

Adaptivity in E-learning systems

Alshammari, M. , Anane, R. and Hendley, Robert J.

Accepted post-print version deposited in [CURVE](#) November 2014

Original citation:

Alshammari, M. , Anane, R. and Hendley, Robert J. (2014) 'Adaptivity in E-learning systems' in Proceedings - 2014 8th International Conference on Complex, Intelligent and Software Intensive Systems, CISIS 2014 (pp: Article number 6915500, Pages 79-86). IEEE. DOI: 10.1109/CISIS.2014.12

Publisher:

IEEE

<http://dx.doi.org/10.1109/CISIS.2014.12>

Statement:

"© 2014 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works."

This version may differ to the final published version. Copyright © and Moral Rights are retained by the author(s) and/ or other copyright owners. A copy can be downloaded for personal non-commercial research or study, without prior permission or charge. This item cannot be reproduced or quoted extensively from without first obtaining permission in writing from the copyright holder(s). The content must not be changed in any way or sold commercially in any format or medium without the formal permission of the copyright holders.

CURVE is the Institutional Repository for Coventry University

<http://curve.coventry.ac.uk/open>

Adaptivity in E-Learning Systems

Mohammad Alshammari¹, Rachid Anane², Robert J. Hendley¹

¹School of Computer Science, University of Birmingham
{m.t.m.alshammari, r.j.hendley}@cs.bham.ac.uk

²Faculty of Engineering and Computing, Coventry University
r.anane@coventry.ac.uk

Abstract—Traditional e-learning systems have been, typically, designed for a generic learner, irrespective of individual knowledge, skills and learning styles. In contrast, adaptive e-learning systems can enhance learning by taking into account different learner characteristics and by personalising learning material. Although a large number of systems incorporating learning style have been deployed, there is a lack of comprehensive, comparative evaluations. This paper attempts to bridge this gap by comparing a number of adaptive e-learning systems. It considers three main perspectives: the learner model, the domain model and the adaptation model. A set of criteria is generated for each perspective, and applied to a representative sample of adaptive e-learning systems.

Keywords- *learning technologies; learning style; learner model; domain model; adaptation model; adaptive e-learning systems*

I. INTRODUCTION

Learning can be defined as the process of acquiring knowledge or skills [1]. It involves three fundamental forms of interaction: learner-learner, learner-instructor and learner-content [2]. However, traditional e-learning systems tend to neglect the diversity of learners, their abilities, their knowledge and skills, and the learning context.

Adaptation is often proposed as a way of overcoming these limitations. In the context of user system interaction it is defined as a process of tailoring a system to meet the user's requirements and preferences [3]. Adaptive e-learning systems can consider learner characteristics such as knowledge, affective state and learning style as a basis for providing adaptation. Among these characteristics, learning style is one of the most important factors in learning [4]–[6]. The scope of its applicability in e-learning has been an active area of research [7].

Adaptive e-learning systems based on learning style generally use different learning style models. This raises the issue of what models and theories are suitable and effective. In addition, there is a lack of high quality empirical evaluation regarding their effectiveness [7]–[10] and of comparative work on these systems [3], [7], [10]–[12]. Some investigations deal with adaptive systems in general [3], [11], [12], whereas others focus more specifically on adaptivity based on learning style [7]–[10].

This paper attempts to bridge the gap in evaluation by using a more comprehensive approach to adaptivity in e-learning systems. Three perspectives are considered in the

comparison of a number of adaptive e-learning systems: learner model, domain model and adaptation model.

The remainder of the paper is structured as follows: Section II presents the background on learning style and related models. Section III provides a comparative evaluation of some adaptive systems. Section IV offers some discussion on adaptivity, and Section V concludes the paper.

II. BACKGROUND

Adaptive e-learning systems (AESs) are an enhancement to the traditional, generic approach to learning systems; they personalise and recommend learning material to meet individual needs [18]. Different research themes are considered when dealing with AESs [3]. One theme concerns learner modelling and adaptation approaches. AESs normally build a learner model that incorporates different learner characteristics to support adaptation [3], [19]. Another theme is associated with the introduction of new adaptive techniques and methods in systems such as in MetaLinks [20] and INSPIRE [21], or with the development of frameworks and authoring tools for AESs such as in AHA! [22] and InterBook [23]. Reusability and interoperability of learning content in AESs is a more recent research theme. Learning material can be independent of the platform, and may be annotated in a way that facilitates adaptation. However, it has been suggested that AESs cannot be supported by the current generation of e-learning standards due to the complexity of adaptation [24], [25].

Besides the identification of the learning style, an effective AES requires a clear commitment to a learner model, domain model and adaptation model [11]. Their characteristics are detailed below.

A. Learning Style

Learning style is considered as one of the most important factors in learning [5]. It is defined as a combination of cognitive, affective and psychological factors that indicate how a learner perceives, interacts with and responds to the learning environment [6]. Despite a lack of consensus, many educational theorists and psychologists agree that recognition of a learning style can make learning more effective [4]–[6], [17]. It has been argued that if a learner has a strong proclivity for a particular learning style, he/she may experience difficulties with learning material

and learning environments that do not support the preferred learning style [5].

A significant number of learning style models and theories have been developed [13], principally by Kolb [14], Honey and Mumford [15], Dunn and Dunn [16] and Felder-Silverman [5]. A comprehensive and clear learning style model has yet to be identified [17].

B. Learner Model

Learner modelling has been central to Intelligent Tutoring Systems (ITS) since 1970 [31]. An ITS uses the information encapsulated in the learner model in order to modify and adapt the way it interacts with a learner [9]. According to Self, a learner model is “what enables a system to care about a student” [32]. A number of learner characteristics can be maintained in a learner model. Essalmi et al. identify 16 attributes, including knowledge, skills, goals and learning style, motivation and emotion, as a source for providing adaptation [8].

Learner modelling involves different stages such as data elicitation, model representation and maintenance. Data elicitation is usually based on explicit methods via user-generated feedback (such as questionnaires, like/dislike and rating) or implicit methods, which consider system-generated feedback (such as mouse movements, time spent and page visits) [33], [34]. Although explicit methods are considered more reliable and more accurate [35], learners may be reluctant to provide explicit feedback [36]. In contrast, implicit methods allow learners to focus entirely on their main task. A large amount of data can be captured through an implicit method. However, the complexity of the processing, analysis and classification of data may outweigh its advantages.

A good survey of relevant approaches and techniques over the last decade is provided by Chrysafiadi and Virvou who present the overlay, stereotype, Bayesian network and ontological models [37]. The key concept behind the overlay model is that the learner’s knowledge is a subset of the whole domain. Stereotype models classify a group of people who share the same preferences or interests, or follow a certain type of behaviour. Bayesian network can be used to represent a wide range of learner characteristics. The network contains nodes (i.e. variables) and arcs to define probabilistic relationships between those variables. The ontological model is an explicit specification of real-world concepts and their relationships.

C. Domain Model

A domain model is an abstract representation of part of the real world. It is composed of a set of domain knowledge elements [3] and is the result of capturing and structuring knowledge related to a specific domain [38]. Knowledge types can be mainly classified as declarative (i.e. the what?) or procedural (i.e. the how?). The structure of the domain models is particularly relevant in the field of ITS, expert systems and hypermedia systems [3], [39].

A domain model can be represented in frame-based, network-based or logic-based schemes. A frame-based representation contains frames that have a number of

attributes that describe learning concepts. A network-based representation is formed of nodes to represent concepts, and edges to represent the relationships between them. For example, a tree-like structure can be considered as a hierarchical network-based model. A logic-based representation usually deals with procedural knowledge which can be expressed as rules: *if (condition) then (conclusion)*.

An important concern in domain models is how to annotate metadata and organise learning material and learning objects, in particular. The role of learning objects is increasingly being recognised in learning systems. Weller defines a learning object as “a digital piece of learning material that addresses a clearly identifiable topic or learning outcome and has the potential to be reused in different contexts” [40]. Various standards and guidelines for describing, sequencing, storing, and manipulating learning objects have been proposed. Dublin Core and IEEE LOM, in particular, can potentially support the reuse of learning objects and enhance the adaptation process.

D. Adaptation Model

An adaptation model bridges the gap between the learner model and the domain model by matching relevant learning material, or sequence of objects, to the needs and characteristics of an individual learner. Brusilovsky put forward one of the most popular taxonomies for adaptive technology: adaptive presentation and adaptive navigation [18], [19]. More recently, Knutov et al. proposed adaptive content as a third category [11]. This combined taxonomy offers a useful perspective on what can be achieved in adaptive systems.

Bunt, Carenini and Conati provide a comprehensive coverage of adaptive content and presentation techniques [41]. These cover various operations such as inserting, modifying, removing and sorting or zooming, layout changing and annotations. Adaptive navigation recommends selective learning paths and curriculum sequencing. Other examples include link generation, direct guidance and hiding. Brusilovsky reviews many adaptive navigation techniques and illustrates them with relevant examples [42].

III. COMPARATIVE EVALUATION

This section offers a comparison of a representative sample of AESs by using three different perspectives: learner model, domain model and adaptation model. The systems were selected according to two criteria. First, each system should consider the learning style in a learner model as the main source of adaptation. Second, each system should contain at least three main models, including learner model, domain model and adaptation model.

In this comparison nine representative systems were selected: MASPLANG [43], [44], INSPIRE [21], iWeaver [45], TANGOW [46], [47], AHA! [22], WELSA [48], Protus [49], eTeacher [50] and LearnFit [51]. These systems differ in their focus on learner modelling approaches, learner characteristics, domain models, adaptation methods and application models.

TABLE 1. LEARNER MODEL

SYSTEM	LEARNER CHARACTERISTICS MODELLED	MODEL REPRESENTATION	LEARNING STYLE MODEL	DATA ELICITATION METHOD
MASPLANG	Knowledge, Learning Style	Overlay Model, Inferred Model	Felder-Silverman Model	Explicit (questionnaire), Implicit (student actions)
INSPIRE	Knowledge, Learning Style	Overlay Model	Honey and Mumford Model	Explicit (questionnaire), Manual
iWeaver	Preferences, Learning Style	[not specified]	The Dunn & Dunn Model	Explicit (questionnaire)
TANGOW	Knowledge, Learning Style	Overlay Model	Felder-Silverman Model: Only 2 dimensions: understanding and perception.	Explicit (questionnaire)
AHA!	Preferences, Learning Style	Overlay Model	Combination of several models	Manual
eTeacher	Performance, Learning Style	Bayesian Network	Felder-Silverman Model: Only 3 dimensions: perception, processing and understanding.	Explicit (questionnaire), Implicit (student actions)
WELSA	Learning Style	Stereotype Model, Inferred Model	Unified Learning Style Model (ULSM)	Implicit (student actions)
Protus	Knowledge, Learning Style	Inferred Model	Felder-Silverman Model	Explicit (questionnaire), Implicit (student actions)
LearnFit	Preferences, Learning Style	Bayesian network	Myers-Briggs Type Indicator (MBTI)	Explicit (questionnaire), Implicit (student actions)

A. Learner Model

The properties that are considered in each learner model are learner characteristics, representation, learning style model and data elicitation method. Table 1 gives a summary of learner models in the systems. The majority of AESs consider at most three learner model characteristics, knowledge, preference and learning style [8]. The most common combination includes level of knowledge and preferences. These characteristics are however not confined to the AESs that incorporate learning style [7], [8].

The overlay model representation of learner knowledge is the most widely used representation. In MASPLANG [43], [44], INSPIRE [21] and TANGOW [46], [47], it allows the logging of learner's actions and interactions to infer and build the learner model (i.e. inferred learner model). Protus [49] uses sequential pattern mining and association rules to recommend learning material based on visited pages and test results. An inferred learner model used in MASPLANG is generated from visits and time spent on learning material [43], [44]. eTeacher [50] and LearnFit [51] rely on Bayesian network to model learning styles. The stereotype representation, applied in WELSA aims to group learners based on their learning styles [48].

A survey of AESs that integrate learning style identified the Felder-Silverman model [5] as the most preferred; it was used by approximately 50% of 74 peer-reviewed articles on that subject between 2000 and 2011 [7]. Other systems are based on the Honey and Mumford model [15], the Dunn

and Dunn model [52], and Myers-Briggs Type Indicator (MBTI) [53]. Some systems such as TANGOW [46], [47] and eTeacher [50] refer to subsets rather than to a full learning style model.

With regard to data elicitation methods, systems such as INSPIRE [21], iWeaver [45] and TANGOW rely on explicit methods [46], [47] whereas Protus [49] and WELSA [48] use implicit techniques, such as visit and time spent on learning material. A combination of explicit and implicit methods is used in eTeacher [50], MASPLANG [43], [44] and LearnFit [51] systems. A manual selection of learning style proposed by INSPIRE [21] and AHA! [22] assumes that learners know their learning style before interacting with the system.

B. Domain Model

A domain model is viewed in terms of domain model representation, learning object standards and application domain. They are presented in Table 2 for each system. A hierarchical network, i.e. tree-like structure is the most used domain model representation; it may have an arbitrary number of levels. Table 2 displays AESs with 4-level [48], [50], [51] and 3-level [21], [46], [47], [49] hierarchical networks.

Only three out of nine systems refer to e-learning standards such as IEEE LOM, SCORM or Dublin Core. The INSPIRE system [21] makes use of the ARIADNE Recommendation metadata standards whereas the Dublin Core standard is the basis for the WELSA system [48]. More appropriately, the IEEE LOM standard is used in the

TABLE 2. DOMAIN MODEL

SYSTEM	MODEL REPRESENTATION	LEARNING OBJECT STANDARD	APPLICATION DOMAIN
MASPLANG	Hierarchal Network: Concepts, procedures, nodes and their relationship links	None	Computer Network: TCP/IP Protocols
INSPIRE	Hierarchal Network: Goals (topics to be learned), concepts (related lessons) and educational materials (facts, procedures, exercises)	ARIADNE metadata standard.	Computer Architecture
iWeaver	Hierarchal Network: Seven lessons	None	Interactive Multimedia and Web design
TANGOW	Hierarchal Network: Tasks, sub-tasks and educational materials	None	Theory of Computation
AHA!	Hierarchal Network: concepts and their relationship (prerequisite)	None	Adaptive Hypermedia
eTeacher	Hierarchal Network: Course, unit, topics and reading materials	None	Artificial Intelligence
WELSA	Hierarchal Network: Chapter, sections, sub-sections and learning objects	Dublin Core and Ullrich Instructional Ontology [60].	Artificial Intelligence (Constraint satisfaction problems)
Protus	Hierarchal Network: Topics, lessons, and educational materials	None	Principles of Programming (Java)
LearnFit	Hierarchal Network: Course, chapter, concept and learning object	IEEE LOM standard	Introduction to PHP Programming

LearnFit system [51]. Finally, most application domains and courses are related to computer science topics.

C. Adaptation Model

This section compares adaptation models in AESs based on the taxonomy of adaptive technologies proposed by Brusilovsky [18], [19] and Knutov et al. [11]. Table 3 identifies the adaptation methods used in the systems as adaptive content, presentation and navigation.

The TANGOW [46], [47] and WELSA [48] systems apply a content fragment generation technique. A learning unit is divided into fragments, and the systems provide adaptation by composing and recommending an appropriate sequence of fragments. AHA! [22] and WELSA [48] implement a fragment dimming and stretch-text/highlight technique to learning material text and objects based on their relevance to learners. Link sorting/ordering is used to prioritise links depending on the learner model. This technique is utilised extensively in AESs. Link annotation has been applied in MASPLANG [43], [44], INSPIRE [21] and eTeacher [50]. Link generation, successfully implemented by Protus [49], LearnFit [51] and eTeacher [50], is considered as a relatively new technique in the field of adaptive navigation. Direct guidance is another popular technique; it allows learners to navigate easily to previous or next pages. Link hiding removes or disables links to less relevant pages or items. It is implemented by MASPLANG [43], [44], iWeaver [45], and TANGOW [46], [47].

IV. DISCUSSION

In this section the learner model, the domain model and the adaptation model are considered within the wider research context of AESs.

A. Learner Model

Although learner attributes such as knowledge, style, skills or affective state are the subject of intensive research, most models in AESs consider three learner attributes at the most [8]. The level of knowledge is considered in most systems [8], quite often in combination with learning style.

Scant attention has been paid to incorporating affective state, learning style and motivation in a learner model with an AES. Leontidis and Halatsis note that system design tends to be based on cognitive states such as knowledge and skills, neglecting emotional factors, mood and personality of learners [57]. Martin and Briggs propose a framework for instructional design, calling for the integration of cognitive and affective states [58]. Similarly, O'Regan claims that affective state is inherently associated with e-learning [59].

Although incorporating new combinations of learner attributes is desirable, selecting the most appropriate and effective learning style model and theory in AESs is still a contentious issue. The most widely used learning style model was proposed by Felder and Silverman [5] and is considered to be more appropriate than other models for e-learning [7], [43], [44], [46], [47], [49], [50]. It provides extensive details on learning style categories and a valid tool for assessments; it also promotes a teaching style that corresponds to each learning style category.

TABLE 3. ADAPTATION METHODS

SYSTEM	ADAPTIVE CONTENT	ADAPTIVE PRESENTATION	ADAPTIVE NAVIGATION
MASPLANG		Link annotation, media format	Direct guidance, link hiding
INSPIRE		Link annotation, link sorting, media format	Link generation, direct guidance
iWeaver		Link sorting, media format	Direct guidance, link hiding
TANGOW	Fragment generation	Link sorting, media format	Link generation, direct guidance, link hiding
AHA!	Fragment dimming, stretch-text/highlight	Link sorting, media format	Direct guidance
eTeacher		Link annotation	Link generation, direct guidance
WELSA	Fragment generation, fragment dimming, stretch-text/highlight	Link sorting, media format	
Protus		Media format	Link generation, direct guidance
LearnFit		Media format	Link generation, direct guidance

A number of issues related to adaptation based on learning style have been raised. Brusilovsky and Millán point out that, “careful studies are rare and success stories are very few” [9]. To date, there has been little agreement on what aspects of learning style need to be modelled, and how to provide adaptation. Brown et al. call for more high-quality work in evaluating the effectiveness of learning style in AESs [10]. Likewise, Akbulut and Cardak conclude that, “empirical and pedagogical evaluations of the current projects with more robust methodologies are needed” [7].

Provision of AESs requires robust diagnosis of learner characteristics to build effective, accurate and reliable learner models. Little has been done to identify learning style implicitly and to support dynamic learner modelling [7]. Although an explicit approach based on questionnaires may be more reliable and accurate [35], learners may be less motivated to participate in a lengthy process [36]. The accuracy and currency of implicit methods is still an open question.

In learner models, the level of knowledge is usually represented as an overlay model. Although this model is simple and effective in some cases, it cannot represent misconceptions and incorrect learner knowledge. It may therefore be inadequate on its own, and is often combined with other approaches. Stereotype representation, normally used to cluster learners based on pre-defined categories, may be useful in initialising the learner model quickly. However, it suffers from limitations in its manual management, and learners in such classes may never exist.

Semantic Web, probabilistic models and data mining are driving more of the recent work on learner modelling. For semantic technologies, an ontological learner model provides reasoning mechanisms and reduces internal inconsistencies although the mapping between different ontologies and their maintenance presents a challenge. Representation of learner models may be based on probabilistic models and theories such as Bayesian networks as a well-established mathematical technique. This form of representation can be applied to a variety of learner’s characteristics such as emotion, learning style, knowledge

and skills. Moreover, there are other approaches for supporting adaptation, for instance, based on fuzzy logic or evolutionary algorithms. These approaches and representations may be better viewed as complementary, rather than competitive approaches. Issues of accuracy and efficiency may be a serious impediment to the combination and application of a wide range of learner attributes in different contexts and domains.

B. Domain Model

The domain model is usually represented as a hierarchical network with different levels. This approach is widely used in AESs beside other representations such as frame-based and logic-based representations. This representation is flexible for storing and managing knowledge, and thus offers a powerful mechanism for domain modelling. Identifying the relationships between learning concepts may enhance the domain model representation and facilitate adaptation.

Most AESs use computer science topics such as programming languages, networks and artificial intelligence as application domains. They appear particularly suitable for adaptive systems. Relevant learning content used in AESs is often referred to as learning resources, learning material or learning objects. It was noted, however, that learning content in most AESs does not conform to e-learning standards, a limitation that may prevent the sharing and reuse of learning objects in particular. This may indicate an undue reliance on less structured learning content in many AESs.

The dynamic selection of learning objects is rarely addressed in AESs. Constructing appropriate learning paths, course sequencing and recommending appropriate learning objects in accordance with the learner’s characteristics is an effective form of adaptation in learning.

C. Adaptation Model

The adaptation model links the learner and the domain models by bridging the gap between learners and learning

material. An adaptation model is implemented by the application of a number of adaptive techniques.

Content adaptation is not sufficiently applied in AESs. This may indicate a difficulty in applying adaptive content techniques effectively. One reason could be the effort to author different content fragments for a specific learning concept, so the system can adapt by selecting the most appropriate fragment. This technique is known as content fragment generation and applied in TANGOW [46], [47] and WELSA [48] systems. It may be effective in some cases; however, constructing different versions of learning material is also time-consuming and less productive. Another reason is that learning content cannot be easily read or understood by machines. There is always a need for a human to explicitly organise material to meet adaptation rules. It is only the case when learning material is known beforehand. Other techniques related to adaptive content are fragment dimming and stretch-text/highlight. The former is usually applied to text when it is not relevant to learners as in AHA! [22] and WELSA [48] systems. The latter is a useful technique and can effectively draw learners' attention to important content if it is applied appropriately.

Zooming/scaling and layout changing techniques fall into the adaptive presentation category. They are not usually considered in AESs since their application in learning systems is not obvious. The relevance of these techniques depends on the situation. For visually-impaired learners specific learning objects may be zoomed into whereas for learners using tablets and small screen devices, layout changing may be appropriate. Adapting media format for learners constitutes another popular technique. Satisfaction with different media formats may depend on context and domain and requires careful measurement. Moreover, there should be a level of controllability on media formats.

Link sorting/ordering is useful for non-contextual links, namely those not fundamentally related to the current learning object [42]. Thus, link sorting may work with external links that lead to other information sources. It may not be appropriate to use this technique in contextual links as it conflicts with usability standards such as consistency. Some learners may prefer the order of links and menus to be stable and to appear as they first encountered them. Instead of applying the sorting technique, link annotation may be more suitable and could be applied without interference with usability standards to determine the current status of the concept link, such as whether it has been visited or not.

Another classic adaptive navigation technique is direct guidance. It is used in most AESs but has been superseded by new approaches such as curriculum sequencing and learning paths. This generates different learning paths for learners based on their preferences or knowledge level. Applied incorrectly, it may disrupt the learning process and disengage learners. The link hiding technique is related to adaptive navigation, and removes/hides irrelevant pages. It may be more useful if links are revealed gradually [42].

The process of adaptation should not be made in isolation; instead, data on other models should be available to inform the adaptation model. The main challenge is to determine which adaptive techniques are most effective in

e-learning in the different classifications (i.e. adaptive content, presentation and navigation), and when and how AESs can provide adaptation in different cases, particularly for those that integrate learning style.

Although, adaptive methods and techniques have been applied extensively, there is still a need for a reference model that can help in mapping learning content and instructional strategies into these techniques.

D. Research Issues

Although AESs may enhance learning and provide successful personalised services to learners, there are some barriers to optimal service provision. AES research seldom considers the usability challenges of adaptation. Jameson considers a number of usability threats to adaptivity including controllability, consistency, privacy, and predictability [54]. These challenges may outweigh the benefits of adaptivity in e-learning systems [30]. A possible research avenue is to compare AESs that afford learners some control over the adaptive behaviour with those that do not. This may assist in the identification of where adaptation should be applied [55].

Collaborative learning and social network technologies are other issues that are not targeted in AESs. Observing how learners with different learning styles interact with these systems can be a source of valuable information and provide better insight into designing AESs. This is particularly relevant if learning style is the main source of adaptation.

Learning analytics, a recent concept in education, defined as the measurement, collection, analysis and reporting of learner-system interaction and their contexts [56], can also contribute to the understanding of learners' needs and can optimise learning environments. It is applied, for instance, in Massive Open Online Courses (MOOCs) to investigate learner-course interaction.

The impact of context-aware technologies in e-learning is another promising research area. Understanding the context of learner-system interaction is an important factor in the provision of adaptation and recommendation in AESs.

V. CONCLUSION

This paper has presented a comparison of adaptive e-learning systems that incorporate learning style, in terms of three perspectives: learner model, domain model and adaptation model. A set of relevant criteria was introduced in order to provide an insight into the range of methods and techniques used in a representative set of AESs. This investigation has promoted a particular approach to AESs' comparative evaluation, and has raised a number of issues.

Learner models are usually concerned with the level of knowledge and the learning style. However, different combinations of learner attributes have not yet been fully investigated. For example, more research is required into combining learning style with motivation, ability or emotion. In this respect, a Bayesian network is a useful tool which has the potential for integrating different attributes.

Domain models are usually represented as a hierarchical network and offer some flexibility in the management of

knowledge. However, the relationships between learning concepts should be identified clearly to enhance these models. In addition, the adaptation process can be facilitated by the provision of learning content metadata that conforms to established e-learning standards. The absence of e-learning standards in most of the AESs, which were considered points to learning content with limited structure, and highlights potential reusability limitations.

A wider application of applying adaptive content techniques has suffered from the constraints of domain model representation and from a lack of understanding of learning material semantics. Furthermore, a reference model is required to support mapping content and instructional strategies into adaptive methods and techniques. This may provide a better approach to adaptivity in different learning contexts.

Usability issues and research areas such as collaborative learning, social networks and context-awareness can assist in the development of AESs. Learning analytics and data mining techniques are also generating more interest. The learner-system interaction in AESs, in particular, generates useful data, which can contribute to a better understanding of AESs and to the design of better learner models.

Future work will consider other perspectives such as instructional models and strategies, and will cover evaluation methodologies and the monitoring of AESs.

REFERENCES

- [1] J. D. Bransford, A. L. Brown, R. R. Cocking, and others, *How people learn*. National Academy Press Washington, DC, 2000.
- [2] M. G. Moore, "Editorial: Three types of interaction," *Am. J. Distance Educ.*, vol. 3, no. 2, pp. 1–7, 1989.
- [3] P. Brusilovsky, "Adaptive Hypermedia for Education and Training," *Adapt. Technol. Train. Educ.*, p. 46, 2012.
- [4] R. P. Bostrom, L. Olfman, and M. K. Sein, "The importance of learning style in end-user training," *Mis Q.*, pp. 101–119, 1990.
- [5] R. M. Felder and L. K. Silverman, "Learning and teaching styles in engineering education," *Eng. Educ.*, vol. 78, no. 7, pp. 674–681, 1988.
- [6] J. W. Keefe, "Learning style: An overview," *Student Learn. styles Diagnosing Prescr. programs*, pp. 1–17, 1979.
- [7] Y. Akbulut and C. S. Cardak, "Adaptive educational hypermedia accommodating learning styles: A content analysis of publications from 2000 to 2011," *Comput. Educ.*, vol. 58, no. 2, pp. 835–842, 2012.
- [8] F. Essalmi, L. J. Ben Ayed, M. Jemni, S. Graf, and others, "A fully personalization strategy of E-learning scenarios," *Comput. Human Behav.*, vol. 26, no. 4, pp. 581–591, 2010.
- [9] P. Brusilovsky and E. Millán, "User models for adaptive hypermedia and adaptive educational systems," *Adapt. web*, pp. 3–53, 2007.
- [10] E. J. Brown, T. J. Brailsford, T. Fisher, and A. Moore, "Evaluating learning style personalization in adaptive systems: Quantitative methods and approaches," *Learn. Technol. IEEE Trans.*, vol. 2, no. 1, pp. 10–22, 2009.
- [11] E. Knutov, P. De Bra, and M. Pechenizkiy, "AH 12 years later: a comprehensive survey of adaptive hypermedia methods and techniques," *New Rev. Hypermedia Multimed.*, vol. 15, no. 1, pp. 5–38, 2009.
- [12] D. Hauger and M. Köck, "State of the art of adaptivity in e-learning platforms," in *Workshop at Adaptivity and User Modeling in Interactive Systems ABIS 2007*, 2007.
- [13] E. Popescu, "Diagnosing students learning style in an educational hypermedia system," *Cogn. Emot. Process. Web-based Educ. Integr. Hum. Factors Pers. Adv. Web-Based Learn. B. Ser. IGI Glob.*, pp. 187–208, 2009.
- [14] D. A. Kolb, "Experiential learning: Experience as the source of learning and development," 1984.
- [15] P. Honey and A. Mumford, *Learning styles questionnaire*. Organization Design and Development, Incorporated, 1989.
- [16] R. Dunn and K. Dunn, "Learning style as a criterion for placement in alternative programs," *Phi Delta Kappan*, pp. 275–278, 1974.
- [17] H. Pashler, M. McDaniel, D. Rohrer, and R. Bjork, "Learning styles concepts and evidence," *Psychol. Sci. public Interes.*, vol. 9, no. 3, pp. 105–119, 2008.
- [18] P. Brusilovsky, "Methods and techniques of adaptive hypermedia," *User Model. User-adapt. Interact.*, vol. 6, no. 2, pp. 87–129, 1996.
- [19] P. Brusilovsky, "Adaptive hypermedia," *User Model. User-adapt. Interact.*, vol. 11, no. 1, pp. 87–110, 2001.
- [20] T. Murray, J. Piemonte, S. Khan, T. Shen, and C. Condit, "Evaluating the need for intelligence in an adaptive hypermedia system," in *Intelligent Tutoring Systems*, 2000, pp. 373–382.
- [21] K. A. Papanikolaou, M. Grigoriadou, H. Kornilakis, and G. D. Magoulas, "Personalizing the Interaction in a Web-based Educational Hypermedia System: the case of INSPIRE," *User Model. User-adapt. Interact.*, vol. 13, no. 3, pp. 213–267, 2003.
- [22] N. Stash, A. I. Cristea, and P. De Bra, "Adaptation to learning styles in e-learning: Approach evaluation," in T. Reeves and S. Yamashita (Eds.), *Proceedings of World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education*, 2006, pp. 284–291.
- [23] P. Brusilovsky, J. Eklund, and E. Schwarz, "Web-based education for all: a tool for development adaptive courseware," *Comput. Networks ISDN Syst.*, vol. 30, no. 1, pp. 291–300, 1998.
- [24] F. Mödritscher, V. M. Garcia Barrios, and C. Gütl, "Enhancement of SCORM to support adaptive E-Learning within the Scope of the Research Project AdeLE," in *World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education*, 2004, vol. 2004, no. 1, pp. 2499–2505.
- [25] M. Rey-López, P. Brusilovsky, M. Meccawy, R. P. Díaz-Redondo, A. Fernández-Vila, and H. Ashman, "Resolving the problem of intelligent learning content in learning management systems," *Int. J. E-Learning*, vol. 7, no. 3, pp. 363–381, 2008.
- [26] P. De Bra and L. Calvi, "AHA! An open adaptive hypermedia architecture," *New Rev. Hypermedia Multimed.*, vol. 4, no. 1, pp. 115–139, 1998.
- [27] D. Browne, D. and Norman, N., and Riches, *Why Build Adaptive Systems?*, In Browne., Academic Press, London, 1990, pp. 15–57.
- [28] K. Höök, "Steps to take before intelligent user interfaces become real," *Interact. Comput.*, vol. 12, no. 4, pp. 409–426, 2000.

- [29] D. A. Norman, "How might people interact with agents," *Commun. ACM*, vol. 37, no. 7, pp. 68–71, 1994.
- [30] T. Tsandilas and M. C. Schraefel, "Usable adaptive hypermedia systems," *New Rev. Hypermedia Multimed.*, vol. 10, no. 1, pp. 5–29, 2004.
- [31] J. A. Self, "Student models in computer-aided instruction," *Int. J. ManMachine Stud.*, vol. 6, pp. 261–276, 1974.
- [32] J. A. Self, "The defining characteristics of intelligent tutoring systems research: ITSs care, precisely," *Int. J. Artif. Intell. Educ.*, vol. 10, pp. 350–364, 1999.
- [33] S. Gauch, M. Speretta, A. Chandramouli, and A. Micarelli, "User profiles for personalized information access," *Adapt. web*, pp. 54–89, 2007.
- [34] D. Kelly and J. Teevan, "Implicit feedback for inferring user preference: a bibliography," in *ACM SIGIR Forum*, 2003, vol. 37, no. 2, pp. 18–28.
- [35] X. Amatriain, J. Pujol, and N. Oliver, "I like it... i like it not: Evaluating user ratings noise in recommender systems," *User Model. Adapt. Pers.*, pp. 247–258, 2009.
- [36] E. Agichtein, E. Brill, and S. Dumais, "Improving web search ranking by incorporating user behavior information," in *Proceedings of the 29th annual international ACM SIGIR conference on Research and development in information retrieval*, 2006, pp. 19–26.
- [37] K. Chrysafiadi and M. Virvou, "Student modeling approaches: A literature review for the last decade," *Expert Syst. Appl.*, vol. 40, no. 11, pp. 4715–4729, Sep. 2013.
- [38] M. Clark, Y. Kim, U. Kruschwitz, D. Song, D. Albakour, S. Dignum, U. C. Beresi, M. Fasli, and A. De Roeck, "Automatically structuring domain knowledge from text: An overview of current research," *Inf. Process. Manag.*, vol. 48, no. 3, pp. 552–568, 2012.
- [39] B. Brecht, G. McCalla, J. Greer, and M. Jones, "Planning the content of instruction," in *Proceedings of 4-th International Conference on AI and Education*, Amsterdam, 1989, pp. 24–26.
- [40] M. Weller, "Learning objects, learning design, and adoption through succession," *J. Comput. High. Educ.*, vol. 19, no. 1, pp. 26–47, 2007.
- [41] A. Bunt, G. Carenini, and C. Conati, "Adaptive content presentation for the web," *Adapt. web*, pp. 409–432, 2007.
- [42] P. Brusilovsky, "Adaptive navigation support," *Adapt. web*, pp. 263–290, 2007.
- [43] C.-I. Peña, J.-L. Marzo, and J.-L. de la Rosa, "Intelligent agents in a teaching and learning environment on the Web," in *Proceedings of the international conference on advanced learning technologies*, 2002, pp. 21–27.
- [44] C. I. de Carrillo and others, *Intelligent agents to improve adaptivity in a web-based learning environment*. Universitat de Girona, 2004.
- [45] C. Wolf, "iWeaver: towards' learning style'-based e-learning in computer science education," in *Proceedings of the fifth Australasian conference on Computing education-Volume 20*, 2003, pp. 273–279.
- [46] E. Alfonseca, R. M. Carro, E. Martín, A. Ortigosa, and P. Paredes, "The impact of learning styles on student grouping for collaborative learning: a case study," *User Model. User-adapt. Interact.*, vol. 16, no. 3, pp. 377–401, 2006.
- [47] P. Paredes and P. Rodriguez, "A mixed approach to modelling learning styles in adaptive educational hypermedia," *Adv. Technol. Learn.*, vol. 1, no. 4, pp. 210–215, 2004.
- [48] E. Popescu, C. Badica, and L. Moraret, "Accommodating learning styles in an adaptive educational system," *Inform.*, vol. 34, no. 4, pp. 451–462, 2010.
- [49] A. Klasnja-Milicevic, B. Vesin, M. Ivanovic, and Z. Budimac, "E-Learning personalization based on hybrid recommendation strategy and learning style identification," *Comput. Educ.*, vol. 56, no. 3, pp. 885–899, 2011.
- [50] S. Schiaffino, P. Garcia, and A. Amandi, "eTeacher: Providing personalized assistance to e-learning students," *Comput. Educ.*, vol. 51, no. 4, pp. 1744–1754, 2008.
- [51] E. El Bachari, E. H. Abelwahed, and M. El Adnani, "E-Learning Personalization Based on Dynamic Learners Preference," *Int. J. Comput. Sci. Inf. Technol.*, vol. 3, no. 3, 2011.
- [52] R. Dunn and S. Griggs, "Synthesis of the Dunn and Dunn learning styles model research: who, what, when, where and so what the Dunn and Dunn learning styles model and its theoretical cornerstone," *St. Johns Univ. New York*, 2003.
- [53] I. B. Myers, M. H. McCaulley, and R. Most, *Manual: A guide to the development and use of the Myers-Briggs Type Indicator*. Consulting Psychologists Press Palo Alto, CA, 1985.
- [54] A. Jameson, "Adaptive interfaces and agents," *Human-Computer Interact. Des. Issues, Solut. Appl.*, p. 105, 2009.
- [55] H. Ashman, T. Brailsford, and P. Brusilovsky, "Personal services: Debating the wisdom of personalisation," in *Advances in Web Based Learning-ICWL 2009*, Springer, 2009, pp. 1–11.
- [56] G. Siemens and P. Long, "Penetrating the fog: Analytics in learning and education," *Educ. Rev.*, vol. 46, no. 5, pp. 30–32, 2011.
- [57] M. Leontidis and C. Halatsis, "Affective Issues in Adaptive Educational Environments," *A chapter Cogn. Emot. Process. Web-Based Educ. Integr. Hum. Factors Pers. Mourlas, C., Tsianos, N., Ger. P.(Eds.), IGI Glob. Hershey, USA*, pp. 111–133, 2009.
- [58] B. L. Martin and L. J. Briggs, *The affective and cognitive domains: Integration for instruction and research*. Educational Technology, 1986.
- [59] K. O'Regan, "Emotion and e-learning," *J. Asynchronous Learn. networks*, vol. 7, no. 3, pp. 78–92, 2003.
- [60] C. Ullrich, "The learning-resource-type is dead, long live the learning-resource-type," *Learn. Objects Learn. Des.*, vol. 1, no. 1, pp. 7–15, 2005.