# Personalised trails and learner profiling within e-Learning environments

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# TRAILS

The World-Wide-Web has had a major impact on enabling large, diverse and geographically distributed communities of learners to access Technology Enhanced Learning. Systems combining technological learning tools with personalisation that caters for individual styles and learning preferences have the potential to radically alter the landscape of learning.

A recent development has been in the use of learning objects (LOs) – cohesive pieces of learning material that are usually stored in a repository, allowing teachers and learners to search for LOs of interest to them. Learners engage with LOs in the form of trails – time-ordered sequences of LOs.

Examples of LO trails are:

(i) a school-child navigating through course materials,
(ii) a learner navigating through the literature on a subject, or
(iii) a visitor navigating through a museum.

By following and creating trails, the learner navigates through a space of LOs creating a personal trail that can be evaluated and accessed in a structured manner. These directly observable LO trails are related to learners' non-observable cognitive trails.

Trails are the subject of the *Personalised and Collaborative Trails of Digital and Non-Digital Learning Objects* project (TRAILS for short). TRAILS is a one-year Jointly Executed Integrating Research Project within the Kaleidoscope Network of Excellence, an IST project funded under EU FP6. At the core of the programme is the view that trails can provide structure to learners' information space and thus can assist them in achieving their objectives. TRAILS brings together experts from computer, social and cognitive sciences in order to:

- generate a framework for describing, classifying and understanding trails of LOs;
- study the pedagogical and cognitive aspects of personalised trails;
- investigate the types of individual need (personalised, individualised, collaborative, context dependent and content dependent) which learners have in terms of trails;
- evaluate and assess methods, which cater for learner needs;
- produce a schema for representing these learner needs in a specific user profile;
- produce a schema for integrating learner needs with appropriate LO metadata;
- design a system for mapping the patterns of trails created by learners and for producing a training needs analysis for targeting future learner experiences;
- investigate different types of LOs and how they may form trails;
- specify the requirements which trail-support places on e-Learning systems;
- work towards a standard for LOs in trails which is compatible with current standards.

# Executive Summary

This is the first deliverable of Workpackage 4 of the TRAILS project. The objectives of Workpackage 4 are as follows:

- To study what support is needed for individuals and groups of learners within an e-learning system.
- To study what profiling information is needed for personalisation within an e-learning system.
- To investigate how personalised and collaborative trails emerge in an e-learning system.
- To investigate how personalisation and collaborative filtering technology can assist in mining and presenting such trails.

This deliverable focuses on the aspects of these objectives that are related to personalisation and personalised trails. We first introduce and define the concepts of personalisation and personalised trails (Section 1). Personalisation requires that a user profile be stored, and so we assess currently available standard profile schemas and discuss the requirements for a profile to support personalised learning (Section 2). We then review techniques for providing personalisation and some systems that implement these techniques, and discuss some of the issues around evaluating personalisation systems (Section 3), and look especially at the use of learning and cognitive styles to support personalised learning (Section 4). We then look at personalisation in the field of mobile learning, which has a different take on the subject (Section 5), and in commercially available systems, where personalisation support is found to currently be only at quite a low level (Section 6). We conclude with a summary of the lessons to be learned from our review of personalisation and personalised trails.

The first objective above is addressed throughout the deliverable, as the main concepts behind personalisation are introduced and the different ways in which it can support learners explored. The second objective is covered by Section 2, which looks in detail at schemas for learner profiling. The third and fourth objectives are also tackled throughout the document, with different approaches to the issues of how personalised trails are produced and the benefits of each approach being discussed by different sections.

# 1 Introduction – personal trails, personalisation and personalised trails

This is the first deliverable in Workpackage 4 of the TRAILS project. Workpackage 4 is about personalised and collaborative trails of learning objects (LOs), and this deliverable focuses on the former: personalised trails.

There has been much talk from all quarters recently of "personalised learning", and the phrase seems to mean many different things to different people. It is therefore important for us to explain exactly what we mean by the term "personalisation" in the context of this Workpackage and this deliverable.

*Personal trails* are trails that have been followed by an individual learner through some learning environment. In terms of our taxonomy of trails from D22.2.1 (Schoonenboom *et al.*, 2004a) they are *emergent LO trails*, as they emerge from the behaviour of an individual learner. For this reason they could be also be called *individual trails*. Personal learning trails manifest themselves in many ways – they can be short-term or long-term, and will vary greatly in the granularity of the events considered as single nodes along the trail. So, for example, one personal learning trail might be the list of LOs visited during an hour-long session working in an on-line e-learning environment, and another could be the list of qualifications gained between the ages of 15 and 25 on a *curriculum vitae*.

The recording of personal trails can be a useful activity for learners – it allows reflection on what has been done, and perhaps the opportunity to re-visit sections of the trail that has been followed so far. Indeed, the "history" of web page accesses stored in a web browser is designed specifically to allow users to easily locate and revisit things they have already seen. The learner portfolio – a collection of representative pieces of work from over a period of time – is an important kind of personal trail. At present, portfolios of work are usually kept as "evidence" for some sort of assessment activity or to demonstrate to third parties (i.e. someone who is not the learner or instructor) that they have acquired skill at some competency, but the role of the portfolio can easily be modified or augmented to also act as a focus for reflection by the learner on what they have done. Techniques for visualisation of personal trails, such as those reported in D22.2.2 (Schoonenboom *et al.*, 2004b), can further serve to foster reflection in learners.

Personal trails of this sort are not the direct focus of this deliverable, but are important to personalised trails in two main respects:

1. A personal trail emerges when a learner follows a personalised trail.
2. Personal trails, such as a recent history of accesses to LOs or a portfolio of work, can form an important part of the learner profiles needed to create personalised trails.

When we talk about *personalisation*, we mean a process whereby machines (computer systems, learning environments, etc.) automatically adapt their behaviour to cater for the needs or preferences of different individuals. At the simplest level this takes the form of customisation – users can adjust various system settings stored in a profile and the system will reflect the changes. Examples of customisation are things like setting the desired font size in a web browser, a website that "remembers" if the user prefers a yellow or blue background to the pages, and being able to set a picture as the background on a PC's "desktop". All of these systems remember a user's preferences and adjust their behaviour accordingly, yet we would hesitate to call this real personalisation – customisation is just remembering some user settings for a predictable behaviour.

Real personalisation begins to happen when the system uses the information it has about the user to anticipate their needs and provide them with something that they want or need. In this case it is not just remembering a setting for something that the user knows about (which font size, colour, picture, etc.), but actually adapting new behaviour to what the user is most likely to want. Much work on personalisation has been focussed on hypertextual environments, such as the web. Web personalisation is any action (by a web server) that tailors the Web experience to a particular user, or set of users. For example, a news site that suggests new stories that returning visitors may be interested in, a share trading site that automatically shows stock prices that the user may be interested in and a search site that returns results biased towards the user's interests all provide real personalisation of some sort.

Within the systems that provide this sort of personalisation there is a further distinction to be made between (1) systems that base their personalisation functionality on a static profile of data submitted explicitly by the user, and (2) systems that base their personalisation on a profile that automatically adapts over time to take account of user behaviour. This second class of personalisation systems are truly adaptive, as the system learns about the user and what the user needs automatically and adapts accordingly. In systems based on a static profile the user will need to prevent their profile from going "stale" by regularly updating the information stored by the system if the personalisation is to remain relevant to their current preferences. It is the second class of personalisation systems that, as we said in (2) above, may record personal trails to inform the personalisation they perform – for example, a personalised news website may record a history of the stories read by each user (i.e. the users' personal news trails), and base future recommendations on this.

We are now in a position to say what we mean by *personalised (learning) trails*. Personalised trails are sequences of LOs that a system suggests to individual learners (or groups of learners) based on what it knows about each particular learner's (or group's) preferences. Possible personalised trails could be of widely differing lengths and durations. At one end of the spectrum a web-based learning system could suggest just one page at a time (i.e. the "next best page" for each individual) to learners as they navigate through the learning environment. Such a system would be similar to web page recommender systems such as Letizia (Lieberman, 1995) and WebWatcher (Joachims *et al.*, 1997). Somewhere in the middle of the scale, a personalised learning programme for a degree module could be suggested to a learner, making sure that all the necessary prerequisite background courses are taken. At a higher level again, a personalised trail through university, postgraduate and professional qualifications could be suggested to a school leaver whose ambition is to become a lawyer.

Systems that suggest personalised trails in this way are truly in their infancy still, and no systems have yet been developed that can provide the kind of personalised trails described above. Hence in this deliverable we will consider the technologies that could form the basis of components of a personalised trails system, and the systems that have begun to implement elements of the functionality required to create personalised trails.

The rest of the deliverable is structured as follows: All personalisation systems need to store some form of profile about the user, so Section 2 looks at current standards for learner profiles and considers which elements will be necessary for personalised learning. Section 3 briefly reviews some of the techniques used for personalisation, looks at the current state-of-the-art in adaptive learning systems and considers some of the difficulties in reliably evaluating systems providing personalisation. Section 4 looks at the use of learning and cognitive styles as the basis for personalisation, and reviews three systems that have taken this approach to personalised learning. Section 5 considers personalisation in mobile learning, where it is conceived somewhat differently from our description of personalisation in this introduction. The state-of-the-art in personalisation provision in the commercial sector is the focus of Section 6, and in Section 7 we conclude with some observations about the issues surrounding personalisation and personalised trails.

# 2 Learner profiling for personalisation

All systems providing personalisation will need to store information about the users in a profile. What information needs to be stored in the profile will depend on the exact functionality of the system – different kinds of personalisation will require different information about the user. The data most useful for personalising the learner's experience will include, for instance, preferred learning styles, current levels of attainment, learning goals, wider interests, locality, languages and learning history. Much of this information will be common across most systems and several "standard" user profile schemas have been developed to aid interoperability between systems and to reduce duplication of data in multiple profiles where possible.

Personalisation is not the only (and usually not even the main) reason for storing a user profile, and the standard schemas mostly focus on the storage and transfer of data to aid the administration of educational institutions (for example, learners moving between institutions, exam entry and internal monitoring processes) rather than targeting data that may be useful for providing personalised access to learning content. This means that some of the important data for personalisation mentioned above is not included in the proposed standards.

As yet none of the proposed schemas seems to have really taken off as the *de facto* industry standard, possibly because each of the specifications has its drawbacks, and none is generally sufficient on its own. Recently, however, IMS's Learner Information Package seems to have been gaining more widespread acceptance.

In the remainder of this section we review some of the current standards and specifications for recording and storing personal information, and consider their suitability for use as the basis of a user model (i.e. learner profile) in systems providing personalisation. The list is by no means exhaustive, but is representative of the range of available specifications.

## 2.1 vCard

The Internet Mail Consortium maintains the vCard format[1]. The vCard schema covers the basics of personal (and business) information by holding the information usually found on a business card. It lacks any information useful for personalisation, but is a standards-based specification that can be (and is) used as the basis for more involved user and learner profiles.

[1] http://www.imc.org/

## 2.2 eduPerson

US universities use the eduPerson (UCAID, 2002) scheme to transfer information about people involved in higher education (both staff and students). It holds some additional attributes to those included in vCard (such as affiliation, entitlement, preferred language), but is really an administrative tool and does not hold much that is useful for personalisation.

## 2.3 Educational Modelling Languages (EMLs)

The CEN's Information Society Standardization System (CEN/ISSS) survey of EMLs defines an EML as "*a semantic information model and binding, describing the content and process within a 'unit of learning' from a pedagogical perspective in order to support reuse and interoperability*" (Rawlings *et al.*, 2002). Six languages are reviewed – all have XML bindings, and some (3 out of the 6) also have SGML bindings. All of the proposals mainly concentrate on the description of learning material rather than on the people involved in the learning process, although an EML should allow the modelling of both.

OUNL-EML (Open University of the Netherlands) and PALO (Rodríguez-Artacho, 2002) also model people; People are modelled in terms of the roles they play (what activities they participate in), for workflow modelling. This kind of user modelling may be of some use in creating personalised trails, although additional information such as current learner goals, experience and preferences (which are not covered by workflow modelling) are also desirable in a user model.

OUNL-EML can "*describe personalisation aspects within units of learning, so that the content and activities within units of learning can be adapted based on the preferences, prior knowledge, educational needs and situational circumstances of users*" (Rawlings *et al.*, 2002). These personalisation aspects could include personalised trails that have been authored into the learning material. It also includes a "personal dossier" for individual students, which records assessment, grading and "time-spent on assignment" information. Such personal portfolios can be used as a personal trail record for reflection and assessment, as discussed further in Trails Deliverable 2.2 (Schoonenboom *et al.*, 2004b).

## 2.4 IEEE Public and Private Information – Learner specification (PAPI-LEARNER)

PAPI-Learner is a proposed standard from the IEEE, still in draft version although not modified since 2002 (IEEE LTSC, 2002). It specifies both the syntax and semantics of a learner model that can be used to characterise a teacher or learner. It identifies six types of profile information, each of which has separate security and administration. They are identified by their initial letter:

**N**ame – personal information primarily used for administration

(e.g., name, address, social security number)

**R**elations – learner's relationships with other users of the system

(e.g., cohorts, classmates)

**S**ecurity – security information

(e.g., public and private keys, credentials)

**M**y Configuration – preferences to improve human-computer interaction

(e.g., useful and unusable I/O devices, learning styles, physical limitations)

**G**rades – performance information

(e.g., grades, reports, log books)

**W**orks – portfolio information as an illustration of abilities and achievements

(e.g., accomplishments, works)

The standard profile data can be extended with additional information to give "conforming" data, although it will not be "strictly conforming".

## 2.5 IMS Learner Information Package (IMS-LIP)

IMS-LIP was developed to enable interoperability of IMS-compliant servers, although it beginning to gain wider acceptance as a standard for many educational systems (IMS, 2001). Earlier in 2004 it was chosen as the basis for the CEN/ISSS "Guidelines for the production of learner information standards and specifications" (CEN, 2004), effectively making it the basis of a European standard for the transfer of learner information. The purpose of this standard is to facilitate learners in presenting their credentials and achievements at both a national and European level, but a profile based on the standard could also be used as a basis for the provision of personalisation.

The IMS-LIP data model describes the characteristics of a learner needed to aid "recording and managing learning-related history, goals, and accomplishments; engaging a learner in a learning experience; discovering learning opportunities for learners" (IMS, 2001).

## 2.6 A schema for representing learner needs?

IMS-LIP and PAPI are the main profile specifications that include the detailed information most useful for personalisation – learner history, current activities and goals. However, they provide only a syntactic framework for storing such information within their data structures, by providing a placeholder for free-text descriptions. The machine-processability of these parts of the profile is thus limited – these sections of the profiles are designed to be read by people rather than machines. Without any formal or standard way to express learner goals, learning outcomes and learning objectives any machine “understanding” for matching will need to be based on the matching of similarities between unstructured blocks of text.

The syntactic structure provided by specifications such as IMS-LIP and PAPI can be taken advantage of to aid machine interoperability if the fields for free-text entries are populated not with completely free text, but instead populated using structured vocabularies designed to express the relevant information (i.e. learner’s competencies, goals and preferences). The use of Semantic Web technologies such as the Resource Description Framework (RDF) or Web Ontology Language (OWL) (W3C, 2004a,b) is one possible way to define such structured vocabularies. The use of RDF to encode the whole profile data (and not just the free-text sections) gives the additional advantage of being able to pick elements from multiple schemas while remaining interoperable with other (RDF-aware) systems (Dolog and Nejdl, 2003; Keenoy *et al.*, 2003): rather than needing to invent another data model for learner profiling for personalisation, the demographic and other common data catered for in existing schemes (such as IMS-LIP and PAPI) can be represented using the relevant elements from the existing schemes, and this can be enriched with extra elements where necessary (e.g., for recording competencies, goals and learning styles to aid personalisation – these are the areas that are generally lacking in existing proposals). This approach (i.e. selecting the required fields from multiple profiling schemes) helps to avoid the problem of a new proprietary profile format for each new system developed – each particular system will need a slightly different set of user data depending on the personalisation technique employed, but all can use RDF to pick-and-choose the required elements rather than design a new profile specification.

Different personalisation systems employing different personalisation algorithms will require different types of personal information to be stored in the user profile in order to perform properly. We therefore, following Keenoy *et al.* (2003), would say that rather than recommending a particular specific schema that should be used for all user profiling, the best approach may be for each system to create the schema it needs to provide its functionality, using a technology such as RDF to choose elements from existing schemas (i.e. from namespaces that already exist) where possible, and making public in a new namespace any additional schema elements found to be necessary. This is the approach taken by the SeLeNe project, which used elements of IMS-LIP, PAPI and IMS-RCD, and created a public namespace for the additional profile elements required for the SeLeNe system at `http://www.dcs.bbk.ac.uk/~kevin/selene/rdf/learner`. Such an approach should make learner profiles as interoperable between different systems as possible, while not constraining the possibilities for individual systems.

## 2.7 Standard representation of trails

We have seen that in order to be able to provide personalised trails to learners, a system must use a learner model of some form. It must also have some representation for the possible trails. There is currently no standard for the representation of trails of LOs, and this lack of a standard presents an opportunity for the development of a framework for the specification of trails. IMS Learning Design (IMS, 2003) does allow the modelling of trails within a learning environment, as shown by Schoonenboom *et al.* (2004a), but the representation is not simple nor is it suitably generalisable to be used for the full range of types of user trail we would like to represent, such as learner histories. Keenoy *et al.* (2003) suggest a simple RDF model for trails that allows the specification of a sequence of resources, the type of trail (emergent, authored or derived), a name for the trail and some additional annotation. One approach would be to use the taxonomy of trails developed by Schoonenboom *et al.* (2004a) to extend the range of possible types of trail allowed in this schema (i.e. by defining further subclasses of Keenoy *et al.*'s 'TRAIL' element), to produce a more generalised RDF model. Another possibility is to use the metadata schema proposed by Schoonenboom *et al.* (2004b) as the basis of a standard representation of trails. However, we feel that any specification towards a standardisation effort should grow out of practice rather than theorising. In the field of e-learning standards it seems there has often been too much theorising and not enough practice, resulting in standards and specifications that are not usable "off the shelf" and that no one is really happy with. In practice either of the possibilities for trail representation described above is likely to need further refinement based on experience before being suitable for a standard. For this reason we suggest that there should be more practice in modelling and using learner trails before any effort to settle on a "standard" representation.

# 3 Adaptive instructional systems for personalised learning

## 3.1 Techniques for personalisation

We have seen that providing personalisation requires a user profile to be stored. Whatever the schema for the profile looks like, the system must obtain data about the user to populate the profile before any personalisation can be done. There are two possibilities for how the necessary data can be collected:

1. *Explicit* collection of the data: users' preferences are found explicitly, by asking them to submit the necessary information manually before any personalisation can be provided. The data collection process could be as simple as ticking boxes to show which LOs or web pages are relevant to them, or as detailed as the completion of long forms with personal information, and descriptions of interests and goals. Explicitly entered profile information is considered to be "high quality", but users generally dislike having to spend time and effort submitting data to a system, especially when the benefits may not be immediately obvious. This can make the explicit collection of sufficient profile data difficult.
2. *Implicit* collection of the data: users' preferences are inferred from their normal interactions with the system. The interactions monitored (either by the personalisation application or at a system level) could be things such as visiting a web page (and the time spent viewing it), following a hyperlink, scrolling down a page and bookmarking, saving or printing a page. The advantage of collecting profile data this way is that the user is relieved of the burden of having to supply and keep up-to-date the necessary information, but implicit measures of interest are generally thought to be "lower quality" than explicitly gathered preferences (Nichols, 1997).

Implicit and explicit data collection methods can of course be used in conjunction with one another to populate a user profile. In this case the user can supply as much or as little high quality information to the system explicitly as they like, and this can be augmented with information inferred from the user's interactions with the system with no further user effort.

We said in the introduction that much of the work done on personalisation has been focussed on web personalisation – personalising web pages or recommending web content based on the user's preferences. The techniques that have been developed used to achieve this generally fall into one of two categories: (1) content-based personalisation and (2) collaborative filtering (Mobasher *et al.*, 2000; Nichols, 1997).

Content-based systems personalise based on features of the content they manage – for example, search results might be personalised by ranking highly those pages where term frequency analysis of the keywords in the result page matches similar analysis of keywords in the user profile that reflect the user's interests, or news stories may be recommended to a user when they are on a topic that the user has previously expressed an interest in. Recommendations are based on a profile built up from analysis of the content of items that the user has rated in the past and/or the user's personal information and preferences. Pure content-based filtering systems have several shortcomings and some critical issues remain to be solved, including that only a shallow analysis of some specific kinds of content (mainly text documents) are available and that users can only receive recommendations similar to their earlier experiences, and the sparseness problem of item rating information (Kwak and Cho, 2001; Lee *et al.*, 2001).

Collaborative filtering techniques, on the other hand, take no account of the content managed by the system, but instead personalise based on system usage, specifically the behaviour of other similar users of the system – for example, search results might be personalised by ranking highly those pages that have been rated highly by users similar to the current user who viewed those pages in the past. For some more on collaborative filtering-based personalisation see TRAILS deliverable 4.2 (Keenoy *et al.*, 2004).

Personalisation systems are often recommendation systems of one sort or another – they recommend something (web pages, news stories, LOs, or some other content) to users based on their personal profile. Another approach to personalisation is to adapt the presentation of information to the individual user, thus personalising a generic information space without necessarily recommending items. The provision of personalised trails can encompass either or both of these approaches to personalisation:

- A personalised trail could be recommended to the user from a set of possible trails, as in a recommender system;
- A set of items (for example, a set of search results or a set of LOs selected by the user) could be organised into a personalised trail, as in an adaptive presentation system;
- A trail of recommended LOs can be organised into a personalised trail and presented to the user, in which case it the process has both recommendation and adaptive presentation aspects.

The following subsections concentrate on the application of such techniques to provide personalised learning in e-learning systems. We discuss the most widely implemented approaches to the development of adaptive e-learning systems – intelligent tutoring systems and adaptive hypertext systems. The source for much of the information in these sections is Jonassen (2004).

## 3.2 Intelligent tutoring systems

Intelligent tutoring systems (ITSs) are adaptive instructional systems developed with the application of Artificial Intelligence (AI) methods and techniques. ITSs are developed to resemble what actually occurs when student and teacher sit down one-on-one and attempt to teach and learn together. As in any other instructional systems, ITSs have components representing the content to be taught; inherent teaching or instructional strategy, and mechanisms for understanding what the student does and does not know. In ITSs, these components are referred to as the problem-solving or expertise module, student-modelling module, and tutoring module. The expertise module evaluates the student's performance and generates instructional content during the instructional process. The student-modelling module assesses the student's current knowledge state and makes hypotheses about his or her conceptions and reasoning strategies employed to achieve the current state of knowledge. The tutorial module usually consists of a set of specifications for the selection of instructional materials the system should present and how and when they should be presented. AI methods for the representation of knowledge (e.g., production rules, semantic networks, and scripts frames) make it possible for the ITS to generate the knowledge to present to the student based on his or her performance on the task, rather than selecting the presentation according to predetermined branching rules. Methods and techniques for natural language dialogues allow much more flexible interactions between the system and the student. The function for making inferences about the cause of the student's misconceptions and learning needs allows the ITS to make qualitative decisions about the learning diagnosis and instructional prescription, unlike the microadaptive model, in which the decision is based entirely on quantitative data. Furthermore, ITS techniques provide a powerful tool for effectively capturing human learning and teaching processes. It has apparently contributed to a better understanding of cognitive processes involved in learning specific skills and knowledge. Some ITSs have not only demonstrated their effects for teaching specific domain contents but also provided research environments for investigating specific instructional strategies and tools for modelling human tutors and simulating human learning and cognition (Ritter and Koedinger, 1996).

Theoretical issues about how to learn and teach with emerging technology, including AI, remain the most challenging problems.

## 3.3 Adaptive hypermedia and adaptive web-based instruction

In the early 1990s, adaptive hypermedia systems inspired by ITSs were born (Brusilovsky, Schwarz, and Weber, 1996). They fostered a new area of research combining adaptive instructional systems and hypermedia-based systems. Hypermedia-based systems allow learners to make their own path in learning. However, conventional hypermedia learning environments are a non-adaptive learning medium, independent from the individual user's responses or actions. They provide the same page content and the same set of links to all learners (Brusilovsky, 2000, 2001; Brusilovsky and Pesin, 1998). These kinds of traditional hypermedia systems have been described as "user-neutral" because they do not consider the characteristics of the individual user (Brusilovsky and Vassileva, 1996). Researchers tried to build adaptive and user model-based interfaces into hypermedia systems and thus developed adaptive hypermedia systems. The goal of adaptive hypermedia is to improve the usability of hypermedia through the automatic adaptation of hypermedia applications to individual users. For example, a student in an adaptive educational hypermedia system is given a presentation that is adapted specifically to his or her knowledge of the subject and a suggested set of the most relevant links to pursue (Brusilovsky, Eklund, and Schwarz, 1998) rather than all users receiving the same information and same set of links. An adaptive electronic encyclopaedia can trace user knowledge about different areas and provide personalised content. A virtual museum provides adaptive guided tours in the hyperspace. Adaptive hypermedia or adaptive Web-based systems have been employed for educational systems, e-commerce applications such as adaptive performance support systems, on-line information systems such as electronic encyclopaedias and information kiosks, and on-line help systems. Since 1996, the field of adaptive hypermedia has grown rapidly (Brusilovsky, 2001), due in large part to the advent and rapid growth of the Web. The Web had a clear demand for adaptivity due to the great variety of users and served as a strong booster for this research area (Brusilovsky, 2000).

Because of its popularity and accessibility, the Web has become the choice of most adaptive educational hypermedia systems since 1996. Lieberman's (1995) Letizia is one example of the earliest adaptive Web-based systems. Letizia is the system that assists users in web browsing by recommending links based on their previous browsing behaviours. Other early examples are ELM-ART (Brusilovsky, Schwarz, and Weber, 1996), InterBook (Brusilovsky, Eklund, and Schwarz, 1998), PT (Kay and Kummerfeld, 1994), and 2L670 (De Bra, 1996). These early systems have influenced more recent systems such as Medtec (Eliot, Neiman, and Lamar, 1997), AST (Specht, Weber, Heitmeyer, and Schöch, 1997), ADI (Schöch, Specht, and Weber, 1998), HysM (Kayama and Okamoto 1998), AHM (Pilar da Silva, Durm, Duval, and Olivié, 1998), MetaLinks (Murray, Condit, and Haugsjaa, 1998), CHEOPS (Negro, Scarano and Simari, 1998), RATH (Hockemeyer, Held, and Albert, 1998), TANGOW (Carro, Pulido, and Rodríguez, 1999), Arthur (Gilbert and Han, 1999), CAMELEON (Laroussi and Benahmed, 1998), KBS-Hyperbook (Henze, Naceur, Nejdl, and Wolpers 1999), AHA! (De Bra and Calvi, 1998), SKILL (Neumann and Zirvas, 1998), Multibook (Steinacker, Seeberg, Rechenberger, Fischer, and Steinmetz, 1998), ACE (Specht and Oppermann, 1998), and ADAPTS (Brusilovsky and Cooper, 2002).

### *Definition and adaptation methods*

Adaptive hypermedia systems can be defined as "all hypertext and hypermedia systems which reflect some features of the user in the user model and apply this model to adapt various visible and functional aspects of the system to the user". *Functional aspects* mean those components of a system that may not visibly change in an adaptive system. For example, the "next" button will not change in appearance but it will take different users to different pages (Schwarz, Brusilovsky, and Weber, 1996). An adaptive hypermedia system should (a) be based on hypertext link principles, (b) have a domain model, and (c) be capable of modifying some visible or functional part of the system on the basis of information contained in the user model.

Adaptive hypermedia methods apply mainly to two distinctive areas of adaptation: (1) adaptation of the content of the page, which is called content-level adaptation or adaptive presentation; and (2) the behaviour of the links, which is called link-level adaptation or adaptive navigation support. The goal of adaptive presentation is to adapt the content of a hypermedia page to the learner's goals, knowledge, and other information stored in the user model. The techniques of adaptive presentation are (a) connecting new content to the existing knowledge of the students by providing comparative explanation and (b) presenting different variants for different levels of learners. The goal of adaptive navigation support is to help learners find their optimal paths in hyperspace by adapting the link presentation and functionality to the goals, knowledge, and other characteristics of individual learners. It is influenced by research on curriculum sequencing, which is one of the oldest methods for adaptive instruction (Brusilovsky, 2000; Brusilovsky and Pesin, 1998). Direct guidance, adaptive sorting, adaptive annotation, and link hiding, disabling, and removal are ways to provide adaptive links to individual learners. ELM-ART is an example of direct guidance. It generates an additional dynamic link (called "next") connected to the next most relevant node to visit. However, a problem with direct guidance is the lack of user control. An example of the link-hiding technique is HYPERTUTOR. If a page is considered irrelevant because it is not related to the user's current goal or presents material that the user is not yet prepared to understand, the system restricts the navigation space by hiding links. The advantage of hiding links is to protect users from the complexity of the unrestricted hyperspace and reduce their cognitive load in navigation.

Adaptive annotation technology adds links with a comment that provides information about the current state of the nodes. The goal of the annotation is to provide orientation and guidance. Annotation of links can be provided in textural form or in the form of visual cues, for example, using different icons, colours, font sizes, or fonts. Also, this user-dependent adaptive hypermedia system provides different users with different annotations. The method has been shown to be especially efficient in hypermedia-based adaptive instruction. InterBook, ELM-ART, and AHM are examples of adaptive hypermedia systems applying the annotation technique. To provide links, annotation systems measure the user's knowledge in three main ways: (a) according to where the user has been (history based); (b) according to where the user has been and how those places are related (prerequisite based); and (c) according to a measure of what the user has shown to have understood (knowledge based) (Eklund and Sinclair, 2000). Brusilovsky (2000) stated that "adaptive navigation support is an interface that can integrate the power of machine and human intelligence: a user is free to make a choice while still seeing an opinion of an intelligent system". In other words, adaptive navigational support has the ability to decide what to present to the user, and at the same time, the user has choices to make.

### *User modelling in adaptive hypermedia systems*

As in all adaptive systems, the user's goals or tasks, knowledge, background, and preferences are modelled and used for making adaptation decisions by adaptive hypermedia systems. In addition, more recently the user's interests and individual traits have been studied in adaptive hypermedia systems. With the developed Web information retrieval technology, it became feasible to trace the user's long-term interests as well as the user's short-term search goal.

The user's individual traits include personality, cognitive factors, and learning styles, as discussed in Section 2. Like the user's background, individual traits are stable features of a user. However, unlike the user's background, individual traits are not easy to extract. Researchers agree on the importance of modelling and using individual traits but disagree about which user characteristics can and should be used (Brusilovsky, 2001).

### *Limitations of adaptive hypermedia systems*

We have found little empirical evidence for the effectiveness of adaptive hypermedia systems. Specht and Oppermann's study (1998) showed that neither link annotations nor incremental linkages in adaptive hypermedia system have significant separate effects. However, the composite of adaptive link annotations and incremental linking was found to produce superior student performance compared with to that of students receiving no annotations and static linking. The study also found that students with a good working knowledge of the domain to be learned performed best in the annotation group, whereas those with less knowledge appeared to prefer more direct guidance. Brusilovsky and Eklund (1998) found that adaptive link annotation was useful to the acquisition of knowledge for users who chose to follow the navigational advice. However, in a subsequent study (Eklund and Sinclair, 2000), link annotation was not found to influence user performance on the subject. The authors concluded that the adaptive component was a very small part of the interface and insignificant in a practical sense. Also, De Bra (2000) points out that if prerequisite relationships in adaptive hypermedia systems are omitted by the user or just wrong, the user may be guided to pages that are not relevant or that the user cannot understand. Bad guidance is worse than no guidance. Evaluating the learner's state of knowledge is the most critical factor for the successful implementation of an adaptive system.

## 3.4 A note on the evaluation of personalisation systems

Systems providing personalisation pose some unique problems when it comes to evaluating their effectiveness. It is very difficult to precisely define their desired behaviour, as the "best" behaviour will be different for different users, and even different for the same user at different times. Moreover, the behaviour of the system will depend on the quality of the user profile information that has been provided to the system – if the system is provided with too little or incorrect information about the user then it cannot be expected to behave in a way that is "best" for the user.

These factors generally make it very difficult to set up artificial experiments to measure the performance and effectiveness of an adaptive system. For meaningful evaluation an adaptive system must be used by real users with real goals and preferences. Success can then be judged in a number of ways: user satisfaction with the system and its recommendations will be the primary success criteria, and this can be measured using questionnaires completed by users. For e-learning systems a further success criteria will be how well the material taught by the system has been learned, as revealed by tests and assessments of the learner's knowledge after using the system (these could be formal or informal assessments). In this case some non-adaptive "control" system would also need to be used, to enable the measurement of the "value added" by the adaptation. Detailed observation of user behaviour in a controlled experiment, such as how long it takes to complete a particular task with and without the system's adaptation, can also be used, but careful attention must be paid to factors such as profile quality and user familiarity with differing system interfaces.

An invaluable resource that has recently appeared on the web is the Evaluation of Adaptive Systems Hub (EASY-hub)[2]. It provides a detailed review of the literature on the evaluation of adaptive systems, along with links to assessment tools (such as questionnaires), tutorials and guidelines for assessing adaptive systems.

[2] http://www.easy-hub.org/

In this section we have seen a range of techniques used in adaptive e-learning systems to provide personalised learning for the users. The next section focuses on the use of one particular element of the user model – the user's learning or cognitive styles – to provide adaptive support.

# 4 Using cognitive learning styles for personalised e-learning

As we have seen, with the wider introduction of e-learning systems (including virtual learning environments, adaptive hypermedia systems and intelligent tutoring systems), there has been a broad interest in finding and developing methods for personalising educational content for learners. One method for achieving this personalised content is the use of learner modelling. In particular cognitive learning styles have been investigated as having a significant potential for facilitating personalisation, in part this is because the use of cognitive learning styles to support learning reflects a well-established and diverse body of evidence (Coffield *et al.*, 2004a, b; Reynolds *et al.*, 2002). This new interest in cognitive learning styles has prompted a number of recent articles (e.g.: Sampson and Karagiannidis, 2002) as well as a series of research projects (e.g.: EU SeLeNe project[3]; EU iClass project[4]) that have explored personalisation using cognitive learning styles, and while some of the systems are still at prototype stages of development, there is reason to believe that learner modelling will become a central component of personalised learning systems in the future – although the extent to which learning styles will facilitate this development has yet to be significantly proven. Towards this end, this section will provide an overview of what learner styles are, providing a review of three experimental e-learning systems where cognitive learning styles are integrated.

## 4.1 What are learner styles?

Cognitive learning styles vary widely and are measured as specific and non-dynamic attributes given to a group of learners who share a particular approach to learning. Some of the most commonly used learning styles classification systems have included: Honey and Mumford learning styles (Honey and Mumford, 1992); the Myers-Briggs Type Indicator (Keirsey, 1998); multiple intelligences (Gardner, 1993); Kolb learning styles index (Kolb, 1985) and the Felder and Silverman index of learning styles (Felder and Silverman, 1988). However a general cynicism amongst educationalists about the use of learning styles has led to criticisms about its use and some have suggested using other methods of learner modelling, such as personality tests as providing a better approach to personalising content

[3] http://www.dcs.bbk.ac.uk/selene/

[4] http://www.iclass.info/

(Clark, 2004). Furthermore, recent adaptive e-learning systems have relied heavily upon content sequencing as a key pedagogic aspect of adaptive e-learning using LOs to provide personalisation, although the extent to which these sequencing systems will rely upon learning styles is at present untested in the literature.

While the research field of cognitive learning styles is extensive and often confusing (Coffield *et al*., 2004b), a recent systematic and critical review of the literature (Coffield *et al*., 2004a,b) has provided a much-needed critical evaluation of the value and uses of cognitive learning styles in practical application. The reports identify 71 models of learning styles that have developed since the early 20th Century, and categorises 13 of these as major models. While Coffield *et al.* accept the view of Entwistle (1990) that effective learning should not be left to chance and that 'a reliable and valid instrument which measures learning styles and approaches could be used as a tool to encourage self-development, not only by diagnosing how people learn, but by showing them how to enhance their learning' (Coffield *et al*., 2004a, p. 51), the findings on the whole are critical of the use of learning styles – mainly because there is a lack of any common framework, which has led to confusion and a lack of criticality.

Some of the attempts to rationalise the myriad of approaches represented by over 70 models into a coherent whole include an assessment by Curry (1987) which aims to group a range of learning style models into three categories which he defines as: 'instructional preferences', 'information processing style' and 'cognitive style' where cognitive style is regarded as more important for the learner and instructional preferences are of less importance.

Other attempts to rationalise the models (Coffield *et al*., 2004b) have argued for families of learning styles organising them into: constitutionally based; cognitive structure; stable personality type; flexibly stable learning preferences and learning approaches and strategies. One of the underlying problems with the use of learning styles is the inherent assumption that personal qualities such as personality traits or the dominance of particular sensory channels are fixed or genetically determined, and while genetic influences upon personality traits may be weaker than on cognitive abilities the influence of the environment and context where learning takes place also has a significant impact upon the learning processes (Loehlin, 1992; Coffield *et al*., 2004b).

This objection seems to be more about the non-dynamic nature of learning style attribution, rather than about the use of learning styles *per se*. In this case, a simple way around the objection to the use of learner styles in providing personalisation is to have adaptive user models where the "learner style" recorded can change from day to day – either being explicitly updated by the user, or being changed automatically by the system based on user behaviour. This is the approach taken by systems such as INSPIRE, which we discuss shortly.

## 4.2 Review of three e-learning systems that use learning styles

It is difficult to assess the effectiveness of the use of learning styles in adaptive e-learning systems due to the prototypical nature and accompanying small sample sizes of early developments. In the context of learning styles and personalisation, adaptive educational hypermedia systems (Brusilovsky, 1996) have been many of the earliest developed systems that use and test cognitive styles as a basis for personalised learning. Intelligent tutoring systems, building on the earlier computer based training systems (CBT), have also provided early approaches to this method. Although in the past these systems have been considered too expensive, the more recent adaptive hypermedia systems (AHS) bring hypermedia systems and intelligent tutoring systems together in order to adapt web-based educational content for particular learners or learner groups. While many AHS have been developed over the last 15 years (Trantafillou *et al.*, 2004), those that make use of learning styles number considerably fewer (Papanikolaou *et al.*, 2003; Trantafillou *et al.*, 2004; Carver *et al*., 1996). These systems are often based upon instructional design approaches, associated with training, and mainly use cognitive approaches, which are consistent with learning style approaches. A number of adaptive and non-adaptive systems were considered for this review (e.g.: Poyry and Puustjarvi, 2003; Ong and Hawryszkiewyck, 2003) – the three systems have been selected on the basis that they use more demonstrable approaches to the use of cognitive learning styles.

### 4.2.1 INSPIRE (INtelligent System for Personalized Instruction in a Remote Environment)

Papanikolaou *et al.* (2003) developed an adaptive educational hypermedia prototype called INSPIRE which operates at different levels of adaptation, ranging from full system control to full learner control. Both modes of adaptation were regulated by a learner model, which provided information about the learner using knowledge level, the domain concepts and learner styles. Using an instructional design framework, the domain model used for the INSPIRE system ‘represented … three hierarchical levels of knowledge abstraction’ (Papanikolaou *et al*., 2003: p. 226): learning goals, concepts and educational materials. Personalised lesson content could then be generated for a particular goal, organised around specific learning outcomes. Thus the learner model controls the adaptive behaviour of the system through:

- Employing an overlaid model that follows the domain structure and records the learner's knowledge level in the various concepts/goals;
- Recording information that describes learner's interaction with the conveyed content and represents the studying attitude of the learner;
- Storing general information about the learner such as user name, profession, sex, learning style;
- Transparency to the learner and controllable by him/her;
- Dynamic updating of the model during interaction to make it possible for the learner's current state to be stored in the database (Papanikolaou *et al.*, 2003: 231-2).

Learner preferences used in INSPIRE follow the Honey and Mumford learner style classification system (Honey and Mumford, 1992). These preferences are entered into the INSPIRE system via the Honey and Mumford questionnaire, and the learner model records the categories: activist, reflector, theorist and pragmatist. Notably, this model is not static and can be changed by the learner.

An analysis of the system at the University of Athens in the Department of Informatics and Telecommunications was undertaken in the year 2001-2002 using 23 second-year undergraduate students. The investigation centred upon an evaluation of the users' log files, and it was found that learner styles did follow different selection and sequencing of data and the majority of the learners found this useful.

### 4.2.2 AES-CS (Adaptive Educational System based on Cognitive Styles)

Trantafillou *et al.* (2004) have developed a prototype system called AES-CS at the University of Thessaloniki. The prototype was developed to test the hypothesis that cognitive learning styles could benefit learning outcomes. The prototype was developed as part of the Multimedia Technology Systems course in the Computer Science department at the University for fourth-year undergraduate students and was a revised system based upon the evaluation conducted by Trantafillou *et al.* (2002).

AES-CS used Witkin's Field Dependence/Independence (Witkin *et al*., 1977) approach to cognitive learning styles whereby learners are divided into field-independent learners who are generally more analytical in their approach to data and field-dependent learners who are generally more global in their approaches.

> The system was organised into three basic modules: the domain module, the student module and the adaptation module. These three components interact in order to adapt to different aspects of the instructional process, which includes adapting the content according to user's prior knowledge; adapting the presentation of contents through selection and combination of appropriate media; adapting the teaching strategies; modifying the selection of examples and links; and recommending appropriate hyperlinks (Trantafillou *et al.*, 2004, p. 98).

The system prototype makes use of an 'adaptive presentation technique' (Brusilovsky, 1996) that allows for adaptation of the presentation of information according to cognitive learning style and knowledge state, allowing for an appropriate path or sequence through the curriculum to be found, thus providing a personalised trail for the learner (although they do not use this terminology).

The testing of the system used 76 students divided into an experimental group and a control group. According to an analysis of the data extracted from pre-tests, embedded test, post-tests and an attitude questionnaire for the experimental group, the experimental group performed significantly better than students in the control group who were not using an adaptive system. The study found improvements in the experimental group, both in terms of student interactions and outcomes. Furthermore, the students that used the system liked it, found it easy to use and would like to use it again (Trantafillou *et al.,* 2004). Another similar prototype has been developed and tested by Mitchell *et al.* (2004).

### 4.2.3 EDUCE (An intelligent tutoring system)

EDUCE is an Intelligent Tutoring System designed to support 12-14 year old school children learning science (Kelly and Tangney, 2004) and introduces an adaptive presentation strategy based upon Gardner's multiple intelligences (Gardner, 1993). Although not categorised precisely as a learning style classification *per se*, Gardner's classification system is used in an analogous way and offers a similar model for adaptive hypermedia and intelligent tutoring systems.

First proposed in 1983 (Gardner, 1983) the theory of multiple intelligences argues that individuals have different capacities for learning and different 'intelligences' result, including:

linguistic intelligence, logical-mathematical intelligence, musical intelligence and spatial intelligence. EDUCE intended to use Gardner's eight defined intelligences but this prototype uses only four: logical/mathematical intelligence, verbal/linguistic intelligence, visual/spatial intelligence and musical/rhythmic intelligence.

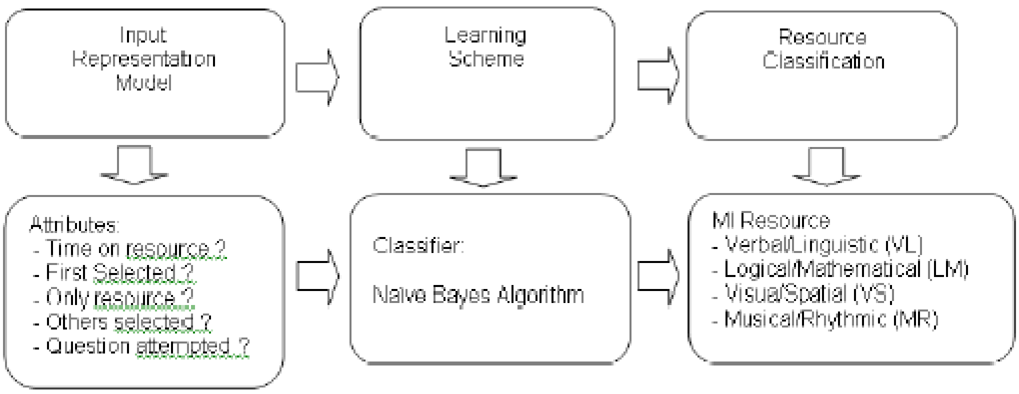


*Figure 1: The different stages in the predictive engine and their implementation within EDUCE. (Reproduced from Kelly and Tangney, 2004)*

EDUCE makes use of Gardner's theory combining it with a student model, a domain model, a pedagogic model, a predictive engine and a presentation model. While the predictive model uses the Bayesian algorithm, the pedagogic model focuses upon presentation and selection but there are plans to use concept sequencing in later versions.

Learning performance is defined here according to learning gain, activity and motivation. While the research study is still underway, one group of 18 boys have already tested the system. The group was divided into two, with one part using the adaptive choice version of EDUCE and the other using free choice. Rather surprisingly for the researchers, the findings suggested that 'learning gain increases where students do not get their preferred learning resource. However on closer examination of the learning activity, it is found that students when given their least preferred learning resource increase their learning activity and are exposed to a wider range of resources' (Kelly *and* Tangney, 2004, p. 687).

## 4.3 Learning styles and trails

Potentially learning styles could also be adapted to support the sequencing approaches of LOs and be used in the formulation and development of learner trails (Peterson and Levene, 2003; Schoonenboom *et al.*, 2004a). Schoonenboom *et al.* argue that sequencing of learning material is as important as the learning material itself – an approach developed in the IMS Learning Design specifications (IMS, 2002). This emphasis upon sequencing of learning content has been adapted from instructional design theory (Gagne, 1985) as well as elaboration theory, where learning becomes increasingly more difficult (Reigeluth, 1983) and has been applied most widely in industry and military training contexts. The sequencing approach is based upon learning as a series of activities rather than reflections, and works particularly well in training contexts where experiences rather than abstract concepts may be learnt through repetitions and experiential learning (Kolb, 1984). However, with the development of e-learning systems the popularity of this approach (which can be more easily measured and evaluated) is now becoming more apparent in formal learning contexts. Based upon the educational modelling language (EML) developed by Rob Koper (2001), systems such as LAMS (Learning Activity Management System) are emerging. LAMS is based upon the notion that smaller units of learning content can be sequenced differently depending upon different context and learner requirements (Dalziel, 2003).

The LAMS system of sequencing reusable LOs is consistent with the notion of learner trails and it is thought that learning styles could be applied to learner trails by using knowledge about the learner's styles to inform the selection and sequencing of material providing personalised learning content. The main advantages of this approach would be to allow for greater adaptivity of the sequencing system (a current problem with the LAMS system) as well as allowing for reflection upon the trails taken. Most notably, perhaps, Schoonenboom *et al.* also propose advantages for the approach in terms of supporting collaborative learning as well as individual study, through setting up trails that can be followed by a group of learners. The LO system could also provide visual navigation for the learner or learner group, showing the LOs completed and indicating LOs yet to be completed.

While it is still unclear which learning styles classification would be used most effectively, it is clear that e-learning systems such as LAMS, based upon IMS Learning Design, could potentially integrate learning styles approaches, allowing for greater flexibility in terms of the choice of ordering LOs. However, the extent to which abstract and reflective learning could be supported (as well as cognitive and perceptual skills based learning) is as yet untested. Moreover, the main challenge here would be to ensure that pedagogical models and approaches could support independent LOs used in different orderings and contexts and whether specified learning outcomes and objectives consistent with the development of analytic and constructivist learning could still be supported.

## 4.4 Conclusions about the use of learning styles

Although there is some scepticism about the application of learning styles in e-learning and adaptive hypermedia systems, the continued interest in the field and the range of possible classification systems that have developed implies a continued interest in applying cognitive learning styles in this way. Ongoing research and development in this area indicates that this and other methods of learner classification will continue to structure the development of prototypes that aim to structure and support stated learning outcomes, particularly those based upon activities (e.g.: LAMS system). Many of these rely upon differences in the sequencing of LOs, creating paths or trails to facilitate wider learner choice and reflecting different learning pace and approaches. It is thought that in time these existent prototypes and systems will become more widely used, however there is clearly a need for a more evaluative and analytical approach to be taken to the different learning style classifications if these systems are to be successful in modelling learning outcomes.

We have so far concentrated mainly on personalisation in web-based e-learning systems. There is a move now to take technology-enhanced learning away from strictly desktop and web-based environments through the use of mobile and wireless technologies. The next section looks at personalisation within the mobile learning domain, which we will see has some different connotations from in our discussion of personalisation so far.

# 5 Personalisation in mobile learning

Deliverable D22.2.1 (Schoonenboom *et al.*, 2004a) included a selective review of research on the use of mobile learning in museums and related contexts (mainly concerning informal learning) and also for field work in learning Science, with the aim of informing issues concerning the use of mobile devices and personalised learning trails. It was argued that "*navigational* learning" (Peterson and Levene, 2003), one of the areas that personalised trails should be able to support, often involves what has been termed a 'free-choice learning' activity (Falk *and* Dierking, cited by Proctor and Tellis, 2003, and Waycott, 2004, forthcoming). Free-choice learning is defined as 'the type of learning guided by a person's needs and interests'.

*Challenges for trails in mobile learning*

There has been an explosion of interest and projects in the area of mobile learning and it would not be possible or productive to review this vast literature – see, for example, the links and projects at the "Mobile Learning Links" page at http://cc.oulu.fi/~jlaru/mlearning/.

However, we would argue that this area, which is fast changing, presents particular challenges to the idea of identifying and representing trails – for example, as well as the use of mobile devices, mobile learning encompasses the idea of learners making use of ubiquitous technologies and embedded devices. These include limitations of standards and specifications: for example, current metadata specifications are really intended for stationary learning. However, Chan and colleagues from the University of Birmingham have proposed some extensions to make such specifications usable for mobile learning, looking at both Learning Object Metadata and Learner Information Profile (Chan *et al.*, 2004).

The Userlab at the Open University is also conducting relevant work on issues concerning generation of metadata and its reuse in different contexts, including the challenge of representing learning in mobile contexts (Brasher and McAndrew, 2003a, b). The IMS Learning Design specification promises pedagogic flexibility, building on OUML's work at the university of Barcelona (see http://www.imsglobal.org/learningdesign/). The specification was published in February 2003 and thus far there have only been R & D prototypes, although the OpenUniversiteitNederland (OU NL) has much content conforming to the specification on which Learning Design was based (OUNL-EML). As yet, there is very little work on this to do with mobile learning. One recent project, though, presented at MLearn 2004, concerns the use of JELD (Java Environment for Learning Design) suitable for running on mobile devices (Arrigo 2004).

**Personalisation and mobile learning**

In this section it is argued that the idea of personalisation is used rather differently in the context of mobile learning than it is in (non-mobile) e-learning for example. There is a current concern, reflected in this project, about how best to tailor learning content in web sites and e-learning according to learners' individual differences. Such differences might include previous knowledge or learning styles. An example of such work is Chen's work (2003) on individual differences in web-based instruction, focusing on cognitive styles. As noted above, the focus of this kind of approach is to tailor information, courses or how such information is presented according to learners' preferences or styles of working. Within mobile learning, however, personalised learning has a rather different meaning: Sharples, one of the leading researchers in this area, is concerned with individuals' learning experiences throughout their lives (Sharples, 2003). In this context mobile devices provide a way for learners to take their experiences with them from one place to another and from one context to another. Such devices should support learners in getting the information that is pertinent to their particular interests and needs, and representing and storing what they have taken from the learning experience in a way that is relevant to them. Sharples's learning model was discussed in Deliverable 22.2.1 (Schoonenboom *et al.*, 2004a), and because of this personal, lifelong emphasis, it was argued that Sharples's model was particularly useful for mobile learning. It is fair to note, however, that much of the emphasis here is on learning *outside* the boundaries of learning institutions; e.g. informal learning that people engage in for much of their time and throughout their lives: in pursuing hobbies (such as gardening) or necessary 'life' activities (filling in tax forms) or learning new skills (e.g. sending emails).

Deliverable 22.2.1 also illustrated how Sharples's theory of personal learning shares a great deal with learning trails:

> "We begin with a person engaged with some activity in the world, carrying out an experiment, perhaps, solving a problem or exploring an environment such as a park of a museum. As the person performs the activity he or she tries out new actions, reflects on their consequences and makes decisions about what to do next. The person is actively constructing an understanding of their activities. There is continual interaction and adjustment between the person's thoughts and actions. Then, in order to gain from that experience, to perform it differently or better in future, the person needs to form a description of themselves and the activities, to explore and extend that description and carry forward the understanding to a future activity… That is the minimum requirement for any person or any system to learn: it must be able to converse with itself about what it knows" (Sharples, 2003, p4).

There is another sense, too, in which mobile learning is personalised learning, and that is the sense in which the devices themselves are personal. Waycott comments that:

> "Such technologies are truly personal, in the sense that they often remain in the hands of the owner, and can be used in many different ways. They also appear to inspire in users a sense of emotional attachment. Thus, understanding how new users appropriate mobile technologies – and how, in turn, those technologies changes the way people do things – is a timely concern." (Waycott, 2004, forthcoming)

## 5.1 Discussion and implications for personal learning trails

In considering the use of mobile technology for learners and supporting learners' trails, we would argue that it is important to have a theoretical approach which includes a social perspective and takes into account the complex ways in which technologies change learners' activities and vice versa. Sharples's model has a particular social perspective and so does Activity Theory, which also provides a focus on how adoption of any new technology affects and changes the learner's activities and likewise, the activities for which technologies are used have an impact on how the device is used and adopted.

The research discussed in Deliverable 22.2.1 on the use of mobiles in museums suggested that the small ‘badge’ type of devices worked best as it is important that the device does not demand too much of the user’s attention and resources and is small enough to be comfortable and unobtrusive.

The issue of how multipurpose the device is, how it fits into learners’ existing activities, and how it fits with other tools also arises. If notebooks are usually used, the mobile device must either allow this or be small enough to allow a traditional notebook to be used alongside it. None of the examples described allowed learners to make their own notes (they were confined to photographing devices, capturing links etc.), yet if the idea of personalised trails and learning in context is to be taken seriously, visitors need to be able to make notes and personalise their learning as they are going about their visit, as well as edit them and change them afterwards.

We have so far looked at the state-of-the-art of mainly experimental systems (both web-based and mobile). The following section briefly reports on personalisation provision in some of the best-rated commercially available (and so more widely used) systems and products.

# 6 Commercial state-of-the-art in e-learning systems

The approach for reporting on state-of-the-art commercial systems has been to choose one of the best rated product currently available on the market. A good source for finding the best-rated application is the Brandon-Hall web site. Other sources of reference are the tracking of the e-learning stock market[5], the press, and informal exchanges between professionals of the Human Resource and Training areas.

Although it is possible to identify providers specialising on collaborative learning or personalisation, and to see which standards they are applying, no explicit information is provided related to the "trail" concept. Therefore the last section of this chapter is an interpretation of features that could be used as trail support with further implementation.

## 6.1 Personalisation in commercially available systems

Differing from Centra[6] and Saba[7], **Skillsoft**[8] is more oriented to content delivery. This

[5] http://www.brandonhall.com/public/ticker/

[6] www.centra.com

[7] www.saba.com

[8] www.skillsoft.com

company is a leading provider of comprehensive e-learning content and technology products, and is considered to be one of the main providers in the corporate training sector. This provider has been chosen for its presumed capacity to bring personalised, just-in-time learning resources. It seems that this multi-modal solution allows learners to choose from available learning resources that best meet their information needs, time constraints and learning preferences.

In addition to the ability to precisely pinpoint needed information, SkillPort's (LMS) usage and time tracking gives a clear picture of learning needs and behaviours and allows to monitor the return on investment.

This facility, oriented to the staff use could be improved and offered as trail support to learners. For example, it allowed seeing how learners like to choose how to access the information: "some of them want to download these book summaries for later reading, others prefer mp3 format". If these records of users' preferences are available to HR why could they not be made available to the learners themselves?

However, **Centra Knowledge Center™** offers also "Personalized Blended Learning". The main feature identified as supporting trails (planned trails) is the **Prescribed Learning Tracks**: Design training programs to meet learners' individual needs. In addition, Centra offers the following competency and skill tracking facilities:

- Tracking and Assessment: Track individuals' current and previous skill levels and learning; **track completion status and effectiveness of assigned activities and assessments**.
- Custom Reporting: Access and download detailed individual progress and performance assessments and **create customized, flexible reports**.

A combination of those "flexible reports" with the completion status of activities and assessments could be proposed as a way to support learners' personalised trails.

## 6.2 Trails Support

An overview of e-learning products providers (including SumTotal[9], DigitalThink[10], Blackboard[11], WebCT, Learn eXact[12], etc.) shows that the functionalities described above are

[9] www.sumtotalsystems.com

[10] www.digitalthink.com

[11] www.blackboard.com

more or less recurring: tracking of learners' data. However this feature is to be understood always as a record of data path and time spent, as well as the passing of test modules. No support to learners trail tracking is apparent. In general, the trend is to link the e-learning system to performance analysis, planning, strategy and evaluation tools.

However, **Blackboard** provides a new functionality that allows instructors to electronically manage the collection and organization of assignments via the integrated Gradebook interface. This could be related to the concept of "planned trails". If this functionality could be improved to support learners, then it could be related to tracking trails and revisiting.

In addition, The *Blackboard Content System* enables students and faculty to easily assemble, present and share their online portfolios. We understand that this portfolio contains academic information prepared by each student. However, we could imagine that data on students' trails could be automatically collected and inserted in the portfolio, for assessment purposes, but also enabling students to have a picture of their learning process to reflect upon.

In conclusion, here is a summary of the various interpretations and possible improvements towards trails support.

- A possible improvement could be to allow the user to revisit the feedback collected during the live sessions.
- Another possibility would be to take advantage of post-event reports, not only to fuel future development criteria, but also to feed back information to learners.
- LMS features, generally oriented to HR or Training staff use could be improved and offered as trails support to learners.
- Dynamic reports stating the completion status of activities and assessments could be proposed as a way to support learners' personalised trails.

## 6.3 Standards

We can observe that most of the leading commercial e-learning systems are tied to the SCORM specifications. However, to be sure of the effective interoperability of these systems it would be wise to check if they are all talking of the same SCORM.

[12] www.learnexact.com

- **Saba** courses published to standards-based formats (AICC, SCORM) and regarding content, extensive support for learning content metadata, as defined by IEEE LOM.
- **Centra** standards compliance are SCORM: Ensure content portability through support for SCORM specifications and IMS: Rapid search and retrieval is facilitated through IMS standard meta-data tagging.
- **SkillSoft**'s e-learning architecture is built to conform to open industry standards such as AICC, SCORM, LRN and IMS. SkillSoft is the first e-learning content supplier to achieve AICC certification. This AICC certification allows SkillSoft's content and platform to integrate effectively with learning management systems, and is a major head-start toward alignment with the emerging SCORM standards.
- **SUMTOTAL** product (Merge between Docent and Click2Learn). Toolbook is conform to SCORM and AICC, the industry's leading learning standards.
- **learn eXact®** is compliant to the SCORM 1.2 application profile and therefore is also conformant to the IMS Content Package 1.1.2, IMS Metadata 1.1 and 1.2, and Run Time Environment: CMI Data Model specifications. learn eXact implements also to the following specifications: IMS Enterprise, IMS QTI Lite, Dublin Core Metadata and AICC level 1.
- **Blackboard** has also released the ADL certified "Content Player Building Block," continuing its tradition of compliance with the SCORM 1.2 specifications.
- **DigitalThink**'s product strategy is closely aligned with the SCORM standard. Their content development organization produces SCORM-compliant custom courseware. L5 is the only SCORM-native learning delivery system available.

# 7 Concluding Remarks

We have seen throughout this deliverable many different aspects of personalisation and different techniques for providing personalised learning.  Work on providing personalised trails as such is certainly in its infancy, although much of the personalisation that is done by current systems can be seen as having trail-supporting aspects: personalised recommendations can be seen as recommendations for “the next best step along your trail”, and link-hiding in adaptive hypertext can obviously be seen as an attempt to suggest certain trails through an environment over others.

We believe that progress in understanding the best methods to provide personalised trails (i.e. suggesting trails of LOs to learners) will be intimately tied to a better understanding of the personal trails created by learners in existing learning environments (both digital and non-digital).  Until we understand what makes the trails already followed by learners “good” or "bad" trails it will be difficult to identify new "good" trails to suggest to learners. Our work in the TRAILS project has allowed us to identify three stages in the effective processing of personal trails. Each of these three areas requires more work to develop a thorough appreciation of the usefulness of personal trails within the wider community, as little work has been done on them so far:

1. **Recording personal trails**: What is the best way to log user activity? What should be recorded? Should trails created in different contexts be recorded separately (e.g., keeping web browsing history separate from the history of documents accessed), or is it better to record trails across mixed contexts (e.g. logging digital LO visits alongside visits to the library to find books, and visits to exhibits in a museum)?
2. **Creating usable trails**: How can trails be extracted from recorded logs? What different ways can they be presented to the user (e.g., visualisations, concept maps)?
3. **Analysing the trails**: What can learners and teachers find out from the extracted trails? How can the most "useful" learning trails be identified? How can instructors identify active and inactive learners?

These personal trails can be any sequence of activities performed by a learner. Many are recorded already – for example, the "History" stored in a web browser, the logs from an e-learning system server (or in fact the logs from *any* system), and the entries in a weblog ("Blog") that form a diary of what has been seen and done recently and so are thus a recorded trail. Many more are not recorded, or are not recorded in a way that it is easy to make use of. We believe these unrecorded trails are of huge potential use – with the right logging, data mining, visualisation and analysis tools these learner trails could be of great benefit to:

- Individual learners – in reflecting and revisiting their trails;
- Wider groups of learners – when useful trails can be extracted and suggested for others to follow;
- Instructors – when recorded trails are as a tool to assess learning;
- Course designers – when the effectiveness of different trails through learning material can be used to inform the design of new courses.

In this deliverable we have seen various personalisation techniques that will be of use in creating personalised trails. Development of a thorough understanding of the trails already created by learners will allow these techniques to be made most effective in suggesting personalised trails for learners to follow.

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