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Review

The contribution of learner characteristics in the development of computer-based adaptive learning environments

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ABSTRACT

The development of learner models takes an active part in upcoming adaptive learning environments. The purpose of learner models is to drive personalization based on learner and learning characteristics that are considered as important for the learning process, such as cognitive, affective and behavioral variables. Despite the huge amount of theoretical propositions of learner characteristics considered as relevant for learner models, practical payoffs are rather sparse. This study aims to overview the empirical research on the mere value of learner models in the development of adaptive learning environments. The results show that a lot of high-quality studies are situated in a rather shattered research field, building few bridges from theory to practice. We conclude with the call for a theory or framework integrating current and past research results that is able to guide theory-based and systematic empirical research having concrete hypotheses on the merits of learner characteristics in adaptive learning environments.

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1. Introduction

Instructional design aims at developing learning experiences and learning environments that promote and support learners' knowledge or skill acquisition (Merril, Drake, Lacy, & Pratt, 1966). These learning experiences and learning environments include activities such as directing learners to appropriate information, monitoring student performance, providing feedback, etc. (Merril et al., 1966). In the field of instructional design, individualization or personalization principles are considered as core notions since the development of supportive learning environments requires taking into account individual differences between learners such as learners' differences in prior knowledge, skills and abilities; differences in demographic and socio-cultural variables (such as internet access); and differences in affective variables (such as motivation) (Shute & Zapata-Rivera, 2008).

There is a large amount of research demonstrating that individualized instruction is superior to the uniform approach of more traditional and one-size-fits-all teaching approaches (for reviews see Cohen, Kulik, & Kulik, 1982; Kadiyala & Crynes, 1998; Kulik, Kulik, & Bangert-Drowns, 1990). One-to-one human tutoring, compared to traditional classroom instruction, makes learning performance to increase with two standard deviations (Bloom, 1984). The strong empirical support for the superiority of individualized instruction has led to the firm confirmation of the mere value of adapting the learning environment to the specific needs of the learner.

Although any form of instruction can be considered as adaptive if it accommodates different learning needs and abilities of the learners (Lee & Park, 2008), rapid growth in computer technology has influenced the development of adaptive learning environments. Recent advances in technology and the integration of these advances in instructional design have led to a mass individualization where personalized instruction is offered simultaneously to large groups of learners (Lee & Park, 2008). And even though the joint efforts of technology and education have resulted in renewing, sophisticated and distinctive approaches to individualized instruction, technology-based adaptive instruction also has its limits. These limits concern not only the applicability of computer technology or to what extent technology is suitable for learning (Dror, 2008). Limits are also experienced in defining the interaction between technology-enhanced learning and the learner, and to what extent technology needs to adapt to the learner, or the other way around.

1.1. Approaches to adaptive instruction

Adapting content and instruction to specific learner characteristics, learner needs and learner (dis)abilities comprises the major part of research on adaptive instruction. In this way, adaptivity can be defined as the capability of a system to alter its behavior according to learner needs and other characteristics (Shute & Zapata-Rivera, 2008). In overviews of adaptive instruction (Lee & Park, 2008; Mödritscher, Garcia-Barrios, & Gütl, 2004; Regian & Shute, 1992) three main approaches are identified:

(1) Macro-adaptive instruction, such as Keller's personalized system of instruction (PSI; Keller, 1968) as an example of the mastery learning approach. This approach assumes that learners primarily differ on their learning rate and that adaptive instruction exists in permitting learners to move through the course at a speed according to their ability and other demands upon their time (go-at-your-own-pace feature);

(2) Aptitude-treatment interaction (ATI), based on the suggestion of Cronbach (1957) to identify the learner's critical aptitudes based on pretask measures and to differentiate treatments in such a way as to maximize their interaction with learners' aptitude or the individual characteristics that determines the probability of success in a given treatment or instruction. Aptitudes may include knowledge, attitudes, (cognitive) abilities, skills, et cetera (Regian & Shute, 1992). More recently, cognitive processing capacity was acknowledged as an influencing aptitude, and new adaptive systems have been developed that integrate the insights of cognitive load theory into the field of adaptive instruction (Corbalan, Kester, & van Merriënboer, 2008; Sweller, van Merriënboer, & Paas, 1998);

(3) Micro-adaptive instruction, that puts information processing central (Regian & Shute, 1992), diagnoses learner's specific learning needs during instruction and subsequently provides appropriate instructional prescription for these needs (Mödritscher et al., 2004). Contrary to macro-adaptive instruction, micro-adaptive models are dynamic and use within-task measures or temporal learner characteristics such as motivation levels to define which instructional treatments are most appropriate in a given situation (Lee & Park, 2008). Typically micro-adaptive models are more fine-grained as they include more learner variables or characteristics than macro-adaptive models. Intelligent Tutoring Systems (ITSs) are examples of micro-adaptive systems, using artificial intelligence techniques in order to provide tailored and on-time instruction to the learner (Lee & Park, 2008).

More specific applications of macro-, ATI, and micro-adaptive instructional strategies can be found, for example, in adaptive hypermedia systems (AHS). Web-based AHS's are adapting to the goals, interests, and knowledge of individual users (Brusilovsky, 2007) and are largely based on the intrinsic interests and present goals determined by the user (Federico, 1999). Other adaptive systems have been built proceeding from a specific pedagogical approach, such as INCENSE, a constructivist adaptive system (Akhras & Self, 2000); COSMO, a motivation-based adaptive system (Lester, Towns, & Fitzgerald, 1999). Other adaptive systems focus on the inclusion of gaming elements and are therefore called game-based adaptive systems (e.g., Paras & Bizzochi, 2005).

The method by which an environment is adapted to the learner defines the categorization into one of the adaptation approaches. Clearly, no strict dividing line can be drawn between the three approaches. Many systems have been developed based on interweaving micro-, ATI, and macro-adaptation. An example of this can be found in the combination between ATI and micro-adaptive instruction as presented by Tennyson and Christensen (1988). These authors proposed a two-stage and iterative approach to adaptive instruction, called MAIS (Minnesota Adaptive Instructional System; Tennyson, 1993). First, an instructional condition is established based on pretask measures of the learner's aptitude variables, such as cognition, affect and memory (macro component). Second, an intelligent tutoring system provides moment-to-moment adjustment of instructional conditions by using procedures that are response-sensitive to declarative and procedural knowledge and higher-level thinking skills (micro component).

Several reviews (e.g., Brusilovsky, 2007; Brusilovsky & Millán, 2007; Lee & Park, 2008; Regian & Shute, 1992; Shute & Psotka, 1996) of adaptive instructional design research have shed light on some major shortcomings and lessons to be learned. A major problem in mastery learning and macro-adaptation is that it is often poorly used in practical classroom situations, leading to large variability in effect size (Regian & Shute, 1992). Also, most macro-adaptive instructional systems have not been implemented as successfully and widespread as hoped (Lee & Park, 2008) because the implementation of adaptive instructional programs into existing programs is rather complex (Glaser, 1977) or teachers are not provided with high-quality training, materials or assistance (Slavin, 1987).

The ATI-approach to adaptive instruction has a risk of suffering from oversimplification of complex relations between individual differences and learning outcomes (Cronbach & Snow, 1977). Although many studies have tried to map relevant aptitude-treatment interactions, empirical verification is very sparse (Shute & Towle, 2003) and shows inconsistent findings caused by methodological shortcomings such as noisiness, confounding designs and low power.

The major part of research on micro-adaptive instruction or ITSs shows positive effects regarding the efficacy of ITSs (Shute & Psotka, 1996), but as Regian and Shute (1992) caution, these results might be misleading due to several shortcomings in the research. One inadequacy in the use of ITSs in educational research is that these systems are often evaluated in terms of artificial intelligence criteria (*'does it work?'*) and not in terms of pedagogical effectiveness criteria (*'does it work efficiently?'*) (Corbett, Koedinger, & Anderson, 1997, Chap. 37). Because of the complexity of ITSs, regular evaluation techniques such as single measurements are not always appropriate for evaluating these complex systems (Mark & Greer, 1993) resulting in a lack of controlled evaluation. Also, valuable learning principles and instructional strategies being absent in many ITSs make specification and evaluation of ITSs difficult (Park, Perez, & Seidel, 1987). Notwithstanding these difficulties the research on cognitive modeling and constraint-based modeling in tutoring systems is highly meritorious. In this research field, empirical research has been set up largely and effectiveness of ITSs, compared to traditional learning, has been demonstrated (for an overview see, Anderson, Corbett, Koedinger, & Pelletier, 1995; Mitrovic, Koedinger, & Martin, 2003; Mitrovic, Mayo, Suraweera, & Martin, 2001).

There is a general conclusion of the feasibility of learners achieving learning goals more efficiently, when instructional design is adapted or accommodated to their individual differences (Federico, 1991). Nevertheless, the practical outcomes and concrete implementations from research in adaptive instruction is limited (Federico, 1999), partly due to difficulties in the concrete translation of theory into instructional techniques. Hence, general and systematic principles of individualized instruction have not emerged (Regian & Shute, 1992).

Although the different approaches to adaptive instruction offer valuable contributions to the development of adaptive learning environments, a great deal of research on adaptive learning environments stands on its own and is sparsely relied on other research or instructional design theories. The goal of this review is threefold: for one thing, we try to elucidate the common grounds of the adaptive systems that have been reported and want to shed light on the underlying building blocks by which these systems have been developed. Secondly, a state of the art is offered of current empirical research on the pedagogical effectiveness of adaptive systems; and in closing, we present some possible directions in the form of questions that can be addressed when developing an adaptive learning environment.

1.2. The framework of adaptive instruction

Current research on computer-based adaptive systems is very much indebted to research on and the development of intelligent tutoring systems (ITSs) and, more specifically, cognitive tutors. Since the framework that is used to create adaptive systems is similar to the models that are included in ITSs, a short overview of ITSs is given first.

Murray (1999) defines an ITS very concisely as a computer-based instructional system with models of instructional content that specify *what* to teach, and teaching strategies that specify *how* to teach. ITSs make inferences about learner characteristics in order to dynamically adapt the environment characteristics. In their ITS review, Corbett et al. (1997) define the goal of ITSs as to engage the learners in sustained reasoning activity and to interact with the learner based on a deep understanding of the learner's behavior. According to Park and Lee (2003), ITSs are developed with a very ambitious goal: to maximally resemble a real-life learning situation, where tutor and learner are in a one-to-one conversation and teach and learn together. In addition, Corbett et al. (1997) state that if the use of such ITSs results in even half the impact of human tutors, then ITSs deliver substantial profit for society. Although currently available systems are not near achieving this goal (Mitrovic et al., 2001), there are ITSs that provide adaptive interaction and that show an increase in learning outcomes over a longer time period (Anderson et al., 1995).

To establish a differentiated or adaptive interaction between learner and system, ITSs make use of knowledge about the following components or modules (Akhras & Self, 2002; Corbett et al., 1997; Mödritscher et al., 2004; Paramythis & Loidl-Reisinger, 2003):

(1) *learner model*, also named user or student model, that contains mechanisms for understanding what the student does and does not know. This model typically describes learner characteristics or parameters such as prior knowledge, learning style and cognitive style (Graf, Lin, & Kinshuk, 2008). The model does not only encapsulates general information about the user, but can also be based on a detailed tracking and logging of the learner's behavior within the system. The information in the model thus comes from assessments of characteristics eventually combined with continuously updated inferences of learner characteristics based on a learner's behavior or state. Shute and Towle (2003) made the pertinent remark that validity and reliability of the assessment (and inferences) are critical in the development of a sound learner model. Similarly to the learner model, Paramythis and Loidl-Reisinger (2003) consider the *group model* as a separate category in ITS models. Group models seeks to capture the characteristics of groups of learners based on common characteristics of learners;
(2) expert or *domain model* that contains a representation of the content or knowledge to be taught, as well the relationships between the domain elements;
(3) pedagogical or tutoring or *instructional model* encompassing an inherent teaching or instructional strategy as can be seen as the didactical component of an ITS (Elen, 2000). Paramythis and Loidl-Reisinger (2003) also call this model the adaptation model that defines what can be adapted, and when and how it is to be adapted.

A fourth model, the *interface model*, was mentioned by Sampson, Karagiannidis, and Kinshuk (2002). This model is concerned with the presentation of the learning content to the learner. Most research on the interface model puts emphasis on the use of multimedia content and user exploration. Since this model can be seen as part of the instructional model, we further consider only the learner, domain and instructional model. These three models are part of the definition of ITSs, and, by extension, they are also comprised in more general adaptive learning environments.

Examples of intelligent tutoring systems are the cognitive tutors, based on the principles of cognitive psychology and ACT-R theory (Anderson et al., 1995). In cognitive tutors, instruction is designed with reference to a cognitive model of a student or learner.

This cognitive model focuses on the underlying skill incorporated into the tutor and consists of production rules. This model performs the task in the same way a learner is expected to perform. Hence, this cognitive model of cognitive tutors can be viewed as a combination of the instructional model and domain model. A cognitive tutor is also intelligent in that the tutor provides problems and individualized instructional based on the cognitive model. Examples of cognitive tutors are the Geometry Tutor (Koedinger & Anderson, 1993), the Algebra Tutor (Singley, Anderson, Gevins, & Hoffman, 1989), and the LISP Programming Tutor (Anderson & Reiser, 1985).

Based on the parameter values in the learner model, the domain model and instructional model will be adapted to differentiate and personalize the interaction between the learner and the environment. In short, for most learning environments, the learner model can be seen as a starting point from where adaptation occurs. However, it is not essential that ITSs possess precise learner models in order to work effectively as a tutor (Self, 1990). As Self (1990) noted in this seminal work: "*if we back off from the grand vision and adopt more realistic aims, then solutions for some aspects of the student modeling problem are practically attainable and useful*" (Self, 1990, p.6). Learner models can serve as a good starting point for the development of tutoring systems and adaptive learning environments, however, we cannot expect learner model to be fully able to represent the learner's cognitive, affective and behavioral characteristics.

The extent to which a learner model is used to implement adaptivity in a learning environment creates a distinction between several building blocks of adaptive instruction. This distinction will be discussed later on in this review.

This review aims at presenting an overview of the current parameters that are included in the learner model when developing adaptive learning environments. To do so, a literature search was performed.

2. Methodology

2.1. Search strategy

The adaptive systems discussed in this review were identified through a comprehensive search of three electronic databases: PsycINFO, ERIC and Web of Science. The following search terms were used: "adaptive learning" + technology|"computer-assisted instruction"|"learner model"|"user model"|"intelligent tutoring system"; "intelligent tutoring system"|"adaptive learning environment" + "learner model"|"user model"|learning; "artificial intelligence" + "adaptive"; "individualized instruction"|"intelligent tutoring system"|"adaptive instruction" + "learner characteristics"|"user characteristics". As a secondary search strategy, reference lists of relevant articles were also reviewed. Also, the journals 'International Journal of Artificial Intelligence in Education (IJAIED)' and 'User Modeling and User-Adapted Interaction (UMUAI)' were searched through, as well as the conference proceedings of the AIED conferences (Artificial Intelligence in Education), UM (User Modeling), AH (Adaptive Hypermedia) and UMAP (User Modeling, Adaptation and Personalization).

2.2. Inclusion and exclusion criteria

The following inclusion criteria were used for article selection: research articles with a focus on empirical research mapping the effectiveness of a computer-based adaptive learning environment. Also, a description of the learning environment of interest should be given. A third criterion is that the research must focus on learner characteristics (e.g., cognition, affect or behavior) as design or modeling variables. Since few research articles were extracted that could be categorized as empirical validation of the effectiveness of adaptive systems, we decided to include also theoretical propositions of such systems, mainly found in conference proceedings, in which it was suggested that further research should focus on empirical effectiveness research. Exclusion criteria included articles published in a language other than English, research studies presented as a book chapter and review articles.

2.3. Data extraction and collection

All articles that were considered as relevant after evaluating them according to the criteria were collected and summarized in a database. As a result of the database search, 29 relevant journal articles and two relevant excerpts from conference proceedings were listed. This was completed with 17 journal articles and four excerpts from conference proceedings, selected by the second search strategy. Each publication was labeled based on following categories: publication date, author(s), selected by first or secondary search strategy, name of learning environment/tutoring system/supporting tool, empirical or theoretical study, and some tags identifying the main concepts of the study.

3. Results

Before discussing the results, we would like to point out the difference between learner and learning characteristics. The aim of this study is to provide an overview of how and to what extent learner characteristics are incorporated in adaptive learning environments. Hence, learning characteristics, which focus more on facets of the learning environment itself, were not taken into account. Learning (process) characteristics typically take into account external characteristics such as mobility, place and time, etc. These characteristics are more closely connected to the research field of personalized learning than to the field of adaptive learning based on learner characteristics.

A major observation that can be put forward is the variability in the research domain of adaptive systems. The fact that building such systems is an interdisciplinary research approach, results in studies with often not attuned approaches according to design, method and evaluation. This in turn leads to difficulties in comparing research studies (e.g., by meta-analysis) on the effectiveness of adaptive systems in general, or difficulties in the comparison of studies related to the contribution of learner characteristics in learner modeling. However, from the amount of articles that were reviewed, the common grounds of adaptive systems currently developed can be elucidated, and the underlying building blocks of these systems can be uncovered systematically.

Adaptive instruction can be considered as having a tripartite nature, with two components being indicative for the development of adaptive systems. The first component relates to the source of adaptive instruction (*to what will be adapted?*), while the second component refers to the target of adaptive instruction (*what will be adapted?*). Components are related to each other by pathways of adaptive instruction (*how to translate source into target?*). Starting from this tripartite structure, an overview is given in Fig. 1 of the different building blocks of adaptive instruction.

As an example, this tripartite structure is applied onto an ITS. The typical source of ITSs is the information that can be found within the learner, determining the learner's behavior on a task (VanLehn, 2006). This is represented by the learner's knowledge and the mastery of one or more knowledge components. As a target, typical ITSs contain an outer loop and inner loop, with the outer loop describing which task the learner should do next, and with the inner loop representing the support related to steps within a

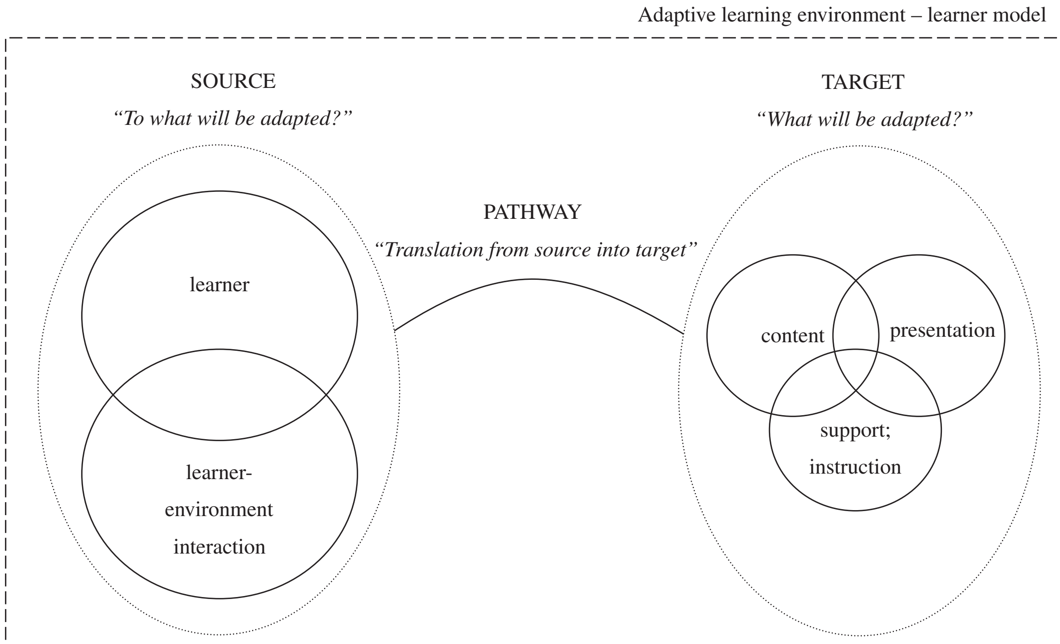

Fig. 1. The tripartite structure of adaptive instruction.

task, such as hints, minimal feedback and error-specific feedback (VanLehn, 2006). This inner/outer structure is closely related to the earlier distinction between macro and micro-adaptive instruction. Whereas macro-adaptive instruction focuses on the pace by which learners can learn and which tasks are offered next (the outer loop function in ITSs), micro-adaptive instruction puts information processing central and focuses dynamically on the needs of learners within a task. Hence micro-adaptive instruction is a typical characteristic of the inner loop in ITSs described by VanLehn (2006). The translation from the source information into the target information occurs by for example rule-based step analysis, containing 'if…then…'-rules to determine if, for example, a student has mastered a specific knowledge component.

3.1. Source of adaptive instruction – To what will instruction be adapted?

Referring back to the three main approaches to adaptive instruction (micro-, macro-, and ATI-adaptive instruction), a more general breakdown can be presented based on the source of adaptive instruction. While macro-adaptive and ATI-based instruction adapts from pretask measures of rater static learner characteristics (e.g., prior knowledge), micro-adaptive instruction uses rather dynamic measures, stemming from the interaction between learner and environments, to realize adaptive instruction. Accordingly, the source of adaptive instruction can either be situated in the learner as such (1), in the interaction between the learner and the environment (2), or in a combination of (1) and (2).

If the goal is to adapt to the learner as such, learner characteristics are put central. Hence, developers of adaptive learning environments are in search for learner characteristics that are crucial for effective learning and try to map the influence of those characteristics on the learning process and outcomes. Relevant learner characteristics are included in the learner model, which can be considered as essential for a system to be adaptive, or to behave differently for different users (Brusilovsky & Millán, 2007). The nature of the information that is included in the learner model varies. Brusilovsky and Millán (2007) distinguish five features that can be included. One group of features can be considered as changeable and rather unstable, such as the learner's knowledge that can be increasing or become less accessible during the learning process, and the learner's interests and goals (instrumental goals or learning goals). Another group consists of rather stable and unchangeable features such as the learner's background, cognitive style and learning style. Not all features are included in developing learner models (Brusilovsky & Millán, 2007). This was also expressed by Park and Lee (2003) as a shortcoming of ATI research, since this research adapts instruction to one or two selected and measured learner characteristics of aptitude variables. Learning results from a long-term integrated interplay between several identifiable and unidentifiable characteristics, and their interaction with task and environment characteristics. Simplifying and reducing such a complex process as learning to one-to-one relationships may hinder the development and design of effective adaptive learning environments.

Notwithstanding the large agreement on the relative importance of modeling learning characteristics and the use of these features for adaptation (Brusilovsky & Millán, 2007), there is considerable disagreement which specific features in the overall learner model are worth modeling, or are worth modeling more than others. The combination of empirical research on effectiveness of adaptive systems with theoretical propositions for the development or optimization of new or existing system, leads to the classification of three groups of individual characteristics that are placed centrally in learner models of adaptive learning environments.

(1) *Cognition*. A first group consists of cognition related characteristics such as working memory capacity (Graf et al., 2008), intelligence (Kelly & Tangney, 2002), prior knowledge (Graesser, Jackson, & McDaniel, 2007), cognitive style (Triantafillou, Pomportsis, Demetriadis, & Georgiadou, 2004), learning style (Germanakos, Tsianos, Lekkas, Mourlas, & Samaras, 2008; Graf et al., 2008), and learning goals or goal orientation (Kelly & Tangney, 2002).
(2) *Affect*. A second group comprises affective characteristics of the learner, like frustration, confusion and eureka/delight (Graesser et al., 2008), certainty and frustration

Table 1
Overview of sources of adaptation in computer-based adaptive learning environments.

Source of adaptation "To what is adapted?"	Reference	Empirical/theoretical research
Learner		
Learning style	Martinez and Bunderson (2000) [SILPA]	Empirical
Learning style; cognitive style	Conlan, Dagger, and Wade (2002) [OPAL]	Theoretical
Learning style	Sun, Joy, and Griffiths (2007)	Theoretical
Culture	Reiners and Dreher (2009)	Empirical
Learner's episodic knowledge	Weber (1996) [ELM]	Empirical
Learner's affective and cognitive states	D'Mello et al. (2008), Graesser et al. (2008), D'Mello and Graesser (2009) [AUTOTUTOR]	Empirical
Learner's intrinsic and extrinsic motivation	Montazemi and Wang (1995)	Empirical
Learning styles; working memory capacity	Graf et al. (2008)	Theoretical
Cognitive style	Triantafillou et al. (2004) [AES-CS]	Empirical
Learner knowledge; aptitude, educational background	Shute (1995) [SMART-STATLADY]	Empirical
Learning style	García et al. (2007)	Theoretical
Mood; motivation; cognition	Beal and Lee (2005) [WAYANG-WEST]	Theoretical
Working memory capacity	Lusk et al. (2009)	Empirical
Learner knowledge	Koedinger and Anderson (1993) [PUMP Algebra Tutor]	Empirical
Learner knowledge	Anderson and Reiser (1985) [LISP Programming Tutor]	Empirical
Learner knowledge	Koedinger and Anderson (1993) [GEOMETRY Tutor]	Empirical
Learner knowledge; learner errors	Mitrovic, Martin, and Mayo (2002) [SQL-Tutor]	Empirical
Learner and learner-environment interaction		
Learning style; learning achievement; learning effectiveness; concentration degree	Tseng, Chu, Hwang, and Tsai (2008a) [TSAL]	Empirical
Learner background; relative learning achievement; concentration; patience	Tseng et al. (2008b) [MALS]	Empirical
Prior knowledge; average time between two clicks; relative number of errors	Ketamo (2003)	Empirical
Learner goals and preferences learning style; knowledge; performance	Vassileva and Bontchev (2006)	Theoretical
Goal-level; language; knowledge; reading time; success rate; etc.	Melis and Andres (2005) [ACTIVEMATH]	Theoretical
Learner preferences; knowledge	Ray (1995); Ray and Belden (2007) [MEDIAMATRIX]	Theoretical/empirical
Learner knowledge; behavior	Xu and Wang (2006) [IeLS]	Empirical
Learner's cognition (intelligence; aptitude; achievement) and affect (motivation; perseverance; personality)	Tennyson (1981, 1987) [MAIS]	Theoretical
Learner knowledge; learning style; goal; last login; favourite pages; time spent	Papanikolaou, Grigoriadou, Kornilakis, and Magoulas (2003) [INSPIRE]	Empirical
Learner background; multiple intelligences; learning behavior	Kelly (2008) [EDUCE]	Empirical
Learner knowledge; logical ability, arithmetic ability, etc	Milne, Cook, Shiu, and McFadyen (1997) [ATULA]	Empirical
Learner demographics; profile and execution information; log information	Romero et al. (2006)	Empirical
Learner demographics; learner activities; collaborative activities	Read, Barros, Bárcena, & Pancorbo (2006) [COPPER]	Theoretical
Demographic features; affective states; topics of study; behavioral data	Reategui, Boff, and Campbell (2008)	Empirical
Learner's help-seeking behavior	Aleven et al. (2006)	Empirical
Personal data; performance data and individual preferences; teaching history	Jeremic et al. (2009) [DEPTHS]	Empirical
Self-efficacy by pretest and physiological measures	McQuiggan et al. (2008) [CRYSTAL ISLAND]	Empirical
User perceptual preference characteristics; traditional user profile	Germanakos et al. (2008)	Theoretical
Number of tries; grades; input from devices (datagloves; mouse/keyboard; haptic devices)	Hospers et al. (2003) [INES]	Theoretical
Personal data; interaction parameters; knowledge of concepts; student characteristics (e.g., knowledge level; multimedia type preferences; concentration level; etc)	Koutsojannis and Hatzilygeroudis (2003)	Theoretical
Actions over time; abilities; motivation; learning style	Fazlollahtabar and Mahdavi (2009)	Theoretical
Learner-environment interaction		
Learner's behavior	Mitrovic, Djordjevic-Kajan, and Stoimenov (1996) [INSTRUCT]	Theoretical
Learner's behavior	Mitrovic et al. (2002) [SQL-Tutor]	Experimental
Plan or goal-recognition; knowledge assessment	Conati et al. (2002) [ANDES]	Empirical
Frequency of studying events; patterns of studying activity; timing and sequencing of events; content analysis	Hadwin, Nesbit, Jamieson-Noel, Code, and Winne (2007)	Theoretical

(Forbes-Riley, Rotaru, & Litman, 2008), mood (Beal & Lee, 2005) and self-efficacy (McQuiggan, Mott, & Lester, 2008), with this last notion situated on the boundaries between cognition and affect.

(3) *Behavior*. The last group can be described as different behavioral styles while working in a computer-based learning environment. These behavioral characteristics can be considered as forthcoming from the learner's cognitive and/or affective states and are therefore strongly related to them. Individual characteristics that interact with the learner's behavior in the learning environment are also called interaction parameters and may include the need for learner control (Lawless & Brown, 1997; Tennyson, 1980), the need for help or feedback (Koutsojannis, Prentzas, & Hatzilygeroudis, 2001), the degree of self-regulated learning (Azevedo, 2005), or the number of tries per task, received grades and the exercises already made (Hospers, Kroezen, Nijholt, op den Akker, & Heylen, 2003).

Irrespective of the source of adaptive instruction – the learner, the interaction between learner and environment, or both – most of the developed learner models stay behind the bars of theoretical propositions and only few learner models have been empirically tested. One exception to this general remark is the research field of ITSs and learner or student modeling. The general view to learner models in this domain is strongly related to Self's view on student modeling (Self, 1990). As Mitrovic argued about learner models: "*they should be precise enough to guide instruction, and computationally tractable at the same time*" (Mitrovic et al., 2001, p. 931). Typical for ITS research is that both the knowledge and the behavior of the learner is taken into account in the process of tutoring. The main part of ITSs research makes use of cognitive modeling, representing the knowledge of learners by production rules. Cognitive tutors organize instruction around cognitive models of the competence that a learner is asked to learn (Anderson et al., 1995). Cognitive tutors generate immediate feedback and compares the steps taken by the learner with one or more steps or rules in the production system. A more recent approach to student modeling can be found in the work of Mitrovic and colleagues (Mitrovic et al., 2001, 2003). The approach of constraint-based modeling, originally proposed by Ohlsson (1994) focuses on performance errors and faulty knowledge and considers the recognition and correction of errors as core activities in the learning process. The main difference between cognitive tutoring and constraint-based modeling is that the former focuses on procedural production rules and evaluates learners' actions, while the latter tends to focus on declarative knowledge in the form of constraints and evaluates the problem state a learner has arrived at (Mitrovic et al., 2003). Both research fields have frequent and varied demonstrations of not only tutor implementations in education but also of research on the effectiveness of the systems.

Table 1 gives an overview of research studies, both empirical and theoretical, focusing on the learner model. Studies that are already situated in the stage of empirically testing an approach ('*does it work?*') but did not yet implement the approach in a learning environment ('*does it work efficiently?*') are also labeled as empirical. This is for instance the case in the AUTOTUTOR studies (D'Mello, Craig, Witherspoon, McDaniel, & Graesser, 2008; D'Mello and Graesser, 2009; Graesser et al., 2008). Although AUTOTUTOR is capable of detecting affective states, to our knowledge no empirical studies have been reported showing the implementation of the detection approach into an adaptive tutoring condition. Hence, the approach of detecting affective states may be very valuable in itself, the mere value of creating adaptive learning environment based on affective states of the learner remains inconclusive.

3.2. Target of adaptive instruction – What instruction will be adapted?

Similar to the unresolved issues that exist in defining relevant learner characteristics and interaction parameters, the target of adaptive instruction comes in many forms and at many times and in various methods. A first and most applied dimension of the target of adaptive instruction is the learning material itself or the content (Ketamo, 2003; Reategui, Boff, & Campbell; 2008; Tseng et al., 2008b). Accompanying support (Aleven, McLaren, Roll, & Koedinger, 2006; Conati, Gertner, & van Lehn, 2002; Mitrovic, Martin, & Mayo; 2002), display (Jeremic, Jovanovic, & Gasevic, 2009; Romero, Ventura, Gibaja, Hervás, & Romero, 2006), and other elements (e.g., hints, prompts, agents) that are part of the instructional design and learning process can be adapted to the learner and/or his interaction with the environment.

A second dimension comprises the time-related aspects of adaptive instruction. Adaptation can be static, taking place before the task or instruction starts and is then based on pretask measures of learner characteristics. Learner models then contain longer-term, more general information (Rich, 1979). Based on the outcome of the measures, an instructional strategy for the learning situation is chosen, which is a typical example of ATI-based research and/or macro-adaptive instruction. Triantafillou et al. (2004) give a demonstration of this approach by selecting a specific instructional style based on the learner's cognitive style as measured in terms of field (in)dependency. This approach of selecting a specific strategy for a given instructional situation is difficult, because context effects are ignored. Effects of adaptive instruction may vary for different instructional contexts (Park & Lee, 2003). Since context is not only determined by characteristics that differ between learners, but also by intra-individual differences (e.g., several learning moments), the call to take into account a more dynamic approach of modeling becomes stronger. This dynamic and run-time adaptation, taking place while the learner interacts with the environment, is typically what ITSs are aiming at. In this case, learner models contain short-term, highly specific information (Rich, 1979). In their research on modeling affective variables in learning environments, McQuiggan et al. (2008) stressed the mere value of dynamic models and their more accurate prediction of the learner's self-efficacy during problem solving. Although several studies report the successes of dynamic detection and prediction, it is remarkable that no research articles have been found related to the implementation and empirical evaluation of dynamic modeling in an adaptive learning environment.

Finally, the third dimension concentrates on the method by which adaptive instruction is offered. The different methods can be situated on a continuum, representing the degree of control an instructor or learner can be engaged in. On the one side there are the program- or instructor-controlled adaptive systems, where the system is fully controlled by the instructor, starting from a learner model that is developed based on learner characteristics and/or interaction parameters that have been judged as relevant for the learning process (Conati et al., 2002; Koutsojannis et al., 2001; Nokelainen, Tirri, Miettinen, Silander, & Kurhila, 2002; Shute, Graf, & Hansen, 2005; Triantafillou et al., 2004).

Moving from the utmost instructor-led adaptive instruction to learning environments where the learner can exert control, the notions of shared control (Corbalan, Kester, & van Merriënboer, 2009; Corbalan et al., 2008) and adaptive guidance/adaptive advisement (Bell & Kozlowski, 2002) are situated. Shared control covers a two-step approach, where, in a first stage, learning tasks with suitable characteristics are selected by the system resulting in a subset of appropriate tasks. Afterwards, in a second stage, the learner selects one task from this subset to work on. Critical in this notion of shared control is the provision of advisement to the learner and its visibility. This is in line with the description of adaptive advisement, given by Bell and Kozlowski (2002). This instructional technique has been designed to provide learners with information regarding future learning tasks, items, or directions that should be taken for improvement. Adaptive guidance finds its 'raison d'être' in enhancing or compensating the self-regulation skills of learners, while the main goal of shared control is to enhance motivation of learners by giving them control. Besides the work of Corbalan and her colleagues (Corbalan, 2008; Corbalan et al., 2008; Corbalan et al., 2009), the work of Triantafillou et al. (2004) regarding the AES-CS system (Adaptive Educational System based on Cognitive Styles) also demonstrates the notion of shared control in an adaptive system. The AES-CS system is able to adapt to the learner's cognitive style, measured as field dependency/field independency. Also, AES-CS allows learners to change the initial adaptation based on their individual needs. It was shown that students studying through the AES-CS performed significantly better than students in the control group, studying through a traditional hypermedia-based environment.

In line with the notion of shared control, the research on open learner models should be situated. An open learner model (OLM) 'opens' the content of the learner model to the learner. It refers to making the learner model explicit to the learner so as to provide more information for self-assessment, reflection and responsibility for the learning process (Bull et al., 2008). OLMs can be represented by the use of skill meters and graphs, a tree with prerequisites and lecture structure, animations, or even haptic feedback (Bull, Abu-Isa, Ghag, & Lloyd, 2005). Some OLMs permit interaction with the student and hence offer more control on the learner model by the learner itself. Learners can edit their model if they think it is inaccurately representing their knowledge or they can provide additional information that is not in the model yet. Research has demonstrated that learners are likely to use an OLM to support navigation (Bull et al., 2008) and hence, to define the target of learner-defined instruction.

Table 2 presents an overview of research studies, both empirical and theoretical, with their target of adaptive instruction. Again, studies that already empirically tested an approach, but however did not implement the approach in an adaptive learning environment are also labeled as empirical.

3.3. Pathways of adaptive instruction – How to translate source into target?

Adaptivity in a system does not make that system intelligent, or the other way around. Adaptive and intelligent technologies are two different notions (Brusilovsky & Peylo, 2003), representing two different approaches. While adaptive systems take into account the information in the learner models and thereupon behave differently for different students or groups of students, intelligent systems apply artificial intelligence techniques to provide more and better support or instruction for their learners. Clearly, many ITSs fall under the category of intelligent systems, behaving non-adaptive since they offer the same support regardless of learner characteristics (Brusilovsky & Peylo, 2003), while most hypermedia-oriented environments can be categorized into adaptive systems. There is no clear-cut distinction between the two groups of systems (Brusilovsky & Peylo, 2003), and both adaptive and intelligent systems act as neighbors, intertwined and leveling up their research. Not taking into account one of the two technologies in this review would result in a poor and inadequate overview of current research in adaptive (and intelligent) learning systems. Hence, we discuss the reviewed pathways for both techniques, adaptivity

Table 2
Overview of targets of adaptation in computer-based adaptive learning environments.

Target of adaptation "What is adapted?"	Reference	Empirical/theoretical research
Content		
Content	Ketamo (2003)	Empirical
Content	Vassileva and Bontchev (2006)	Theoretical
Content	Sun et al. (2007)	Theoretical
Content	Tseng et al. (2008b) [MALS]	Empirical
Personalized suggestions of content	Reategui et al. (2008)	Empirical
Web-based raw content filtering	Germanakos et al. (2008)	Theoretical
Presentation and instruction		
Presentation and instruction	Milne et al. (1997) [ATULA]	Empirical
Instructional strategies	Tennyson (1987) [MAIS]	Theoretical
Adaptive group formation	Read et al. (2006) [COPPER]	Theoretical
Hints; prompts; short feedback; summaries; assertions; etc	D'Mello et al. (2008), Graesser et al. (2008), D'Mello and Graesser (2009) [AUTOTUTOR]	Empirical
Meta-cognitive guidance	Aleven et al. (2006)	Empirical
Appropriate feedback	Mitrovic et al. (2002) [SQL-Tutor]	Empirical
Adaptive pacing	Montazemi and Wang (1995)	Empirical
Interactive help	Conati et al. (2002) [ANDES]	Empirical
Mastery decisions; remediation decisions	Shute (1995) [SMART-STATLADY]	Empirical
Instruction	Beal and Lee (2005) [WAYANG-WEST]	Theoretical
Content and presentation/instruction		
Content; presentation; instruction	Martinez and Bunderson (2000) [SILPA]	Empirical
Content; presentation; instruction	Reiners and Dreher (2009)	Empirical
Difficulty level; presentation style	Tseng et al. (2008a) [TSAL]	Empirical
Personalized navigation structure	Conlan et al. (2002) [OPAL]	Theoretical
Feedback; suggestion	Melis and Andres (2005) [ACTIVEMATH]	Theoretical
Adaptive navigation; adaptive presentation	Kelly (2008) [EDUCE]	Empirical
Level of material	Ray (1995); Ray and Belden (2007) [MEDIAMATRIX]	Theoretical/empirical
Messaging	Xu and Wang (2006) [IeLS]	Empirical
Lesson contents; navigational route	Papanikolaou et al. (2003) [INSPIRE]	Empirical
Adaptive navigation; adaptive presentation	Romero et al. (2006)	Empirical
Appropriate exercises; giving hints	Weber (1996) [ELM]	Empirical
Adaptive navigation; adaptive presentation	Jeremic et al. (2009) [DEPTHS]	Empirical
Adaptive presentation; navigational control; feedback	Triantafillou et al. (2004) [AES-CS]	Empirical

and artificial intelligence. Table 3 summarizes the results of the literature search.

3.3.1. Adaptive systems

In adaptive learning environments, connecting the source of adaptive instruction, i.e., the learner and the learners' interaction with the environment, with the target of adaptive instruction, is also called the modeling process. Brusilovsky and Millán (2007) distinguish three types of learner modeling. First, there is the approach of stereotype modeling, aiming at clustering all possible learners that make use of the adaptive environment into several groups. The notion of stereotype modeling originally stems from the work of Rich (1979), who called stereotypes clusters of characteristics. A user is characterized by a set of facets, or characteristics, each having a value. This group of facets and their values is called a stereotype. What is also required for effective stereotype modeling is a set of triggers. Triggers can be seen as events being representative for the appropriateness of a particular stereotype (Rich, 1979). Considering the occurrence (or non-occurrence) of triggers, stereotype modeling tries to cluster individual learners into several groups, based on common learner characteristics. All learners within the same group receive the same instruction adapted to the group profile. Stereotypes can assist in creating adaptivity of the form: *Users who loved reading a book by author X will also love to read a book of author Y but will not like to read a book of author Z* (Kay, 1994). A shortcoming of this approach is that the modeling process is rather coarse-grained because it captures only the most salient characteristics of a learner, and provides only a first step towards individualization of the learning environment and learning process. This type of group-modeling was also mentioned by Paramythis and Loidl-Reisinger (2003) who consider the group model as a separate category in ITS models, next to the learner model.

A more fine-grained modeling approach is feature-based modeling, that is currently the dominant approach in web-based adaptive systems (Brusilovsky & Millán, 2007). Feature-based learner models incorporate specific characteristics of the learner, like individual characteristics such as the learner's knowledge, interests and goals. Feature-based learner models also want to dynamically track changes in the learners' individual characteristics, so that an up-to-date model can be delivered during the learner's interaction with the environment since learner's characteristics such as interests and goals may change during interaction with the environment (Brusilovsky & Millán, 2007).

Finally, Brusilovsky and Millán (2007) consider the combination of stereotype models with feature-based models as a third approach and promising direction. In this approach, the user can be classified firstly according to a stereotype model where after an individual feature-based model is initiated (Tsiriga & Virvou, 2003). This approach allows to deal with a typical "new user" or "new learner" problem, where no profile information of the learner is available and the modeling process has to start from scratch (Brusilovsky & Millán, 2007). Based on characteristics defined on a group level, such as age, education, profession and gender, and provided by the learner, the learner is associated with a (set of) predefined stereotype(s). Based on this (set of) stereotypes, a feature-based model can be developed that is based on more individual characteristics such as learner's goals, interests and knowledge.

Other approaches of modeling include constraint-based modeling and modeling of misconceptions or bug models. Constraint-based modeling, largely illustrated in the work of Mitrovic and colleagues (Mitrovic & Ohlsson, 1999; Mitrovic et al., 2001) aims at reducing task complexity. This type of modeling focuses on erroneous knowledge, departing from the assumption that only describing what is already known by the student is not sufficient. The problem state of a learner is therefore critical in constraint-based modeling. This type of modeling is strongly related to bug models, where a list of possible errors, or misconceptions, is defined in advance and included in the model. Possible errors can include either elementary errors or erroneous sequences of actions (Vassileva, 1990).

Table 3
Overview of pathways of adaptation in computer-based adaptive learning environments.

Pathway of adaptation	Reference	Empirical/theoretical research
Rule-based		
Rule-based	Tseng et al. (2008a) [TSAL]	Empirical
Rule-based	Ketamo (2003)	Empirical
Rule-based; agent-based	Sun et al. (2007)	Theoretical
Rule-based	Melis and Andres (2005) [ACTIVEMATH]	Theoretical
Rule-based; input by learner	Ray (1995); Ray and Belden (2007) [MEDIAMATRIX]	Theoretical/empirical
Fuzzy rule-based	Xu and Wang (2006) [IeLS]	Empirical
Fuzzy logic; multicriteria decision-making	Papanikolaou et al. (2003) [INSPIRE]	Empirical
Rule-based	Milne et al. (1997) [ATULA]	Empirical
Rule-based inference system	Romero et al. (2006)	Empirical
Case-based reasoning approach	Weber (1996) [ELM]	Empirical
Production rules; similarity based learning algorithm	Mitrovic et al. (1996) [INSTRUCT]	Theoretical
Production rules	Aleven et al. (2006)	Empirical
Constraint-based modeling	Mitrovic et al. (2002) [SQL-Tutor]	Empirical
Fuzzy sets	Jeremic et al. (2009) [DEPTHS]	Empirical
SMART rule-based (promotion/demotion rules); regression equations	Shute (1995) [SMART-STATLADY]	Empirical
Neurules (hybrid rules integrating symbolic rules)	Koutsojannis and Hatzilygeroudis (2003)	Theoretical
Neuro-fuzzy learning system (fuzzy logic and neural networks)	Fazlollahtabar and Mahdavi (2009)	Theoretical
Probability based		
Self-adaptable SCORM; metadata	Vassileva and Bontchev (2006)	Theoretical
Naïve Bayes algorithm; dynamic student profile	Kelly (2008) [EDUCE]	Empirical
Granularity expert-centric networks; multidimensional stereotypes	Read et al. (2006) [COPPER]	Theoretical
Bayesian networks	Conati et al. (2002) [ANDES]	Empirical
Decision tree; Naïve Bayes	McQuiggan et al. (2008) [CRYSTAL ISLAND]	Empirical
Bayesian networks	García et al. (2007)	Theoretical
Other		
Recommender system; virtual character	Reategui et al. (2008)	Empirical
Neural network	Montazemi and Wang (1995)	Empirical

3.3.2. Intelligent systems

Several artificial intelligence techniques can be used in order to create stereotype-based, feature-based or combinatorial learner models. Traditionally rule-based decisions (if…then…) determined the outcome of adaptive instruction, where rules were set by the instructor prior to the learning process. Tutoring systems exhaustively demonstrate the application of rule-based analysis. More recently, applications of Bayesian probabilistic approaches have been reported by Conati et al. (2002), Nokelainen et al. (2002) and Shute et al. (2005). A Bayesian network (Pearl, 1988) is a graphical model that encodes probabilistic relationships between variables of interest. Such models help to manage uncertainty in learner modeling, which is necessary because we make inferences about the beliefs, abilities, future actions, etc. of learners (Jameson, 1996). One of the advantages of the use of Bayesian networks lies in its structure that is ideal for combining prior knowledge which often comes in causal form, and observed data. Applied to the development of learner models in adaptive learning environments, the prior knowledge consists of the stereotype model that is based upon the learner's goals, tasks and interests, whereas the observed data is extracted from the interaction between the learner and the environment. Even in the case of missing data, a frequently occurring problem in the learning sciences, Bayesian networks can be used (Ben-Gal, 2007). Although many of the variables in Bayesian networks are binary, variables with more than two outcomes are also possible. An example of this is given in the work of García, Amandi, Schiaffino, and Campo (2007), who proposed a Bayesian network for detecting students' learning styles. The Bayesian network proposed by García et al. (2007) showed high value in detecting students' learning styles with high precision. Also, in the research of Conati et al. (2002), successful implementations of Bayesian networks in order to create student models were demonstrated in the Andes tutoring system.

More recently, a new line or research was reported in which the use of fuzzy logic is placed centrally (Fazlollahtabar & Mahdavi, 2009; Jeremic et al., 2009; Xu & Wang, 2006). Fuzzy logic is considered as a flexible method to easily represent the way human tutors evaluate learners. Evaluation of human tutors is often not clear-cut and results in imprecision. Fuzzy logic is able to deal with this imprecision (Fazlollahtabar & Mahdavi, 2009). Fuzzy logic can be combined with neural networks, which are able to learn from noise or incomplete user data. Also, neural networks can generalize over similar cases and then use this generalized knowledge to recognize new and unknown sequences (Fazlollahtabar & Mahdavi, 2009). In learner modeling, neural networks are able to predict learner's responses and errors and are therefore able to offer adaptive learning paths based on predicted responses of learners.

For a thorough overview of the uncertainty management in learner modeling, we refer the reader to the work of Jameson (1996), who discusses the main paradigms in uncertainty modeling, and also provides examples of systems that incorporated this type of modeling.

4. Discussion

Although the aforementioned research describes implementations of learners' individual characteristics, there is sparse data related to the empirical effectiveness of including specific cognitive, affective or behavioral individual characteristics in learner models with respect to enhancing the learning process or increasing the learning outcomes. And, as Shute already stated in 1995, "*therefore, there is limited data supporting a particular paradigm's validity*" (Shute, 1995, p. 3). Shute suggests to remediate this sparseness of empirical data by starting more systematic research in the area. Shute makes a plea for researchers to start with "*a coordinated stream of methodological research and development, altering specific features of existing systems and evaluating the results of those changes in accordance with a principled approach*" (Shute, 1995, p. 3). Almost 15 years after Shute expressed this concern, her call for more systematic research is still very germane. Accordingly, in his review of adaptive instruction in hypermedia environments, Federico (1999) mentioned pretask cognitive aptitudes, abilities, within-task cognitive mechanisms and dynamic acquisition measures as individual difference indices for adaptive instruction. Federico stated that, despite the voluminous research results and theoretical propositions in adaptive learning research, "*theoretical or conceptual problems, in addition to methodological difficulties, have limited the practical payoff from research in adaptive instruction, …*" (Federico, 1999, p. 662). More recently, Park and Lee (2003) also expressed their concern about the lack of scientific evidence that has been accumulated in the research on characteristics and background variables that should be considered in adaptive instruction. In this way, it is difficult to provide guidelines for creating adaptive learning environments (Park & Lee, 2003).

To enable a more systematic approach to the research of learner modeling, the research studies discussed in this review were categorized in accordance with a tripartite model of adaptive instruction. This model comprises two interrelated components, representing the source (*to what will be adapted?*) and target (*what will be adapted?*) of adaptation. The components are related by the pathway to adaptation (*how to translate source into target?*).

4.1. Source of adaptation

Exploring the results associated with the first component, the source of adaptation, it is confirmed that there is a general agreement towards including more or less the same learner characteristics in order to create a learner model (Shute & Towle, 2003). Park and Lee (2003) gave an overview of some learner characteristics that serve as aptitude variables in developing adaptive instruction, such as intellectual ability, cognitive styles, learning styles, prior knowledge, achievement motivation, and self-efficacy. However, to date and to our knowledge, no comprehensive review has been given of the improvement in learner modeling when several individual characteristics are taken together or have we found any experimental research that reports on the effects on the learning process and learning outcomes. Nor has there been any research on the relative importance of learner characteristics in order to create a learner model that is able to integrate all relevant learner characteristics that are needed in order to create effective adaptive learning environments.

Most of the research studies reported in this review focus on integrating learner characteristics with learner behavior, such as concentration, time-on-task or help-seeking behavior. The surplus value of including these interaction parameters is generally assumed, but again, no empirical research studies are available on this topic. Future research could concentrate on the relative importance of learner's behavior and learner's characteristics and their mutual dependence in building the learner model.

4.2. Target of adaptation

When answering the question "*What to adapt?*" a variety of possibilities can be pulled out. Few studies focused on adapting the content, while the major part of reviewed studies adapt to a combination of content, presentation and instruction/support. It is however difficult to make a clear-cut distinction between the targets of adaptation. As an example, adaptive navigation support technologies include direct guidance, sorting, hiding, annotating and map adaptation (Brusilovsky, 2001). This technique affects both the content that is presented (e.g., degree of information), the degree of support (e.g., guidance or not) and the presentation techniques (e.g., hypertext or linear text). Although plenty of technologies (such as probabilistic or rule-based modeling) and knowledge (such as which learner characteristics are worth modeling) are available to implement adaptive instruction into a learning environment, there is less research available on the effectiveness of these technologies in education. Future research could focus on the differential benefits and costs of using such techniques for adaptation. For example, one could search for the differential effectiveness of 'hiding' as adaptive technology used in various settings with various learners.

4.3. Pathway of adaptation

Since adaptive and intelligent learning environments are greatly indebted to ITSs, the initial pathways resembled very much the rule-based analyses included in ITSs. Recently, with the stronger connections between intelligent and adaptive learning systems, other approaches entered. Currently, Bayesian networks, fuzzy logic and neural networks are considered as new approaches to the development of learner models. However, based on our review, we can conclude that all of these newer techniques are still in the very early stage of development, and none of the techniques has been concretely implemented in an adaptive system. We are in great anticipation of future research testing the pedagogical effectiveness of adaptive learning environments based on these new technologies.

Shute and Towle (2003) stated that adaptive learning is flourishing as a research field, but there is an indisputable risk of excavating the concept of adaptive learning. Adaptive instruction encloses much more than adapting the content or instruction to meet the constraints of the learning device, or adapting the interface to meet the needs of learners with different abilities and characteristics. As many researchers are involved in defining adaptivity as an adjustment of content or interface, based on assessments of learning styles or cognitive styles, only few are concerned about adaptivity as integral part of instructional design and therefore testing the effectiveness of the instructional design (Shute & Towle, 2003).

An additional line of research includes the integration of (adaptive) learner control into learning environments. Learner control as an instructional method can be considered as an alternative approach to the development of adaptive learning environments (Park & Lee, 2003) and may be at least as effective in obtaining adaptivity as the more high-technological artificial intelligence techniques. This notion has not been discussed in this review since no studies have been focusing on learner control as instructional technique in adaptive learning environments. The degree and type of learner control that is offered to learners could be adjusted to their needs, abilities and goals. Although previous research demonstrated that offering control to the learners can engage the learner in more effective learning, results are often ambiguous (e.g., Friend & Cole, 1990; Goforth, 1994; Large, 1996). The risk of offering control to the learners is that already good learners (i.e., advanced, high self-regulation skills, prior knowledge, high motivation, etc.) will benefit more from learner control and that less skilled learners will become even worse since learner control can have detrimental effects on their learning process (Hannafin, 1984). This however does not imply that learner control is not effective as instructional strategy. The central question is in which contexts learner control is more appropriate to be exercised in. These contexts are determined by the sources of adaptivity, such as learner's cognition, affect and behavior. Adaptability of a system, operationalized as the degree and type of learner control that is offered based on the learner model, could serve as an additional target of adaptive instruction.

5. Conclusion

By presenting a tripartite structure of adaptive instruction we have tried to elucidate the common grounds of the bunch of adaptive systems that has been developed. Also, we have shed light on the underlying building blocks by which these systems have been developed by presenting sources, targets and pathways in adaptive instruction. Secondly, the results of this review focusing on adaptive and intelligent learning environments, show an auspicious trend towards more systematic research and more empirical evaluation studies of techniques for learner modeling. This is in line with the review of Chin (2001), who reported an upward trend in the use of empirical evaluations of user-adapted interaction in learner modeling systems. Nonetheless, for the time being, it seems that the practical implementation and empirical evaluation of this techniques and models into adaptive learning systems is still small-scaled, compared with the bunch of theories that has been developed.

We conclude with the call for a bottom-up theory development integrating current and past research results. Providing the adaptive and intelligent learning systems research field with a practice-based framework, will engage researchers into more structured en systematic empirical research having concrete hypotheses on the merits of learner characteristics in adaptive learning environments.

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