's knowledge	–
53	Chen (2008)	–	School students	Mathematics	• Intelligent multi-agent • Data mining technique (genetic algorithm)	• Evaluation of learners • Adaptive learning content • Adaptive learning navigation	• Learner's knowledge • Learner's responses to learning activities	• Learners performance (experimental/ control group) • learner's knowledge • Learner's experiences	–

Note: NLP, Natural Language Processing; ANN, Artificial Neural Network; CBR, Case-Based Reasoning; SVM, Support Vector Machine.

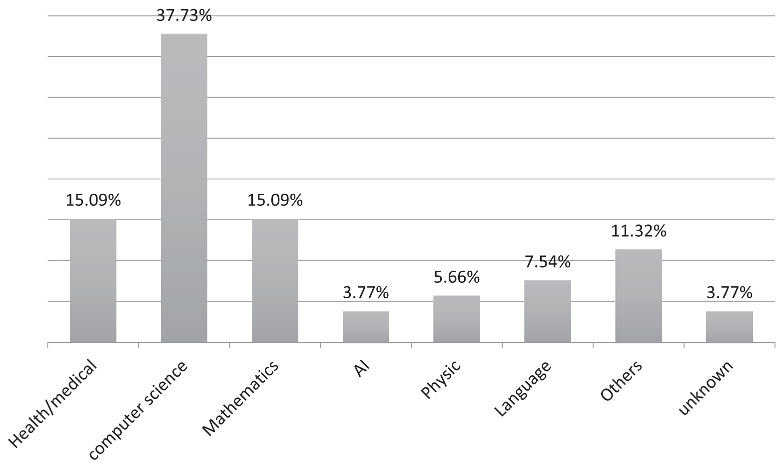

Figure 2. Frequency of educational fields in ITSs.

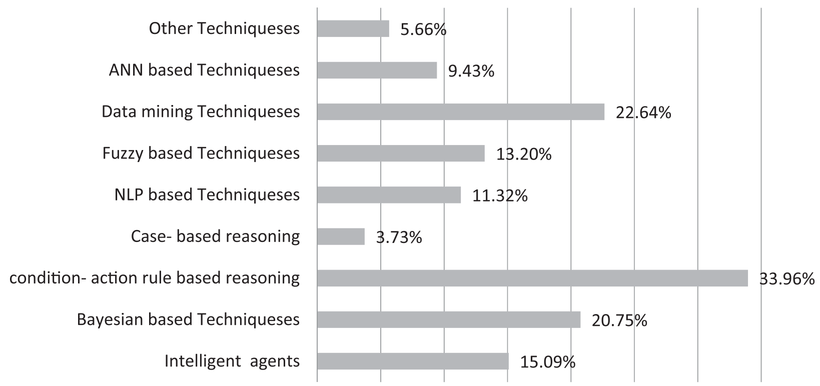

Figure 3. Frequencies of used AI techniques in the ITSs.

4.6. User interface

The user interfaces of ITSs were mainly web-based, where 54.71% and 15.09% were client computers and mobile-based, respectively.

5. Discussion

Having analyzed the different variables in ITSs, we answered some questions that were arisen in this field.

Table 2. The purposes of applying AI techniques in ITSs.

The purposes of applying AI techniques in ITSs	Frequency (%)
Adaptive feedback, hint or recommendation generation	52.83%
Defining, classification, or updating the learner's characteristics	56.60%
Learner's evaluation	45.28%
Presenting adaptive learning material or content	41.50%
Adaptive learning path navigation	28.30%
Presenting adaptive test and exercises	5.66%

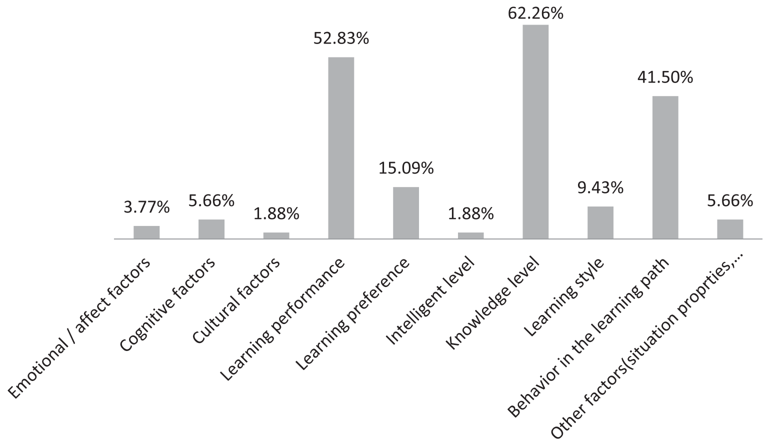

Figure 4. The learner's characteristics for delivering the adaptive learning.

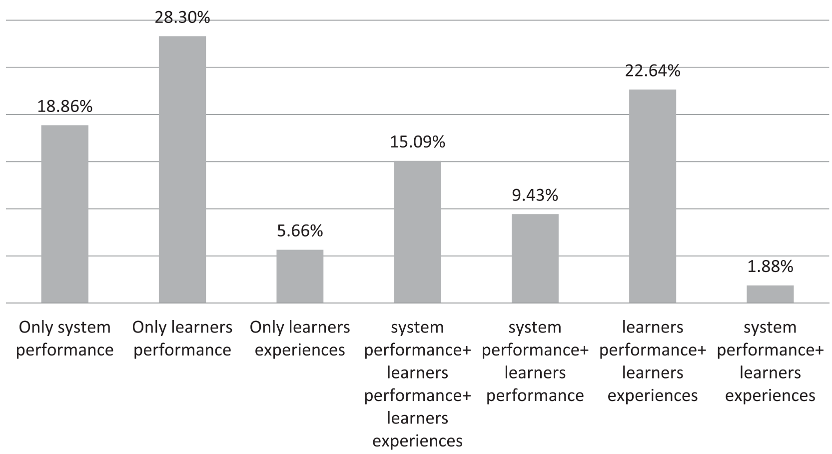

Figure 5. Methods of evaluation in the ITSs.

The studied ITSs were mainly used in the computer science education, where the computer programming (with 55% frequency) was the major educational field. The majority of the audiences in this field were university students (75%). Fuzzy-based techniques (20%) and condition-action rule-based reasoning (20%) were the most frequent AI techniques used for the education of computer programming. They were followed by the CBR (13.33%), the intelligent multi-agent (13.33%), and data mining methods (13.33%).

Health/medical and mathematics fields were in the second rank. ITSs mainly were used for theoretical education including anatomy, physiology, diagnosis in dermatopathology, childhood diseases management, introduction to the anesthesia machine, and clinical reasoning. Most of the audiences in these fields were university students (87.5%). The Bayesian-based techniques were used in 50% of these systems. Further, the NLP-based and intelligent multi-agent approaches were the other AI techniques in the health/medical educational filed.

The ITSs designed for school student education in mathematics was the third frequent systems. They were mainly designed by condition-action rule-based reasoning (83.77%).

Based on this review, condition-action rule-based reasoning was the most frequent technique in the designed ITSs, especially in computer programming and mathematics. As the mathematics is the study of numbers, spaces, pattern, and structures (Graham, Knuth, Patashnik, & Liu, 1989), it seems that the rule-based reasoning could be an appropriate option for the problem-solving and decision-making in this field. Meanwhile, the critical thinking is one of the significant processes for problem-solving and decision-making in the health/medical fields. Therefore, the rule-based reasoning has the potential to be applied in the design of ITSs in these fields. However, according to the results of this study, this technique was not used in these fields.

Case-based reasoning is usually applied for solving new problems (cases) by finding the most similar problems and adopting a new case model with the model found and then updating it (Pantic, 2005). Although CBR is not a completely appropriate method for expert systems in non-explicit and non-structure educational domains (Pantic, 2005), there is a niche area for this method in the medical tutor systems (Holt, Bichindaritz, Schmidt, & Perner, 2005). It has been used only in two works (Carter, 2014; Hsieh & Cheng, 2014) for the education of computer programming, and there is a potential application for similar medical case reasoning tasks.

The type of student modeling is the determinant factor for categorizing the ITS types. According to (Ma et al., 2014), the learning outcomes are different when various types of ITSs have been used for the education. We know that the student modeling has mainly been developed by the learning characteristics (McDonald, Knott, Stein, & Zeng, 2013). It is concluded that most ITSs have used the combination of learners' characteristics for constructing the student models, while in the rest of ITSs, only one characteristic has been determinant of the student model.

In this study, the learner's performance was defined as the learner's ability or procedural knowledge (know-how) in learning activities such as problem-solving, decision-making, computer algorithm generation, etc. The learner's performance was the major characteristic applied to the development of the student model after the learner's knowledge (the theoretical knowledge /only know). The learner's behaviors in the learning process include the interaction or feedback with the system, time spent on studying, the number of clicking, and so on which were the second most frequent characteristics. It is obvious that using more information about the learner's current status will empower the student model thereby improving the customized learning.

In addition to the types of student modeling, ITSs could be categorized based on the AI techniques. According to the results of our review, AI techniques have been used in ITSs for various purposes; we categorized them in six groups. These categories and related sub-items have been presented in Table 3.

Table 3. The categorization of the purposes of applying AI techniques in ITSs.

Purpose item	Purpose sub-items
Adaptive guidance	• Adaptive feedback generation • Adaptive hint generation • Adaptive recommendation generation
Adaptive instruction	• Presenting adaptive learning material • Adaptive learning path navigation • Presenting adaptive test and exercises
Learner's evaluation	• Knowledge evaluation • Performance evaluation • Skill evaluation
Define and update the learner's model based on	• Learning style • Knowledge level
Classification / clustering the learners based on	• Affect • Intelligent • Learning style • Learning needs • Characteristics
Others	• Communication • Calculation of level of difficulty of exercises • Classification of learning materials

Definitely, learners play an important role in the evaluation of ITSs, such that the learner's experience is one of the evaluation methods which could address the problems related to the system usability (Mulwa, Lawless, Sharp, & Wade, 2011). However, the results showed that only 5.66% of studies were evaluated only by the learner's experiences, and it has been used more in combination with learner's performance or system performance or both. Indeed, the learner's performance might be the determinant factor in the assessment of effectiveness. In this study, the majority of evaluations (22.64%) were learner-based (learner's performance). The system's performance tests the system by various measurements (part 4.5). Also, the learner's performance evaluation assesses the effectiveness of the system by testing the effect of ITSs on the level learner's knowledge or skill.

In addition, the user interface infrastructure has been an important part of an ITS. The results demonstrated that the web-based user interface is the most frequent (55.1%) infrastructure for the development of ITSs, while only 15.09% of ITSs are mobile-based. However, mobile devices are newly emerging technologies which could facilitate the implementation of instructional methods independent of time and place (Gómez, Zervas, Sampson, & Fabregat, 2014).

6. Conclusion

Educational fields, applied AI techniques, the purpose of AI techniques, learners' characteristics, evaluation, and user interface of ITS were the major factors of ITSs examined by this review. Uses of ITSs as an adaptive learning tool are increasing significantly across different educational fields. Adaptive learning in ITSs has been achieved mainly based on the learner's knowledge and performance. Although ITSs could facilitate reasoning in the learning process, these systems are rarely applied in experimental courses including problem-solving and decision-making. Given the field of study entity, more structural frameworks and rules can become available and more ITSs might be developed to be effective.

Action-condition rule-based, Bayesian network, and data mining were the most frequent AI techniques applied in ITSs. ITSs were mainly evaluated by learner-based methods. In addition, system performance evaluation was the major method in evaluation of ITSs. As the number of mobile devices is increasing rapidly and due to the important role of mobile devices in facilitating personalized learning and also according to the low rate of usage of mobile-based ITSs, the result of this study has recommended development of mobile-based ITSs and evaluation of their implementation.

Disclosure statement

No potential conflict of interest was reported by the authors.

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