# Individual Differences in Adaptive Hypermedia

## Proceedings of the AH 2004 Workshop

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# Preface

The Workshop on Individual Differences in Adaptive Hypermedia is part of the 3rd International Conference on Adaptive Hypermedia and Adaptive Web-based Systems that was held from August 23 to August 26, 2004, at The Eindhoven University of Technology, The Netherlands.

The Workshop explores how to embrace the various dimensions of individual differences into adaptive hypermedia, and investigates the impacts of individual differences on the design, implementation and use of adaptive hypermedia systems.

Individuals differ in traits such as skills, aptitudes and preferences for processing information, constructing meaning from information and applying it to real-world situations. However, existing applications mainly consider users' preferences based on collecting explicit or implicit information, and emphasise on prior knowledge. As a result, it is still not very clear whether adaptive hypermedia systems can accommodate individual differences effectively, in terms of providing individualised navigation support, delivering personalised content, adapting the presentation or the layout to the needs of the user.

The contributions that are presented here cover various dimensions of individual differences, such as the level of knowledge, spatial abilities, learning styles, cognitive styles, accessibility issues and seek to provide answers to the following questions:

- How adaptive hypermedia can improve accessibilities by providing multi modalities that satisfy users with special needs?
- What design guidelines should be established for development, and what criteria are needed for evaluating adaptive hypermedia that can accommodate individual differences?
- How different dimensions of individual differences can be combined in an adaptive hypermedia system?
- What type of information is needed from user profiles to identify the effects of individual differences on user's preferences?
- What kinds of ontologies are needed for representing individual differences dimensions in the user model and the personalisation engine of adaptive hypermedia systems?
- What are the relationships between individual differences and features of adaptive hypermedia systems?

We hope that the Workshop will contribute to the global research in Adaptive Hypermedia by comprehensively reviewing state-of-the-art adaptive hypermedia approaches that accommodate individual differences, will help integrating individual differences theory into adaptive hypermedia applications, and will give some insight into analytical and architectural aspects of adaptive hypermedia that exploit individual differences for personalisation.

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# Accommodating learning style characteristics in Adaptive Educational Hypermedia Systems

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**Abstract.** In this paper we build on research reported in the areas of Adaptive Educational Hypermedia and learning styles in order to deal with critical issues influencing the design of adaptation based on the learning style information. In more detail we concentrate on: (*i*) the different learning style categorizations that have been or could be used for modelling learners' learning style in the context of an Adaptive Educational Hypermedia System and the way these could guide the design of adaptation, (*ii*) the adaptation technologies that could better serve learners with different learning styles, (*iii*) the dynamic adaptation of the system and the diagnosis process including the identification of specific measures of learners' observable behaviour which are indicative of learners' learning style preferences.

## 1 Introduction

As learning styles are a significant factor contributing in learner progress, a challenging research goal is to attempt to represent specific characteristics of learners' learning style within Adaptive Educational Hypermedia Systems (AEHS). Taking into account that many different classifications of learning styles have been proposed in the educational psychology literature, this is a demanding task motivated by the expected learning benefits.

Important decisions underlying the incorporation of learning style characteristics in AEHS demand the synergy of computer science and instructional science, such as: (i) the selection of appropriate categorizations, which are appropriate for the task of adaptation, (ii) the design of adaptation, including the selection of appropriate adaptation technologies for different learning style categorizations and of appropriate techniques for their implementation, (iii) the design of the knowledge representation of such a system in terms of the domain and the learner model, (iv) the development of intelligent techniques for the dynamic adaptation of the system and the diagnosis process of learners' learning style including also the selection of specific measurements of learners' observable behaviour, which are considered indicative of learners' learning style and studying attitude.

The research goal of accommodating learning styles in AEHS design could also be combined with the development of meta-adaptive hypermedia systems capable of selecting the most appropriate adaptation technology following the individual characteristics of the current users and context (Brusilovsky, 2003). To this end, an AEHS should have a number of different adaptation technologies at its disposal and be aware about the limits of applicability of each technology. In this context learning style information can considerably contribute to the decision of the appropriate adaptation technologies for learners with particular profiles, as specific categorizations of learning styles seem to match better with specific adaptation technologies.

In this paper we build on research reported in the literature about different approaches that have been adopted for the design of adaptation based on the learning style information, in order to deal with critical issues for the development of an AEHS based on this information. In more detail we investigate: (*i*) the different learning style categorizations that have been or could be used for modelling learners' learning style in the context of an Adaptive Educational Hypermedia System and the way these could guide the design of adaptation, (*ii*) the adaptation technologies that could better serve learners with different learning styles, and (*iii*) the dynamic adaptation of the system and the diagnosis process including the identification of specific measures of learners' observable behaviour which are indicative of learners' learning style preferences.

## 2 Learning style information in Adaptive Educational Hypermedia

Designing adaptation based on the learning style information builds on hypotheses about the relationship of learning behaviour with learning style. Such hypotheses are necessary for modelling the learners' learning style in the context of an AEHS. Valuable resource in this context is research conducted in the area of educational psychology about learning styles and the way this characteristic influences learners' behaviour and preferences. A variety of learning style categorizations has been proposed which attempt to associate specific characteristics to different categories of learners and propose instruments and methods for assessing learning style (Riding and Rayner, 1998). Such categorizations could provide the necessary theoretical background for designing the adaptive behaviour of an educational system and guide decisions about what the system should offer to learners with different styles and how to do it.

The last years several AEHS reported in the literature use learning style information as a source of adaptation (see Table II). Several of them build on a theoretical background inspired from the learning style research. The objective of this section is to investigate the way different categorizations of learning styles could support the design of adaptation in terms of specific adaptation technologies. To this end we investigate: (*i*) the learning style categories that have been or could be exploited in AEHS and the way several of them have been used for modelling learners' learning style, and (*ii*) the implications that different learning style categorizations have on the design of different adaptation technologies.

**Modelling the learning style information.** Sadler-Smith (1997) identified four broad categories of 'learning style' in an attempt to acknowledge and accommodate the range of aspects of individual differences referred in the educational psychology literature in an holistic way: (i) 'cognitive personality elements' such as field dependence and field independence (Witkin et al., 1977), (ii) 'information-processing style' such as the experiential learning cycle (Kolb, 1984) and the associated leaning styles (converger, diverger, accommodator, assimilator), or the related learning styles suggested by Honey & Mumford (1992), activist, reflector, theorist, pragmatist, (iii) 'approaches to studying' such as deep approach, surface approach, strategic approach, lack of direction, academic self-confidence (Entwistle & Tait, 1994), (iv) 'instructional (i.e. learning) preferences' defined as an individual's propensity to choose or express a liking for a particular instructional technique or combination of techniques, such as dependent learners, collaborative learners, independent learners suggested by Riechmann & Grasha (1974). In this paper we use the term 'learning style' as a representative one for all the aforementioned categories.

In an attempt to organise the different approaches adopted in several AEHS reported in the literature, we identified: (*i*) systems that use the learning style information in order to design the content of instruction, and (*ii*) systems that use the learning style information in order to adapt to the learners' 'form' of cognitive activity (i.e. thinking, perceiving, remembering). The first class of systems usually adopt categorizations of learning styles that belong to the 'information-processing style' or 'instructional (i.e. learning) preferences' categories, while systems of the second class adopt categorizations of learning styles that belong to the 'cognitive personality elements' category.

In more detail, the adaptive behaviour of AEHS that belong to the first category concentrate on the type and usually the sequencing of material they offer based on a framework proposed by the authors (ACE, Arthur, MANIC) or based on research studies (Honey & Mumford, 1992), (Felder and Silverman, 1988) about the type of instructional material that learners with different learning style prefer (INSPIRE, CS383).

The systems of the second category, which are developed based on learner's cognitive style, concentrate on the 'form' of cognitive activity (i.e., thinking, perceiving, remembering) that learners usually adopt (Triantafillou et al., 2003; Bajraktarevic et al., 2003). For example, AES-CS (Triantafillou et al., 2003) uses the Field dependence/independence (FD/FI) styles [14]. AES-CS adopts several instructional strategies that accommodate learners' learning style in relation with: the approaches (global versus analytical approach), the control options (program control versus learner control), the contextual organizers (advance organizer, post organizer), the study instructions (provide minimum or maximum instructions), the feedback, and the lesson structure. Also, Bajraktarevic et al. (2003) use the Holist/Serialist learning styles proposed by Pask (1976) which is aligned with the Wholist/Analytics dimension and with the Global/Sequential categorisation (Felder and Silverman, 1988). Following the adopted approach, the system provides learners with different linking structures of the content tailored to their learning style.

**Implications for Adaptation Design.** The objective of this sub-section is to investigate the way different categorizations of learning styles that focus on different characteristics of learners could support the design of adaptation in terms of specific adaptation technologies.

*Adaptive presentation & curriculum sequencing.* Adaptive presentation and curriculum sequencing technologies aim at tailoring the educational content to learners' learning style (adapt the content or its sequencing). These adaptation technologies could better serve learning style categorisations that deal with learners' preferences of instructional material or instructional strategies, such as those that belong at the 'information-processing style' or 'instructional (i.e. learning) preferences' categories. Representative examples of this approach are the systems Arthur, CS383, ACE, and INSPIRE. Arthur and CS383 use multiple types of resources differing in the media they utilize, whilst ACE and INSPIRE adapt the sequencing of different types of resources to different learning style categories following a variety of instructional strategies. In the first case, the alternative styles of instruction that are adopted for learners with different learning style demand the development of multiple types of educational material using different media for each particular section of the course. In the second case multiple types of resources are reused following a different sequencing based on the learner's learning style. This is an alternative to the commonly used approach of rewriting the same content for each learning style category (McLoughlin, 1999).

*Adaptive navigation support.* The goal of the adaptive navigation support technology is to support the learners in hyperspace orientation and navigation by changing the appearance of visible links. In this context the learning style information could serve as a valuable resource about learners' navigation "habits" and needs. Thus, the design of this technology could be mainly supported by research in the area of learning style categorizations that belong to the 'cognitive personality elements' and deal with the structure and organisation of the contents of instruction, such as the FD/FI dimensions and wholist-analytic dimensions. AES-CS is a representative AEHS that uses the learning style information in order to decide which navigational tools and aids are appropriate in order to help learners organize the structure of the knowledge domain and move accordingly within.

*Adaptive collaboration support.* Learning style information can also be used as the basis for the construction of groups to support collaborative learning. In the context of AEHS, the goal of the adaptive collaboration support technology (Brusilovsky, 1998) is to use system's knowledge about different users (stored in user models) to form a matching collaborating group. Thus, an interesting approach would be to use the learners' learning style information for organizing learners in groups as this characteristic is considered to influence social interaction. Thus, the design of the adaptive collaboration technology could be mainly supported by categorisations that deal with the social dimension of learners. For example, studies have identified a number of relationships between FD/FI dimension and learning, including the ability to learn from social environments (Witkin et al., 1977). Thus, FI individuals tend to enjoy individualised learning, while FD ones cooperative learning. Also, following Honey and Mumford (1992), groups with full range of learning styles in terms of Activists, Reflectors, Theorists and Pragmatists, exhibit better performance compared to randomly constituted groups.

Moreover, different learning style categorizations may assist the design of more than one adaptation technologies such as the verbal-imagery dimension. This learning style dimension interacts with mode of presentation of information (for example textual/verbal or diagrammatic/pictorial modes) and thus it may assist the design of the instructional material in the context of the adaptation presentation technology as well as the design of navigational aids in terms of the adaptive navigational support technology. Although experimental results are promising (see next section) more research has to be conducted in order to learn more about the relationships between learning styles, learning behavior in terms of observable patterns of learners' activity and possible adaptation approaches.

**Open Issues.** Although several learning styles categorizations have been exploited in AEHS, there are many more that have not been considered yet such as those that belong in the category of 'approaches to studying'. What is important in exploiting different learning style categorizations in AEHS is their potential to support and enhance adaptation providing appropriate guidance for AEHS developers. Thus, the wide range of learning style categorizations should be investigated through the ways each categorization could assist the design of the different adaptation technologies or inspire the design of new ones. This research goal has two different values both for the educational psychology area to evaluate the effectiveness and the validity of matching instructional methods to learners' styles and preferences in e-learning, and the adaptive educational hypermedia area to improve the effectiveness and efficiency of adaptation.

## 3 Evaluating the benefits from designing adaptation based on learning styles

Although several AEH systems that use learning style as a source for adaptation have been reported in the literature, just a few empirical studies (usually small scale studies conducted in experimental conditions) have been conducted that prove the effectiveness of the adopted approaches. The goals of such studies concentrate on the effectiveness and/or efficiency of adaptation, which are measured through learners' performance, learning time, navigation patterns, learners' subjective estimation. Different dimensions that are considered in these studies are: (*i*) the relationship between matching and mismatching instructional approaches with learners' learning style (Ford and Chen, 2001; Bajraktarevic et al., 2003) (*ii*) the learning performance and learning time of learners with different learning style in matched sessions (Triantafillou et al., 2003); (*iii*) the navigation patterns of learners with different profiles in matched sessions (Papanikolaou et al., 2003).

Ford and Chen (2001) investigated if the matching of instructional presentation strategies and learners' learning style is linked with improved learning performance. They report that learners of the FD/FI styles who learned in matched conditions scored significantly higher in tests measuring their conceptual knowledge but not in performing practical tasks. Following the authors, these results provide evidence about the learning benefits coming from matching learners' learning style with instructional presentation strategies and indicate the need to take into account qualitative characteristics of expected learning outcomes such as learning, recall and application of conceptual knowledge, in designing adaptation. Triantafillou et al. (2003) conducted a small group evaluation in order to measure the effectiveness and efficiency of the instructional approaches adopted in AEC-CS for FD/FI learners. They found that all learners' performance was increased after instruction in matched conditions. In more detail, they found that the FI learners had better results than the FD ones, although FD learners were improved more than the FI ones. Furthermore, as learners spent less than an hour to complete the courseware (which was designed to correspond to a typical lecture hour), the adopted approach was considered efficient. In this study learners reported their satisfaction from the initial adaptation as well as from the fact that the system was completely controllable by them. In another study reported in (Papanikolaou et al., 2003), the authors analyzed learners' studying behaviour (time spent and hits on resources) and navigation traces by the different learning style categories proposed by (Honey and Mumford, 1992). The main aim of this study was to provide evidence about the way learners that belong to different learning style categories select and use educational resources that are considered beneficial for their styles in INSPIRE. Although this was a pilot study, the results were encouraging, confirming the initial hypotheses on which the presentation and sequencing of resources was based. Lastly the main aim of the study reported in (Bajraktarevic et al., 2003) was to evaluate the effectiveness and the efficiency of the adopted adaptation approach. Effectiveness was measured through learners' performance in matched and mismatched learning-style sessions (Holist/Serialist learning styles), whilst efficiency through learners' browsing time in matched and mismatched learning-style sessions. Learners' performance was significantly higher in matched sessions for all learners, whilst there was not significant difference between browsing times for the matched / mismatched groups.

## 4 Diagnosis of learning style: critical issues influencing adaptation

Vermunt (1996) conceptualises learning styles as consistent patterns of learning activities that are systematically linked to learning beliefs and motivational orientations. Thus, learning styles are not taken to be invariable (at least many of the proposed categorisations), as they may be influenced by the particularities of the learning context and its demands. Along this line, in the context of AEHS, a critical issue for recognising changes in learners' needs and preferences is to determine measures of learners' observable behaviour which are indicative of learners' learning style preferences. Thus, incorporating the learning style information in the context of AEHS requires, apart from a theoretical background, a qualitative analysis (categorization) of learners' steps and/or selections (features/tools of the system that they access/use) as they interact with the system. This information is also valuable in order to study the extent to which the hypotheses about learners' learning style preferences, match their learning behaviour as it is depicted through their actual navigation through the interaction.

Student diagnosis is the process of inferring students' internal characteristics from their observable behavior (VanLehn, 1988). An AEHS, due to the restricted communication channel, is only able to directly obtain raw measurements, by monitoring the interaction with the learner, aiming to identify learners' changing needs and maintain the current state of the learner. Thus, critical issues that should be considered in designing the diagnosis process of learners' learning style are: (*i*) the initialisation of the learner model, (*ii*) the selection of appropriate measures to serve as indicators of learners learning style preferences, and (*iii*) the qualitative analysis of learners' observable behaviour that could support the dynamic adaptation of the system during the interaction.

In this context diagnosis should exploit the two methods usually used for assessing learners' learning preferences (Riding and Rayner, 1998): self-report measures through questionnaires, and observed behaviour choices. Especially the first approach is usually adopted for the *initialisation of the learner model*, whilst the second one for the dynamic adaptation of the system through the interaction. Following the first approach, several systems use specially designed psychological tests designed for particular learning style categorisations (INSPIRE, AES-CS), whilst others use interviews in order to let the learners decide on specific aspects of their learning style preferences (ACE). During the interaction, several systems allow the learners to directly manipulate their learning style expressing their own point of view about themselves and consequently about system adaptation (INSPIRE, AES-CS).

Through the interaction with the system, learner's observable behaviour is, in many cases, the basis for the diagnosis of certain characteristics of the learner such as his/her preferences of the learning material. In such cases, the dynamic adaptation of the system is based on real data coming from learners' interaction with the system. For example, in ACE, the dynamic adaptation of the instructional strategy is based on information coming from monitoring learner's requests on learning materials, as well as on the success of the currently used strategy. The latter is mainly determined by learner's performance in the final tests; repeated occurrences of high performance raise the preference value of a strategy until a threshold is reached. Also, Arthur dynamically adapts the instructional style according to learner's performance in the tests s/he submits. For example, in case the learner scores 70% in a quiz of a concept, then s/he will be provided with material of alternative instructional style; otherwise, the instructional style currently used is supposed to match the learner's learning style. Lastly, MANIC uses machine learning techniques in order to identify learners' preferences by observing his/her interactions with the system.

The selection of measures on which dynamic adaptation is based, is a significant factor influencing its effectiveness. For example, is learners' performance on tests or time spent on educational resources, adequate measures for learners' changing learning style preferences during the interaction? What about the individual characteristics of the learning style categorisation adopted for modelling learners' style, or the hypotheses on which system adaptation is based about learners' style? For example in case of the FD/FI categorization the way learners navigate is more appropriate as an indicator of their style than the specific type of material they select. On the other side this may be a valuable information about categorizations such as Verbalisers / Imagers or Activists / Theorists / Pragmatists / Reflectors. Thus, a critical issue in designing dynamic adaptation based on learners' observable behaviour is to identify which learners' actions are indicators of their style, and should be considered in assessing their changing needs and preferences during interaction.

To this end, valuable resources could be studies reported in the literature investigating which *measures of learners' observable behaviour* are indicative of their learning style preferences and learning behaviour. Indicators that have been investigated for several learning style categorizations are: (*i*) navigational indicators (number of hits on educational resources, preferable format of presentation, navigation pattern); (*ii*) temporal indicators (time spent in different types of educational resources proposed); (*iii*) performance indicators (total learner attempts on exercises, assessment tests) (Reed et al., 2000; Lu et al. 2003; Souto et al., 2002; Papanikolaou et al, 2003). This is a promising research direction which may help us develop deeper knowledge of the complex interactions between learners and educational content and further inspire new approaches in the design of AEHS.

## 4 Conclusions

Especially in a web-based educational system, where the variety of learners taking the same course is much greater, a challenging goal in the design, development and delivery of learning could be the accommodation of learners' individual differences in terms of their learning styles. Towards this end, critical issues on which research in AEHS should focus are: (i) the design of adaptation based on the learning style information (what the system should offer to learners with different styles and how to do it in terms of deciding which adaptation technologies could better serve the aims of the adaptation), (*ii*) the selection of appropriate measures of learners observable behaviour which could serve as indicators of learners learning style preferences, (*iii*) the qualitative analysis of these observable measures that could support the dynamic adaptation of the system during the interaction.

To the above research goals valuable resources are the different categorizations of learning styles proposed in the area of educational psychology. Such information may: (*i*) assist in the design of AEHS which accommodate learners' styles and preferences; (*ii*) contribute to the enhancement of the pedagogical perspective of such systems; (*iii*) assist the evaluation of the effectiveness and efficiency of adaptation; (*iv*) provide directions for future research into the validity of matching instructional methods to learners' styles and the effectiveness of adaptation.

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**Table II.** Comparison of AEHS that use learning style as a source of adaptation

| System | Domain | Learning Style Model | Adaptation based on Learning Style | Diagnosis Approach & Dynamic Adaptation |
|---|---|---|---|---|
| ACE (Specht & Opperman, 1998) | Domain Independent | Learning style preferences: *preferences about sequencing of learning materials* | Sequencing of learning materials according to a particular teaching strategy (learning by example, reading texts or learning by doing), based on learner's interests and material preferences. | Dynamic adaptation of the teaching strategy is based on info coming from monitoring learners' requests on ed. material, and on the success of the currently used strategy (determined by learner's performance in tests). |
| CS383 (Carver et al., 1999) | Computer Systems | Sensing/intuitive, visual / verbal, and sequential/global (Felder and Silverman, 1988) | Lesson media elements presented in a sorted list ranked from the most to least conducive based on learners' learning style. | During the first lesson learners submit the questionnaire proposed by (Solomon, 1992) to identify their learning style. |
| Arthur (Gilbert and Han, 1999) | Computer Science Programming | Learning style preferences: *style of instruction during which learners exhibit satisfactory performance* | Alternative styles of instruction differ in the type of media they utilize: visual-interactive, auditory-text, auditory-lecture, and text style. | Dynamically adapts the instructional style according to learner's performance in the tests s/he submits. |
| AES-CS (Triantafillou et al., 2003) | Multimedia Technology Systems | Field dependent / Field Independent (Witkin et al., 1997) | Adapt amount of control (program vs. learner control), contextual organizers (advance vs. post), instructional support, navigational tools and feedback to assessment questions. | Learners submit the Group Embedded Figures Test (GEFT) questionnaire. Direct manipulation of LM (Learner Model). |
| INSPIRE (Papanikolaou, et al., 2003) | Computer Architecture | Activists, Pragmatists, Reflectors, Theorists (Honey & Mumford, 1992) | Adapt the method and order of presentation of multiple types of educational resources within educational material pages. | Learners submit the questionnaire proposed by (Honey & Mumford, 1992) or they define their learning style. Direct manipulation of LM. |
| MANIC (Stern & Woolf, 2000) | Domain Independent | Learning style preferences: *media (graphic, text), type of instruction, level of content abstractness, ordering of different types of content* | Presentation of content objects using *stretchtext* which allows certain parts of a page to be opened or closed. Sequencing of content objects for a concept based on learner's preferences. | The system dynamically adapts the content presentation by observing learner's interactions with the system. |

# End-User Quality of Experience Layer for Adaptive Hypermedia Systems

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**Abstract.** In the context of new devices and the variety of network technologies that allow access to the Internet, the deployers of Web applications need to ensure that end-users have a positive experience using new applications and they will be willing to re-use them. User experience is dependent not only on the content served to them, but also on the performance of that service. This paper explores a new dimension of individual differences between Web users: end-user Quality of Experience (QoE). It proposes a solution on how to provide satisfactory end-user QoE in the field of educational adaptive hypermedia. A new QoE layer for Adaptive Hypermedia is introduced that attempts to take into account multiple factors affecting Quality of Experience, which might arise from a wide range of Web components (e.g. text, images, video, audio). Usability evaluation based on comparison of a classic adaptive e-learning system with a QoE-aware one has shown that students considered the QoE-aware system significantly more usable than the classic system. Learning performance tests indicated that the changes made by the QoE-aware system did not affect the learning capabilities offered by the classic system.

## 1 Introduction

Extensive research in the area of Web-based adaptive hypermedia has demonstrated the benefit of providing personalized content and navigation support for specific users or users categories. Web users differ in skills, aptitudes and preferences for processing the accessed information, and goals. They may have different perceptions of the same content and performance factors. Finally, they may have special needs due to disabilities. Therefore, many Web adaptive hypermedia applications have been proposed that try to capture and analyse these user related features in order to optimise the user experience with the Web site.

Many of these adaptive hypermedia systems have been applied in the educational area. This research area has attracted huge interest due to its capability for facilitating personalized e-learning, its distributed nature and its simplicity of interaction.

With the advance in computer and communications technology a variety of Internet access devices (e.g. laptop, pocketPC, PDA, mobile phone) have been launched on the market. The type and capacity of the access device, the bandwidth and the state of the network the device operates on, the complexity of the Web pages delivered over a given network all affect the quality of experience for the end-user. Thus, end-users of educational and training services expect not only high-quality and efficient educational material but also a perfect integration of this material with the day-to-day operational environment and network framework. In this context it is significant to highlight a new problem faced by network-based education over the Internet: providing a good level of end-user perceived Quality of Service (QoS), also called Quality of Experience (QoE).

Currently Adaptive Hypermedia Systems for Education (AHSE) place very little emphasis on QoE and its affect on the learning process. This QoE-unaware approach is perhaps unsuited to a general learning environment where one can imagine a student with a laptop moving from a low bandwidth home connection, to a higher bandwidth school connection, and potentially to public transport with a mobile connection with a widely varying bandwidth connection. It should be noted that some AHSs have taken into consideration some performance features, such as device capability [1], in order to improve the end-user perceived quality. However, these account for only a limited range of factors affecting performance (e.g. serving pages in smaller segments if the user has a palmtop rather than a PC) and do not fully address QoE.

Therefore, adaptive hypermedia systems should also take into consideration QoE characteristics when the user profile is built and regularly monitor in real-time any change in the system that might indicate variations of QoE. These include changes in the user's operational environment and also modifications of user behaviour, which might possibly indicate dissatisfaction with service (such as an abort action). This would allow for better Web content adaptation that suites varying conditions.

This paper presents an approach that introduces a new QoE layer to the classic adaptive hypermedia system architecture that would improve the end-user perceived QoS by taking into consideration different performance factors that may affect the end-user satisfaction. This layer provides a Performance Monitor which measures a variety of performance metrics in order to learn about the Web user's operational environment characteristics, about changes in network connection between the user's computer and Web server, and the consequences of these changes on the user's quality of experience. This information is synthesized in a Perceived Performance Model, which proposes strategies for tailoring Web content in order to improve QoE.

To demonstrate the benefits of the proposed QoE enhancement we have deployed it in the open-source AHA! system [2] creating QoSAHA. In this paper we present the results of preliminary tests comparing both performance and usability of AHA! and QoSAHA when delivering an adaptive tutorial in a low bit rate environment. These results indicate that QoSAHA improves performance and user satisfaction with their experience while not affecting the user learning outcome.

## 2 Quality of Experience (QoE) for Web Applications

The term Quality of Experience focuses on the user and tries to understand end-user expectations for QoS. QoE is considered in [3] as the collection of all the perception elements of the network and performance relative to expectations of the users. The QoE concept applies to any kind of network interaction such as Web navigation, multimedia streaming, voice over IP, etc. According to the type of application the user interacts with, different QoE metrics that assess the user's experience with the system in term of responsiveness and availability have been proposed. QoE metrics may have a subjective element to them and may be influenced by any sub-system between the service provider and the end-user. ITU-T Recommendation G.1010 [4] provides guidance on the key factors that influence Quality of Service (QoS) from the perspective of the end-user (i.e QoE) for a range of applications that involves voice, video, images and text. The Recommendation provides a list of parameters that govern end-user satisfaction for these applications.

In the area of World Wide Web applications, QoE has been referred as end-to-end QoS or end-user perceived QoS. Measuring end-to-end service performance, as it is perceived by end-users is a challenging task. Previous research [5, 6, 7] shows that many QoS parameters such as end-to-end response time or page download time, perceived speed of download, successful download completion probability, user's tolerance for delay, and frequency of aborted connections factor into user perception of World Wide Web QoS. Measurement of these parameters may be used to assess the level of user satisfaction with performance. The interpretation of these values is complex—varying from user to user and also according to the context of the user task.

For example, according to a number of studies, user's expectation on the download time is influenced by different contextual factors (e.g. the type of task performed by the user, the duration of time the user interacts with the site, the user's awareness of the connection capabilities) [5, 8]. Currently, there are no standard thresholds for the download time. However, on average a download time higher then 10-12 seconds causes disruption and users loose their attention to the task, while values higher then 30 seconds cause frustration. At the same time it is significant to mention that when the user is aware of his slow connection, he/she is willing to tolerate a threshold of 15 seconds.

End-user perceived QoS has also been addressed in the area of multimedia streaming. Research such as [9, 10, 11] assesses the effect of different network-centric parameters (i.e. loss, jitter, delay), the continuous aspect of multimedia components that require synchronization, or the effect of multimedia clip properties (i.e. frame size, encoding rate) on end-user perceived quality when streaming different type content.

In this paper QoE is addressed only in the area of AHS with applicability in education. Typical e-learning systems may involve a combination of text, images, audio and video, and their quality of service is based on the combination of all of these rather than any individual component. The educational context also has its own set of requirements and user expectations and it is against these that user perceptual quality should be evaluated.

## 3 QoE Layer Enhancement for AHS

Starting from a generic architecture of an AHS that consists of a domain model (DM), a user model (UM), an adaptation model (AM), and an AHS engine [12] we have enhanced the system with an end-user perceived QoS layer [13, 14]. This QoE layer includes the following new components (see Figure 1): the Perceived Performance Model (PPM), the Performance Monitor (PM), and the Perceived Performance Database (PP DB). The PM monitors different performance metrics that may affect the QoE (e.g. end-to-end response time, round-trip time, throughput, and even user behaviour such as abort actions) in real time during user access sessions and delivers them to the PPM. The PPM models this information and suggests Web content characteristics (e.g. the number of embedded objects in the Web page, dimension of the base-Web page without components and the total di-

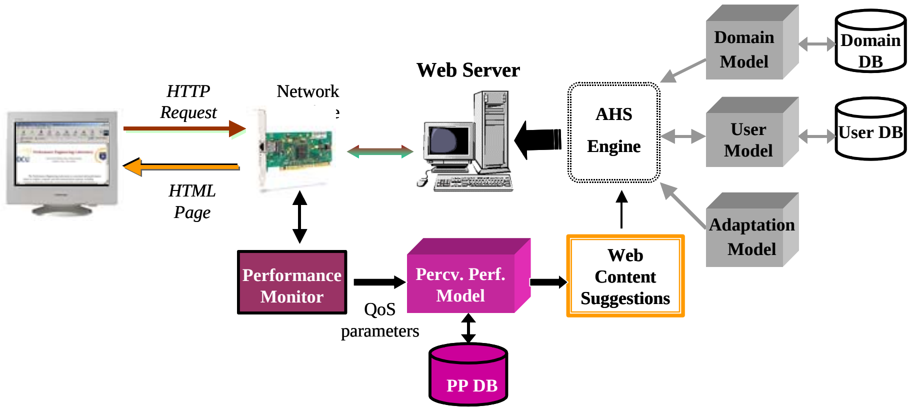


**Fig. 1**. QoE-aware AHS Architecture

mension of the embedded components) that would best meet the end-user expectation related to QoS. These constraints are applied to the Web pages that have already been designed according to the user profile (based on the UM and AM). The PPM model can also take into consideration the users subjective opinion about their QoE explicitly through the use of a form, which asks users to rate their current QoE. This introduces a degree of subjective assessment specific to each user. A more detailed description of the Perceived Performance Model is presented in [13]. PP DB saves user related performance information.

Applying the PPM suggestions involves the alteration of the properties of the embedded images (that are presented as concepts in the DM) or the elimination of some concepts expressed through text, images, paragraphs or other Web page items. These actions would be applied to those concepts the user is least interested in as recorded by the UM.

For Web pages that consist of text and images the alteration /elimination of images would bring the biggest improvement for the access time. This is due to the fact that images represent the largest percentage of the total size of a Web page. For the situation when audio and video components are part of a Web page, strategies that involve size and quality adjustments for audio and video can be applied (e.g. for video compression techniques involving frame rate, resolution and colour depth modifications and respectively for audio silence detection and removal technique). These techniques are studied by the multimedia networking area and they are not detailed in this paper.

### 3.1 A Simple Example

This section presents a simple example of applying PPM suggestions in the case of a Web page being downloaded in a low bit rate environment. As PM indicates that the download time is too long (e.g. greater than 10 seconds), the PPM will seek to reduce the amount of data sent to a calculated value that determine an acceptable download time.

**Step 1: Image Compression.** The first step involves the use of an image compression technique that would reduce the size of the images. Different degrees of compression (expressed as percentage of the original) are applied on each image depending on the user knowledge or interest in the concept represented by the image. If one of the computed compression rates cannot be applied to an image due to the fact that the image compression technique has reached the compression threshold that ensures good quality, an image elimination strategy must be applied.

**Step 2: Image Elimination**. It is based on image removal from the Web page and its replacement with a link to the image. Consequently, if a user does really want to see the image, the link offers this possibility. The algorithm is based on the following rules:

- the image with the lowest interest for the user is replaced with a link
- if the new recomputed total size of embedded objects from a Web page is still higher that the PPM suggestion, perform again step 1 (image compression). In this case a lower compression rates will be applied in the remained images.

## 4 Assessing the Benefits of the QoE Layer Using QoSAHA

For illustration and testing purposes the end-user perceived QoS related enhancements have been deployed on the open-source AHA! system, creating QoSAHA. The AHA! system was developed at the Eindhoven University of Technology, in the Database and Hypermedia group. It was first deployed and used in educational area as an adaptive hypermedia courseware application that supports the "Hypermedia Structures and Systems" course [15, 16]. The following advantages of AHA! allowed us to use it and to demonstrate their benefits by performing different tests using the AHA! tutorial:

- The AHA! has been extensively tested and accepted by the research community.
- The AHA! system architecture respects the generic AHS architecture [17].
- AHA! is open source.
- AHA! version 2.0 includes an adaptive tutorial as example of the adaptive features of the AHA! system.

### 4.1 Evaluation of the QoSAHA

Although many AHSE have been proposed and developed, there is a significant lack of evaluation strategies and comprehensive empirical studies to measure the usefulness and effectiveness of adaptation within the systems and between the systems. There is also much debate on how adaptive hypermedia applications should be evaluated since there is no standard or agreed evaluation framework for measuring the value and the effectiveness of adaptation yielded by adaptive systems. In order to determine the evaluation strategies for QoSAHA system an extensive survey of the research in the adaptive education area with emphasis on Web-base AHSE has been undertaken [18].

We compare the proposed QoSAHA with the original AHA! system both in terms of performance and end-user perception. Simulation tests are used to determine access times for both systems in different bit rate environments. This provides the basis of our performance comparison. Subjective tests are used to compare end-user perceived QoS, user satisfaction, and user learning capabilities for the two systems. These tests have assessed the following evaluation criteria: time taken to complete a task, learner achievement and performance, and usability.

### 4.2 Simulation Tests

Reducing the access time of the Web pages involved in a learning process can produce a significant improvement into the end-user QoE. The simulation tests involve comparative measurements of the access times for the AHA! and QoSAHA systems respectively when a learning task is performed by the user in different operational environments (home modem connection, broadband connection - ISDN and LAN connection) and with various connection throughputs (from 28 kbps to 128 kbps and over). The learning task involved the study of the “AHA! installation” section from the AHA! tutorial consisting of four Web pages. In order to comply with the Web content constraints generated by the PPM, only image compression techniques needed to be used in these tests.

The simulation tests show that QoSAHA system improves the total access time of the learning process for users in low bit rate environments (64 kbps and lower) by up to 37% with a reduction in the quantity of data sent of up to 42%. A subsequent user survey suggests this reduction did not significantly affect the quality of the images. An average of up to 9.7% perceived quality degradation was reported for the lowest bit rate (28 kbps) but still close to the “good” perceptual level. The results are detailed in [14].

### 4.3 Subjective Evaluation

The goal of the subjective evaluation is to compare the learning outcome for users using QoSAHA and AHA! systems and to assess user satisfaction with the two systems. The evaluation tested both learner achievement and usability. The conditions used were the same as those used for the simulation tests (which showed an increase in measured performance using QoSAHA). For our preliminary tests we showed that QoSAHA also improved user QoE without affecting the learning outcome.

#### 4.3.1 Setup Conditions

The laboratory-network setup used for testing involved four desktops PC Fujitsu Siemens with Pentium III (800MHz) processors and 128 MB memory, a Web server IBM NetFinity 6600 with two processors Pentium III (800 MHz) and 1GB memory and one router Fujitsu Siemens with Pentium III (800MHz) processor and 512 MB RAM that has a NISTNET network emulator installed on it. The NISTNET instance that allows for the emulation of various network conditions characterized by certain bandwidth, delay and loss rate and pattern was used to create a low bit rate operational environment with a 56 kbps modem connection (Figure 2). This setup offers similar connectivity to that experienced by residential users and is the same as that used in the simulation tests.

The subjects involved in this study are comprised of forty-two postgraduate students from Faculty of Engineering and Computing at Dublin City University. They were asked to complete a learning task that involved the study of the “AHA! installation” chapter from the AHA! tutorial. The subjects were randomly divided into two groups. One group used the original AHA! system, whereas the second used QoSAHA. No time limitation was imposed on the execution of the learning task.

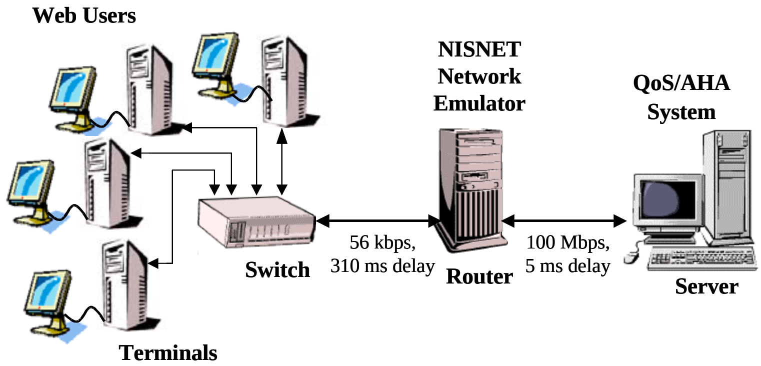


**Fig. 2.** Laboratory-network configuration for the perceptual testing

At the start of the study session the subjects were asked to read a short explanation concerning the use of the system and the required duties. Their duties were as follows:

- *complete a Pre-Test* that consists of a questionnaire with six questions related to the learning topic. The test is used to determine subject's prior knowledge in this domain
- *log onto the system* and proceed to browse *and study the material*
- *complete a Post-Test* at the end of the study period. The Post-Test consists of a questionnaire with fifteen questions that test recollection of facts, terms and concepts from the supplied material, as suggested in Bloom's taxonomy [19].
- *answer a Usability questionnaire* that consists of ten questions categorized into navigation, accessibility, presentation, perceived performance and subjective feedback.

In order to fully assess the subjects learning achievement, both pre-test and post-test questionnaires were devised from the four different types of test-items most commonly used in the educational area: Yes-no, Forced-choice, Multi-choice and Gap-filling test items. These test items have different degrees of difficulty and their corresponding answers have been assigned weights in the final score accordingly. The maximum score for pre-test is 10 points and the maximum score for post-test is 30 points. The final scores were normalized in the range of 0 to 10.

#### 4.3.2 Learner Achievement

Learner achievement is defined as the degree of knowledge accumulation by a person after studying a certain material. It continues to be a widely used barometer for determining the utility and value of distance learning technologies.

**Table 1.** Pre-Test results

| | mean score | min score | max score | sdev |
|---|---|---|---|---|
| AHA! | 0.35 | 0 | 2 | 0.55 |
| QoSAHA | 0.3 | 0 | 2 | 0.53 |

**Table 2.** Post-Test results

| | mean score | min score | max score | sdev |
|---|---|---|---|---|
| AHA! | 6.70 | 4.3 | 9.3 | 1.401 |
| QoSAHA | 7.05 | 4.6 | 9.0 | 1.395 |

We have performed an analysis of the learner achievement in terms of the final scores from the Pre-test and Post-test achieved by the subjects using the QoSAHA and AHA! systems. The results of the Pre-Test and Post-Test are shown in Table 1 and Table 2.

A t-test two-sample analysis, with equal variance assumed, applied on the Pre-Test scores shows that statistically both groups had the same prior knowledge of the studied subject (significance level $\alpha$=0.01, t=0.21, t_critical= 2.42, p(t)=0.41). According to the Post-Test results the mean score of the subjects that used QoSAHA was 7.0 and that for those that used AHA! 6.6. T-test analysis suggests that this difference in mean does not indicate a significant difference in performance between the two groups of users. ($\alpha$=0.05, t=-0.79, t_critical=1.68, P (t)=0.21).

Since the answers for three questions from the post-test questionnaire required the subjects study the images embedded in the studied pages, an analysis of the students' performance on these questions was performed. After the scores related to these three questions were normalized in the range 0 to 10, the mean value of the students' scores was 6.3 for the QoSAHA group and 6.4 for AHA! group, A t-test two-sample analysis, with equal variance assumed again indicates that there is no significant difference in the students performance (t=-0.08, t-critical=2.71, p(t)=0.93, confidence level $\alpha$=0.01) although a slight degradation in the image quality was applied by the QoSAHA system.

In summary, preliminary test results indicate the QoE aware AHA! system did not affect the learning outcome, offering similar learning capabilities as classic AHA! system.

#### 4.3.3 Usability Assessment

At the end of the study session both group of subjects were asked to complete an online usability evaluation questionnaire consisting of ten questions with answers on a five–point scale (1-poor - 5-excellent). The questions were created using the widely used guidelines suggested by Preece [20] for evaluating the Web sites. The questions were categorized into navigation presentation, subjective feedback, accessibility, user perceived performance. The last two question categories seek to assess the end-user QoE. Four questions of our survey relate to these two categories. These four questions assess user opinion in relation to the overall delivery speed of the system (Q6), the download time of the accessed information in the context of his/her experience with Web browsing (Q7), the user's satisfaction in relation to the perceived QoS (Q9) and whether the slow access to the content has inhibited them or not (Q5). The presentation of the results on the QoE related questions for the AHA! and QoSAHA systems is shown in Figure 3.

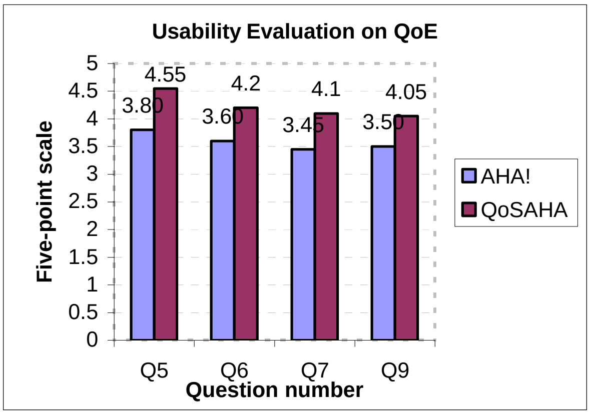


**Fig. 3**. Usability evaluation results on questions that assessed the end-user QoE

As seen from the chart the QoSAHA system has provided a better QoE for the end users, improving their satisfaction to a "good" level in relation to using the system. This was even though the subjects were using a slow connection (56 kbps) during the study and they were not explicitly informed about this. A t-test two-sample analysis on the results of these four questions confirmed that users' opinion on QoE is significantly higher for QoSAHA than for AHA!, stated with confidence level above 99%, ($p<0.01$).

The usability assessment on the other questions related to the navigation and presentation features achieved an average score of 3.83 for AHA! and 3.89 for QoSAHA, demonstrating that these features were not affected by the addition of the QoE enhancements.

An overall view of the results of usability testing of both systems, when all ten questions were considered of equal importance shows that the students considered QoSAHA system (mean value=4.01) significantly more usable then AHA! one (mean value=3.73). These results were also confirmed by the unpaired two-tailed t-test ($t=2.44$, $p<0.03$) with a 97% confidence degree. This achieved 7.5% increase in the overall QoSAHA usability mainly due to higher scores obtained in the questions related to end-user QoE.

## 5 Conclusions

This paper has proposed Quality of Experience (QoE) as another dimension of user characterisation that should be taken into consideration by the personalization process provided by adaptive hypermedia applications. QoE is directly influenced by the operational environment through which the user interacts with the AHS (bandwidth, delay, loss, device capabilities, etc) and by the subjective assessment of the user of perceived performance. The goal of any AHS should be not only to provide the content that would best suit the user's goals, knowledge, or interest but also to provide the best content that would fit the user's operational environment. In this context we have proposed a QoE-layer enhancement for AHS that analyses some key factors that influence QoE and makes a correlation between their values and Web page characteristics that provide the best QoE for the end-user.

For evaluation purpose QoSAHA was created by deploying the QoE layer on the open-source AHA! system used in the educational area. This paper presents a study on the impact that the incorporation of the QoE layer has on learning outcome and on usability of the system in a low bit operational environment (56 kbps). This study is based on a performance comparison between the AHA! system and QoSAHA and involves both simulations and subjective testing.

The evaluation results show that the learning outcome was not affected by the deployment of the QoE enhancement. Most significantly they also suggest that with the price of a slight degradation in quality of the images, an important improvement in system usability was provided by QoSAHA system. This was mainly due to improvements in user satisfaction related to their QoE.

The next stage of the QoE layer evaluation is to perform learning performance and usability assessment for the case of image elimination technique when increase compression would produce high degradation into the image quality. Other evaluation criteria such as time taken to complete a learning task or time taken to search for a term, how many times the subjects have revisited some Web pages during the learning session will be assessed as part of further QoSAHA evaluation.

## Acknowledgements

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# Evaluating Presentation Strategy and Choice in an Adaptive Multiple Intelligence Based Tutoring System

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**Abstract.** EDUCE is an Intelligent Tutoring System for which a set of learning resources has been developed using the principles of Multiple Intelligences. It can dynamically identify learning characteristics and adaptively provide a customised learning material tailored to the learner. This paper describes a research study using EDUCE that examines the relationship between the adaptive presentation strategy, the level of choice available and the learning performance of science school students aged 12 to 14. The paper presents some preliminary results from a group of 18 students that have participated in the study so far. Results suggest that learning strategies that encourage the student to use as many resources as possible are the most effective. They suggest that learning gain can improve by presenting students initially with learning resources that are not usually used and subsequently providing a range of resources from which students may choose.

## 1 Introduction

Research on learning shows that students learn differently, that they process and represent knowledge in different ways, that it is possible to diagnose learning style and that some students lean more effectively when taught with appropriate strategies [24]. EDUCE [15][16] is an Intelligent Tutoring System for which a set of learning resources has been developed using the principles of Multiple Intelligences [10]. It can dynamically identify user learning characteristics and adaptively provide customised learning material tailored to the learner [17]. The multiple intelligence concept defines intelligence as the capacity to solve problems or fashion products that are of value and states that there are different ways to demonstrate this intelligence. It is a concept that offers a framework and a language for developing a broad range of content that supports creative, multi-modal teaching. In EDUCE four different intelligences are used to develop four categories of content: verbal/linguistic, visual/spatial, logical/mathematical and musical/rhythmic intelligences. Currently, science is the subject area for which content has been developed.

This paper describes an empirical study that examines the relationship between the adaptive presentation strategy, levels of choice and the learning performance of science school students aged 12 to 14 in a computer based adaptive learning environment using different versions of EDUCE. The adaptive presentation strategy involves guiding students to resources they prefer and do not prefer to use. The level of choice is determined by the range of resources a student has access to and the extent by which the student is guided to a particular resources by EDUCE.. Learning performance is defined by learning gain, learning activity and motivation. Learning gain is measured by a pre and post test, learning activity is determined by the navigation profile and motivation by the attempts to answer questions.

The goal of the research study is to address the following research questions:

- Does providing a range of learning resources improve learning gain and activity?
- What are the advantages in making adaptive presentation decisions in relation to giving the learner complete control?
- What is the difference between learning gain and activity when presenting resources that are preferred and resources that not preferred?

The results of this study may be significant for researchers and practitioners. For researchers, it will produce specific results that demonstrate the relationship between learning and the availability of different learning resources. For practitioners, it demonstrates how teaching in different ways can affect learning.

## 2 Background

Research has provided a wealth of insight into individual differences and orientations to learning that can be translated into instructional design [7],[11]. Different studies report that when the learner's individual learning style is taken into account, the quality of the learning is enhanced [8], [20], [23]. However, observing and defining learning characteristics is difficult and traditionally questionnaires and psychometric tests are used to assess and diagnose learning characteristics [14], [22].

Gardner's Multiple Intelligence (MI) [11, 12] concept is a psychological theory that addresses what the brain does with information. It defines intelligence as the capacity to solve problems or fashion products that are of value. It states that there are eight different ways to demonstrate this intelligence with each having its own unique characteristics, tools, and processes that represent a different way of thinking, solving problems, and learning. Its use in the classroom has been significant [3] but its application to online learning and intelligent tutoring systems is still undergoing research. However, even though it is a theory and has no specific application method or instructional approach it does offer a structure and language in which to inform the student, domain and pedagogical model of an intelligent tutoring system.

Several systems adapting to the individual's learning characteristics have been developed [4], [5]. However in developing such systems it is not clear which aspects of learning characteristics are worth modelling, how the modelling can take place and what can be done differently for users with different learning styles [2]. In attempts to build a model of student's learning characteristics, feedback from the student is obtained using questionnaires, navigation paths, answers to questions, directly requesting feedback, allowing the user to update their own student model and to make specific adaptations such as sorting links or viewing stretch text.

Machine learning techniques offer one solution in the quest to build a model of learning characteristics [26], [27]. Typically these systems contain a variety of instructional types such as explanations or example and fragments of different media types representing the same content, with the tutoring system choosing the most suitable for the learner. Another approach is to compare the students performance in tests to that of other students, and to match students with instructors who can work successfully with that type of student [13]. Other systems try to model learning characteristics such as logical, arithmetic and diagrammatic ability [19].

EDUCE builds on existing research by modelling the learner's psychological characteristics through the multiple intelligence concept.

## 3 Student Model

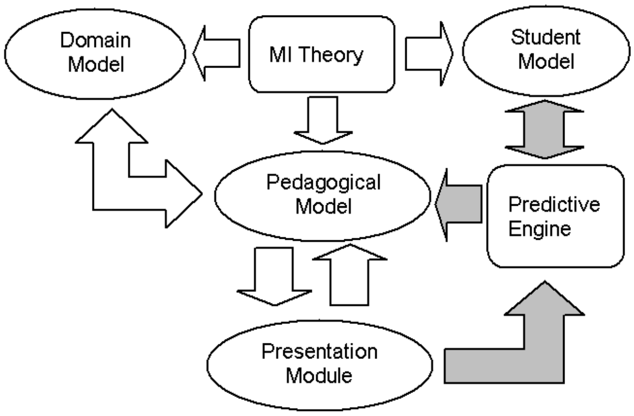


**Figure 1.** Educe Architecture

Fig. 1 illustrates the architecture of EDUCE. It consists of a student model , a domain model, a pedagogical model, a predictive engine and a presentation model. The predictive engine receives input from the presentation module, builds the student model and informs the pedagogical model.

The MI concept inspires the student model in EDUCE. Gardner identifies eight intelligences involved in solving problems, in producing material such as compositions, music or poetry and other educational activities. The intelligences include the logical/mathematical, linguistic/verbal, visual/spatial, bodily/kinesthetic, musical/rhythmic, interpersonal, intrapersonal and naturalist. Currently EDUCE uses the following four intelligences in modeling the student and in the future will be extend to incorporate the other intelligences. The four intelligences is use are

- Logical/Mathematical intelligence (LM) - This consists of the ability to detect patterns, reason deductively and think logically.
- Verbal/Linguistic intelligence (VL) - This involves having a mastery of the language and includes the ability to manipulate language to express oneself.
- Visual/Spatial intelligence (VS) - This is the ability to manipulate and create mental images in order to solve problems.
- Musical/Rhythmic intelligence (MR) - This encompasses the capability to recognise and compose musical pitches, tones and rhythms.

EDUCE builds a model of the student's learning characteristics by observing, analysing and recording the student's choice of MI differentiated material. Other information also stored in the student model includes the navigation history, the time spent on each learning unit, answers to interactive questions and feedback given by the student on navigation choices.

In particular the model that describes how a student uses different resources is built using the following criteria:

- Did the student spend a minimum amount of time using the resources ?
- Did the student spend a long time using the resource ?
- Which resource did the student use first ?
- Did a student use only one resource or multiple resources ?
- Did the student use the resource more than once ?
- Did the student attempt a question after viewing the resource ?
- Did the student attempt a question after viewing the resource and get it right ?

## 4 Domain Model

The domain model is structured in two hierarchical levels of abstraction, concepts and learning units. Concepts in the knowledge base are divided into sections and sub-sections. Each section consists of learning units that explain a particular concept. Each learning unit is composed of a number of panels that correspond to key instructional events. Learning units contain different media types such as text, image, audio and animation. Within each unit, there are multiple resources available to the student for use. These resources have been developed using the principles of Multiple Intelligences. Each resource uses dominantly one intelligence and is used to explain or introduce a concept in a different way. To access each of the intelligences, there is a set of practical techniques, methods, tools, media and instructional strategies.

MI is a theory with a set of principles. It structures and suggests but does not prescribe a particular pedagogical model or set of instructional strategies. Moving from a theory of intelligence to actual implementation is an act of interpretation and there has been a considerable amount of research done in articulating different techniques that can access each of the intelligences [3, 18]. Figure 2 shows EDUCE's model for developing MI material [16]. It describes the range of instructional approaches that will cultivate each of the intelligences.

For example, to emphasis the logical and mathematical mind, strategies described as number, order, logic, representation, puzzles, problem solving , relationships, compare/contrast and outlining may be employed.

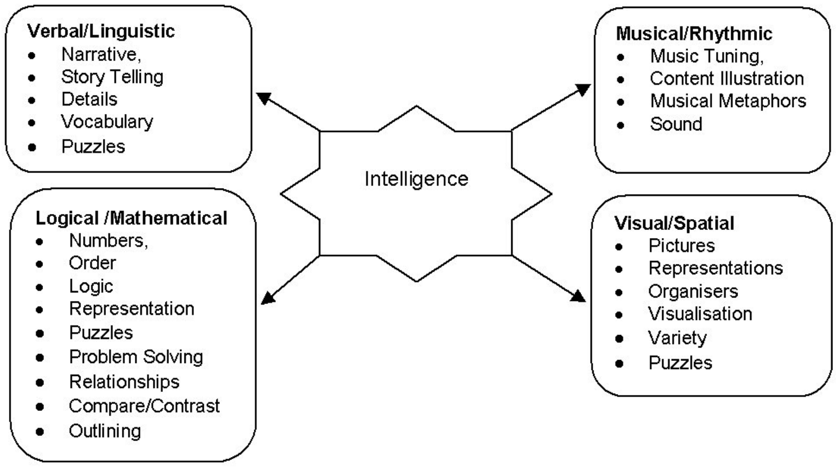


**Figure 2**. Pedagogical Model for developing MI material

Number includes the use of mental arithmetic, calculations and measurements that encourages mental maths, numerical thinking and precision. The arrangement and detection of order can be promoted through the identification of steps, procedures, sequences and patterns. Logic includes the use of scientific, deductive and inductive logic. This can be best realised by examining how reasoning processes operate and how truthful conclusions may be reached. Syllogisms, venn diagrams and analogies may be employed. Visual representation through the use graphs, charts, piecharts, tables, grids, matrices can make mathematical relationships easier to understand. Mathematical representation involves the use of abstract symbols, codes and formulas to represent and communicate concrete objects and concepts. Logic puzzles and games can awaken and arouse reasoning and logical thinking. Problem solving may be promoted through the use of estimation, prediction, exploration and heuristics. Understanding causal knowledge involves the use of questioning, creating meaningful connections between ideas and understanding cause and effect. Classification and the arrangement of information into rational frameworks includes comparing and contrasting concepts, attribute identification, categorisations and ranking. Outlining explains concepts in logical frameworks using logical explanations, logical thought maps and sequence charts.

Figure 3 gives a specific example of how these instructional strategies were used in the tutorial Static Electricity. Content has been developed in the subject area of Science for the age group 12 to 14.

All resources developed have been assessed and validated by expert MI practitioners.

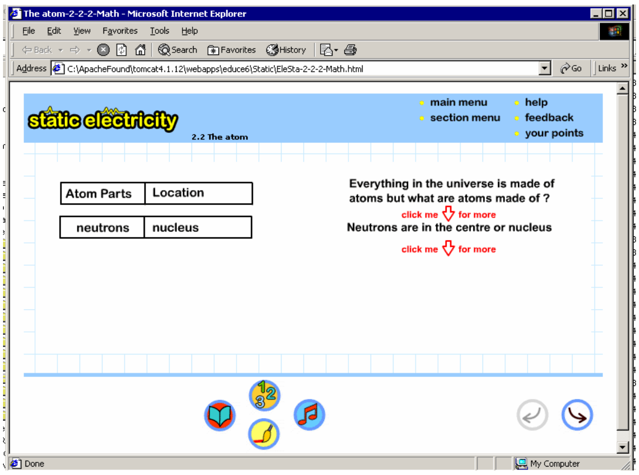


**Figure 3**. Logical/Mathematical Intelligence

## 5 Presentation Module

In the teaching of a concept, key instructional events are the elements of the teaching process in which learners acquire and transfer new information and skills. The EDUCE presentation model has four key instructional events, as shown in Fig. 2. [9]

- *Awaken*: The main purpose of this stage is to attract the learner's attention.
- *Explain*: Different resources reflecting MI principles are used to explain or introduce the concept in different ways.
- *Reinforce*: This stage reinforces the key message in the lesson
- *Transfer*: Here learners convert memories into actions by answering interactive questions

At the Awaken stage, to progress onto the next panel, the learner chooses one from four different options. Each choice will lead to a different resource that predominately reflects the principles of one intelligence. At the Reinforce and Transfer stage the learner has the option of going back to view alternative resources.

Different learners may prefer a different sequence events during the learning process, but the for the purpose of determining which resources a learner prefers the instructional event model is the same for all. The navigation path is designed to force the student to make a conscious choice about which resource is preferred. As learners choose between different MI resources, EDUCE automatically builds a model of the learning characteristics and strengths.

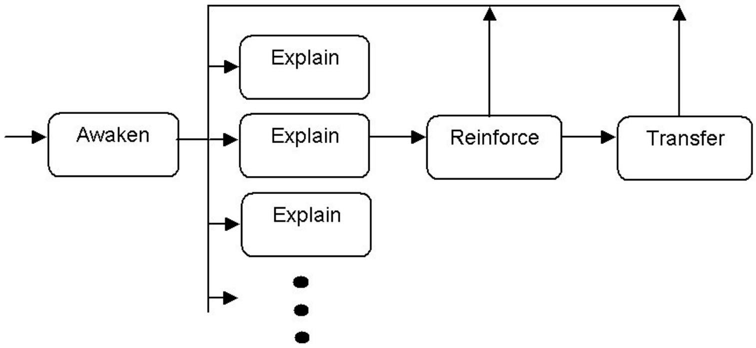


**Figure 2**. EDUCE Instructional Event Model

## 5 Pedagogical Model

The pedagogical model uses the predictive engine to make predictions about which MI differentiated resource a student prefers. Being able to predict student behaviour provides the mechanism by which instruction can be adapted and by which to motivate a student with appropriate material. As the student progresses through a tutorial, each leaning unit offers four different types of resources. The prediction task is to identify at the start of each learning unit which resource the student would prefer. These predictions are used in two ways: to guide the student to preferred resources and to guide the student to resources that are not preferred. The predictive engine is implemented using the Naïve Bayes algorithm [4]. In EDUCE the current focus of the pedagogical model is on content presentation and selection. Later versions will accommodate concept sequencing.

## 6 Research Design

Different configurations of EDUCE support different instructional strategies and levels of choice. The research purpose of the experiment described in this paper is to explore the relationship between the independent variables: instructional strategy and level of choice, and the dependent variable: learning performance. Other variables such as MI profile, gender, previous computer experience and level of ability in school will also be examined. The experiment is intended to provide insight into the advantages and disadvantages of providing a range of resources and of guiding learners to preferred resources.

The instructional strategy or more specifically the presentation strategy for delivery material encompasses two main strategies.

1. *Most preferred*: - showing resources the student prefers to use
2. *Least preferred*: - showing resources the student least prefers to use

For each learning unit, there are four MI based learning resources. Which of these resources is shown first is determined by the dynamic and static MI profile and the instructional strategy. The static MI profile of each student is determined before the experiment using an MI inventory (MIDAS)[25]. EDUCE also builds a dynamic model of the student's MI profile by observing, analysing and recording the student's choice of MI differentiated material. Other information also stored in the student model includes the navigation history, the time spent on each learning unit, answers to interactive questions and feedback given by the student on navigation choices.

The second independent variable is the level of choice. There are four different levels of choice provided to different groups. These include:

1. *Free* – student has the choice to view any resource in any order. No adaptive presentation decisions are made as the learner has complete control.
2. *Single* – student is only able to view one resource. This is determined by EDUCE based on an analysis of the MI inventory completed by the student.
3. *Multi* - student is first given one resource but has the option to go back and view alternative resources. The resource first given to the student is determined by EDUCE based on the analysis of the MI inventory completed by the student. The *Multi* choice level is the same as the *Single* choice level but with the option of going back and viewing alternative resources.
4. *Adaptive* – the student is first given one resource but has the option to go back and view alternative resources. The resource first given to the student is determined adaptively by EDUCE. The predictive engine within EDUCE [17] identifies the most preferred and least preferred resource from the online student computer interaction.

Learning performance is defined mainly by learning gain, learning activity and motivation. To calculate the learning gain each student before and after a tutorial will sit a pre-test and post test. The test for the pre-test and post-test is the same and consists of questions that appear during the tutorial. Learning activity is determined by the navigation profile. It is a measure of the different panels visited, the number of different resources used, the reuse of particular resources and the direction of navigation. Learning motivation or persistence is a measure of the student's progression within the tutorial and the attempts made to answer questions. The questions are multi-choice question with four options. Both learning activity and motivation are analysed to provide informed explanations on learning gain.

Students have been randomly assigned to one of the four groups defined by the levels of choice. Each student sits through two tutorials. They will experience both instructional strategies of least preferred and most preferred. To ensure order effects are balanced out, students are randomly assigned to systematically varying sequence of conditions. The design of the experiment can be described as a mixed between/within subject design with counterbalance.

## 7 Preliminary Results and Future Work

One group of students consisting of 18 boys with an average age of 13 has participated in the study so far. The group was divided into two sets, A and B. Set A use the Free choice version of EDUCE and had the choice to use resources in any order. Set B used the Adaptive choice version of EDUCE where the presentation decisions were made based on the dynamic student profile. Not withstanding the number of participants, the results were analysed to determine differences between the free choice version and the adaptive choice version. For the adaptive version, the results were analysed to determine any differences between the least preferred and most preferred strategy.

A one-way between groups analysis of variance on the learning gain both on the first day and on the second day was conducted to explore the impact of adaptivity and non-adaptivity. The three groups consisted of one group using the free choice version and two groups using the adaptive least/most preferred versions. There was no significant difference between the groups at the $p<0.05$ level. On inspecting the mean increase in learning gain for the different versions it interestingly reveals that the mean for the adaptive least preferred version was greater than the free choice version which was in turn greater than that of the adaptive most preferred version on both days.

To evaluate the impact of learning strategy on learning gain within subject, a paired-samples t-test was conducted There was a statistically significant increase in learning gain using the least preferred strategy ($M=26.25$, $SD=13.024$) and in using the most preferred strategy ($M=10$, $SD=11.95$), $t(7)=2.489$, $p<0.042$). The eta squared statistic (0.47) indicates a large effect size. This initial surprising result suggests 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. It suggests that strategies that increase learning activity and develop all faculties are effective in increasing learning gain.

Currently, the empirical study is underway and on completion more that 200 students will have participated in the research study.

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# Considering Human Memory Aspects to Adapting in Educational Hypermedia*

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**Abstract.** In this paper we target the limited capacity of the human memory while developing adaptive educational hypermedia systems. We discuss implications of remembering and forgetting for the adaptive hypermedia systems development. The forgetting is characterized as a consequence of time passed between two learning events. Knowledge from psychology is used for stating implications of the human memory properties for an improvement of the adaptive learning systems. An experimental implementation of the model of remembering and forgetting is described.

## 1 Introduction

Current adaptive educational hypermedia (AH) systems recognize several aspects of an individual user such as user's goals/tasks, knowledge, background, preferences, interests, or user's individual traits [4]. Important aspect considered in educational AH systems is undoubtedly a level of the user's knowledge related to the learned topic (in the IEEE Personal and Private Information [8] learner profile denoted as the learning performance). The user model reflects current state of the user knowledge related to the presented information as it is comprehended by the AH system. The user's characteristics change (evolve) in the course of learning in accordance with changes of current state of his knowledge (as evaluated by the AH system).

Most current AH systems assume that the amount of user knowledge only grows. But increasing knowledge (as a consequence of the remembering) is not the only process. The user can also *lose* (e.g., forget) some knowledge. The remembered knowledge is not stored in the human memory forever but in the course of time the knowledge can (and some of them will) drop out from the memory.

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Considering mentioned characteristics of the learning process is important during the learning [10]. We presume that a utilization of the human memory aspects while developing an educational AH system would also improve the effectiveness of the AH system usage through an improvement of the learning process. Assume for example the following situation: the adaptive book "presumes" that a user possesses adequate knowledge (prerequisites) for understanding a concept just explained. In spite of truly learned concept some time ago, now – after some time passed from this learning event – the user forgot some of the previously acquired knowledge (because of long time without any repeating). The knowledge forgetting causes inconsistencies between the user model as represented in the AH system (which does not consider the remembering and forgetting in an adaptation of the educational material to the individual) and the actual state of the user's knowledge. As a result, we will likely observe incorrect recommendation of the educational AH system.

Described situation occurs due to not considering specific characteristics of the human memory. In this paper we describe some issues related to the human memory and implications for adaptive hypermedia. We consider the human memory as a new aspect of the user's background modelled in the AH system user model. We give several suggestions for increasing effectiveness of the AH system, especially educational AH systems. In the paper we presume some "minimal amount of knowledge" delivered to the user via the AH system because the effect of the knowledge forgetting process becomes significant with only relatively large knowledge spaces.

The rest of the paper is organized as follows. In the Section 2, we briefly present known facts from psychology about the human memory and the processes of remembering and forgetting. In the next section, we discuss implications of the human memory characteristics for adaptive hypermedia and propose a model, which considers the human memory characteristics. Finally, conclusions and further directions of our research are stated in the Conclusions.

## 2 Background of human memory models

The human mind can be viewed as an information processing system. Its architecture is thought to consist of three basic components: sensory memory, working memory and long-term memory [2]. These components roughly correspond to the input (the human mind perceives information from the outside through the senses), processing (information from the sensory memory is processed in the working memory) and storage (processed information is stored in the long-term memory) (see Fig. 1). Naturally, information stored in the long-term memory can be accessed, or activated to help with the processing in the working memory. Accessing information is perceived as the remembering that can be viewed as a usage of the system (to be able to find information later again). This view provides a useful basis for considering the human memory characteristics during the learning process [10].

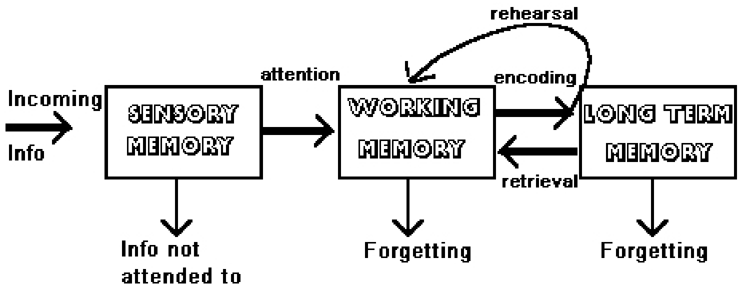


**Fig. 1.** Model of human information processing system [2].

Information stored in the working memory can be looked up much faster than in the long-term memory. The working memory is essential for reading comprehension. Frequently, the read sentence is related to the previous sentences, so the new sentences are considered along previous according their sense. It is believed that this process is accomplished in the working memory (as a consequence people with higher capacity of working memory are able faster understand a text).

One of the most interesting and significant characteristics related to the human mind is the very small capacity of the working memory known as the magical number "seven plus or minus two" [9]. The limited storage capacity of the working memory is accompanied also by a relatively brief duration (estimates range from 12 to 30 seconds without a rehearsal), which results in the information loss.

The forgetting is viewed primarily as a consequence of

- fading (trace decay) over time,
- interference (overlaying new information over the old) or
- lack of retrieval cues.

The information loss can be prevented by means of repeating. Here the elaborative rehearsal which in contrast to maintenance rehearsal involves deep semantic processing of a to-be-remembered information item[1] is more effective [6]. The maintenance rehearsal involves only simple rote repetition aiming at lengthening periods of time the information item is maintained in the working memory. The elaborative rehearsal can be supported by guidelines.

Accessing an information item can be influenced by several factors. Time of searching the information item can be cut down with a good guideline. But the effect of a guideline degrades with the rising number of information items bound with the guideline. Expectant reason is that the system of guidelines brings a hierarchical organization of the information items. The benefit is that the search is performed on the smaller file of information items. However, every new related information item enlarges the file and aggravates the hierarchy.

[1] For example, if an individual is presented with a list of digits for later recall (4968214), grouping the digits together to form a phone number transforms the stimuli from a meaningless string of digits to something that has a meaning.

Mentioned factors imply the forgetting. Function of the volume of remembered information depends on time and has a character of falling an exponential curve. So called the *forgetting curve* was first described by Ebbinghaus in 1885 [7]. To test the retention, Ebbinghaus practiced a list of information items until he was able to repeat the items correctly two times in a row. He then waited varying lengths of time before testing himself again. The forgetting turned out to occur most rapidly soon after the end of practice, but the rate of forgetting slowed as time went on and fewer items could be recalled. It was showed that an individual lost most of the learned information items in first hours (after 8 hours was on average remembered less than 40% information items). After this time is the oblivion less intensive (in average still more than 30% after 24 hours and a bit lesser than 30% after month). Ebbinghaus also discovered that distributing learning trials over time is more effective in memorizing than massing practice into a single session; and he noted that continuing to practice material after the learning criterion has been reached enhances retention.

For the integrity, let us notice that the information items loss can also have biological reasons. It is possible that some biological processes necessary for encoding, storing or searching are disrupted. For example, in a process of embedding knowledge in the memory some structures of brain including hipocamp and amygdala are active. Their mutilation has a negative influence on the process of remembering.

## 3 Some implications for adaptive hypermedia

While designing an educational adaptive hypermedia system we can take an advantage of knowing characteristics of both working and long-time memories. Considering the human memory along other aspects of the student's background brings several assets:

- more accurate information about the state of the user's (student's) knowledge,
- better aid for remembering the knowledge and automatic repetition of lost knowledge,
- more effective (adaptive) assistance for students with memory-problems, or in opposite, assistance for students with more-than-average memory abilities.

First two items are related to the effectiveness of delivery of the educational material by the AH system in general. The last item enables to accommodate individual differences in the human memory capacity for personalization.

To achieve mentioned assets several techniques can be used. The most important are:

- hierarchical organization of the learned material – improves the information access and enables the effective usage of limited capacity of the working memory,
- guidelines for effective information searching – helps to overcome an interference between the information items,

– forming linkages between the concepts (natural or artificial) – results in a possibility of elaborative rehearsal and better structuring of the knowledge space,
– measuring understanding the sense of knowledge (or measure the usage of the knowledge) – helps in planning of the repeating,
– considering a context of the environment – helps to decrease the amount of information items considered at the time by giving contextual cues.

Some of the techniques are already used in designing educational adaptive hypermedia systems or authoring their content [5].

Following discussion is based on our experiments with the adaptive book on computer architecture where we applied knowledge on the human memory characteristics [1]. Our proposals can be easily incorporated to various adaptive hypermedia educational systems.

### 3.1 Modeling the process of remembering and forgetting

The simplest method of modeling the remembering and forgetting information items in the student's memory is an application of the forgetting curve [7]. Using only the forgetting curve directly is insufficient because we can only infer how much per cent from the original grist of the information items has been remembered in some point of time. However, we cannot recognize whether specific information item in a given point of time *is remembered* or has been *lost*.

We can say only that the information item (learned at time $t$ and not repeated) is remembered with high probability (if according to data about the user's memory-losing at time $t$ is remembered more than K% of learned information items, e.g. more than 90%) or lost with high probability (likewise).

We have proposed a simple model which reflects the forgetting. It extends every concept's traditional performance value from the user model [8] with data about how much is the knowledge remembered. We call it *knowledge activity in the memory*. Every knowledge (represented by a concept in the domain model) has defined the knowledge activity in the memory represented by a real number. It's value must be upon given bound B, otherwise the knowledge represented in the concept is considered as being *lost* (from the user's memory). After a successful learning the corresponding concept is set as "learned" and the knowledge activity in the memory is set to a value greater than B. Moreover, after every new user's session with the AH system, the user model reflects the forgetting curve by decreasing the knowledge activity for every concept not being used in the session.

Described approach ensures that the repeated knowledge or knowledge more used are being lost more slowly. The knowledge-remembering model can be supplemented by including hierarchical binds between the knowledge items in a domain.

### 3.2 Remembering and repeating

Knowledge is remembered better if we work more with it. It is not enough if the information item representing a knowledge only appears many times on a page presented to the student. A measure of remembering depends on how much is the knowledge substantial (e.g., whether it is a prerequisite for understanding another knowledge presented on the page, or whether it is necessary for finding-out results of exercises) and on the appearance (layout) of the corresponding information item.

It is advisable to distinguish at least three levels of the rate at which a user has worked with particular knowledge represented by the information item:

– *normal level:* the user has worked with the knowledge in such a way that after the end of the session he has remembered it and can correctly reproduce it;
– *low level:* the user has worked with the knowledge less than in the normal level (e.g., the information item has been mentioned just a few times among many other information items) and
– *high level:* the user has worked with the knowledge more than in the normal level (e.g., the user has intensively and repetitive worked with the information item and successfully passed several exercises related to the knowledge).

While in the first case the *speed of losing* can be computed according to the standard forgetting curve, in the second case the oblivion is faster and in the last case slower. Of course, there is no linear relationship: very high measure of the user's work with a knowledge does not substantially increase its measure of the remembering. The measure of remembering of a knowledge item depends on a "measure of working" with it. However, the raising is very slow from a certain level. The reason lays in the memory limits. It is possible to remember more than at the normal level (e.g., frequently used knowledge, important knowledge) but not substantially more. On the other hand, if the measure of working has been low (e.g., the information item has been put down only once) the probability of remembering the knowledge is very low.

The same is true not only for *learned knowledge*, but also for the *repetition*. After a knowledge has been learned, its activity in the memory in time decreases. By repeating and using the knowledge, its activity in the memory increases. For example, if a user studies a page where the knowledge item K is referenced or repeated, or should be used for understanding other assertions, all these activities increase the knowledge activity in the memory. Of course, there is also important measure of the user's work. For example, if a knowledge was noticed only (in a text, comment, footnote) or announced, then increasing the knowledge activity in the memory is futile.

The open issue is the determination of a list of the knowledge items considered during the inference related to remembering and repeating. It seems that it is not possible particularize the list automatically. We can count up automatically the frequency of textual representation of a given knowledge in the given text but this does not reflect its "importance". It may happen that the knowledge has no textual occurrence in the presented page, however, for understanding the content of the page the user should work with the knowledge intensively (so it is repeated many times). On the other hand, another knowledge item may occur frequently in the text but it is not much important for the comprehension (and therefore not repeated so much). Information on the mapping of knowledge items to the content should be provided by he author of the educational material.

### 3.3 Repetition

Information items the user read on a page are inserted into his working memory. Because of limited capacity of the working memory the information items are either moved to the long-term memory or they are lost. To support the process of moving the information items into the long-term memory (i.e., to enforce the remembering) it is effective to repeat them.

One possibility is a *periodical repetition*. After the user has learned given "amount" of the knowledge, the AH system provides the repetition of the knowledge learned from the previous repetition. The repetition can take several faces. In our adaptive book it is automatically observed how many new knowledge items the user has learned. Providing the summation of the occupied items is greater than the predefined capacity limit the AH system invokes a repetition. The system generates a page with the resume of learned knowledge (occurrence of the knowledge items in the information fragments is tagged by the author). The complexity of the knowledge item is also considered. Described approach does not give exact results, but it ensures a repetition in time closed to the point where the user has learned certain amount of the knowledge.

Other techniques of the repetition realized in our adaptive book are:

- repeat at the end of a lesson the knowledge learned in the lesson (*final repetition*),
- repeat at the beginning of a new lesson the knowledge learned in the previous lesson (*overall introductory repetition*),
- repeat at the beginning of a new lesson the knowledge (assumed) necessary in this lesson (*necessary introductory repetition*).

The same can be applied to sessions or various parts of the book content.

Often it is not practical or possible to repeat all of the knowledge items marked as forgotten. The AH system should select a set of knowledge items for the repetition. Certain number of the knowledge items is selected and only these knowledge items are repeated at the beginning of a new lesson. If there is large number of the lost knowledge items the adaptive book offers a repetition-lesson, aimed for the repetition only.

Selection can be made on several criterions, for example: random selection, selection based on time of the acquisition a knowledge (priority is given to the knowledge acquired longer time ago), selection based on a measure of remembering, i.e. the activity in the memory characteristic is used (priority is given to the knowledge item with lower activity in the memory), selection based on prerequisite-dependencies (priority is given to the knowledge item which is supposed to be in the need of the user in the next study time).

### 3.4 Knowledge space organization

Knowledge space is formed by the concepts (with corresponding information fragments). The concepts are connected by relations. The currently most used approaches to structuring the knowledge space are the hierarchical approach and the network approach [5]. The structure of the hyperspace can aid the repeating in such a way that the repeating one knowledge item may cause the need of repeating (in part or in whole) another knowledge item. The same holds for the forgetting.

For example, if a student is able to compute the volume of a cylinder, he must be able to compute the square of a number. In opposite, if he has forgotten how to compute the square of a number, he will not able to compute the volume of a cylinder. But it is not true that if the student has forgotten to compute the volume of a cylinder, he also has forgotten how to compute the square of a number or that if he remembers how to compute the square of a number he also remembers (and knows) how to compute the volume of a cylinder.

The prerequisite relation is well known relation in adaptive educational hypermedia [3]. Considering the human memory characteristics it is useful to distinguish between *domain prerequisites* and *pedagogical prerequisites*. Let A be a prerequisite of B. If A is a domain prerequisite, the student is constrained in understanding B with requirement to understand A. If A is a pedagogical prerequisite the constraint is weaker and it is possible to comprehend B without knowing A. As an example, let us present expressions in C programming language course. If the adaptive book explains this part using commonalities and differences between C and Pascal languages, then the knowledge about Pascal are denoted as pedagogical prerequisites. The student needs a knowledge of Pascal to understand this part of the content. But, when a repetition process is evoked on the "expressions in C" knowledge item, the Pascal knowledge item is not necessary to be repeated.

There can be an objection that the above is not fully true. We may repeat some topics of Pascal when we repeat C language. For example, some things may be the same (or similar) and the user may have remembered data like "in C it is the same like in Pascal". The user may also remember the page itself, text or/and its graphical layout on the page. It is also possible that when he would hear about some topics of C language, he will bring back some information about Pascal. In all these cases the user will repeat with some knowledge about C language also some knowledge about Pascal. This may happen. But after some amount of time the intensity of repeating related knowledge items will decrease and the user will repeat only already repeated knowledge and its domain-depended prerequisites.

## 4 Conclusions

The research discussed in this paper addresses the possibility of improving effectiveness of learning using adaptive educational hypermedia by considering the human memory characteristics. Important aspect is limited capacity of the working memory. We discussed impacts of the human mind nature to the adaptive hypermedia systems. Our research is supported by experimental adaptive web-based book. Known adaptation techniques (annotations of links and conditional inclusion of fragments) are supplemented by an inference based on a model of the remembering and the forgetting which leads to the repeating. The base for modelling the remembering is the forgetting curve. The forgetting curve can be tuned individually for each user which results in more effective repeating by utilization of individual differences.

We still work on experimental evaluation of issues elaborated in this paper. Our future work will concentrate on using experiments for proving effectiveness of the proposed approach. Naturally, we expect that the proposed models should be tuned for particular usage and differences of the individuals.

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# Discovery of Individual User Navigation Styles

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**Abstract.** Individual differences have been shown to lead to different navigation styles. In this paper we present a pilot study that aims at finding predictors for users' vulnerability to experience disorientation that can be gathered unobtrusively and in real-time. We identified two navigation styles that we called flimsy navigation and laborious navigation that together predict users' perceived disorientation. Our findings suggest that adaptive navigation support that addresses these navigation styles is a promising means to ease the various problems that are commonly associated with users experiencing disorientation.

## 1 Introduction

Individual differences, ranging from gender differences through system experience to cognitive styles, significantly influence the way that people navigate through hypermedia systems [5]. Many of these individual user characteristics can be gathered using questionnaires or standardized tests. However, for adaptive hypermedia systems this approach is often undesirable, as it requires time and effort from the users, which might eventually put them off. Moreover, not all user characteristics are stable or easily measurable: as an example, a user's motivation and concentration is most likely to change over time.

For this reason, it makes sense to provide users with adaptive navigation support based on users' navigation styles [8]. With knowledge of the strategies that users follow, it is easier to recognize patterns in their navigation paths that indicate usability problems that need to be solved. A typical usability problem is that users become disoriented, or *lost* in a web site [18], which means that they are unable to keep track of their positions: at some point users might not know where they are, how they came there or where they can go to. Several characteristics of user navigation, most importantly those related to page revisits, have been related to success measures, such as task outcomes and user's perceived disorientation [5][8][11].

In this paper we present the results of a pilot study that was aimed at finding patterns in user navigation that indicate a user's vulnerability to perceive disorientation while working on goal-directed tasks that require a fair amount of navigation to complete them. We were able to extract two navigation styles – which we called *flimsy navigation* and *laborious navigation* - that performed well in predicting the user's perceived disorientation. In the next section we will describe shortly how individual differences influence user navigation. Navigation styles and measures for user navigation are dealt with in the subsequent section. The presentation of the pilot study and its results will be followed with a discussion on the generalizability of the study and the implications for adaptive navigation support.

## 2 Individual Differences in Web Navigation

There is a vast amount of literature showing and analyzing individual differences involved in web navigation. In [7] it is noticed that novices tend to make use of a linear structure in hypermedia systems, when it is made available, while experts tend to navigate non-linearly. [10] demonstrated that students who had more *domain knowledge* displayed more purposeful navigation and allocated time more variably to different pages. *Spatial ability* is an important determinant of hypermedia navigation performance, as reported in several studies [e.g. 4]; users with low spatial abilities have difficulty in constructing and using a visual mental model of the information space. Students with an internal *locus of control* are reported to be better able to structure their navigation and to take advantage of hypertext learning environments [10].

Research on cognitive mechanisms involved in web navigation gains increasing influence in the HCI community. A cognitive model of web navigation should be able to simulate the navigation behavior of real users, producing the same navigation patterns as actual users would do. Many approaches to user navigation modeling are mostly inspired by the theory on *information foraging* [13]. Information foraging theory assumes that people, when possible, will modify their strategies in order to maximize their information gain. More specifically, users continuously compare the benefits of alternative actions, for example digging further into one information resource versus looking for a different resource. Process models that are based on these theories can analyze or simulate users' actions in terms of their individual evaluations of their expected utility.

## 3 User Navigation Styles

A related line of research aims at directly modeling the user's navigation behavior in order to provide adaptive navigation support in web applications [8]. A dynamic user navigation model could include:

- *syntactic information* (e.g. which links are followed, what does the navigation graph look like, what is the time that users spent on each page)
- *semantic information* (i.e. what is the meaning of the information that the user encountered during navigation)

– *pragmatic information* (i.e. what is the user using the information for, what are the user's goals and tasks)

In this section we focus on the syntactic information. Our aim is to identify patterns in user navigation that indicate problems associated with disorientation, as experienced by the user. In the first subsection we characterize several user navigation styles. In the second subsection we introduce several measures that can be used to capture these navigation styles.

### 3.1 Navigation Styles and Page Revisits

User navigation can range from goal-directed task completion to more unstructured browsing and exploration of the availability of information or services [7]. Routine browsing is an integral part of web navigation, nowadays; typically, users have a small collection of favorite sites that they visit very frequently [5]. Several taxonomies of web browsing behavior are presented in the literature. One of the finer grained taxonomies is presented in [15], a white paper that is clearly targeted at the ecommerce community in which seven patterns are categorized, based on session length, average page view times and the amount of revisits during this session.

Within a navigation session, users often return to pages that serve as *navigational hubs*. Extensive use of these hubs is reported to be an effective navigation strategy [11]. When looking for information, users often employ search strategies that are quite similar to graph searching algorithms, such as *depth first*, *breadth first* and *heuristic* search [2].

With knowledge of the type of session that users are involved in, and the navigation styles that they employ during these sessions, it is possible to recognize navigation patterns that might indicate usability problems.

### 3.2 Measures of User Navigation

User navigation paths can be modeled as graphs, with the vertices representing the pages visited and the edges representing the links followed [8]. Several – mostly graph-theoretic and statistical – methods can be used for analyzing this structure. Typical measures include the total number of pages visited to solve a task, the total time needed to solve a task and the average times spent on single pages [2]. Within the navigation paths, patterns may exist that indicate a user navigation style or problems encountered. In our pilot study we made use of a collection of navigation measures that together describe these patterns. They will be shortly described below. For a more detailed discussion about these measures we refer to [8].

**Number of Pages and Revisits**

As mentioned before, page revisits are very common in web navigation. By capturing various aspects of page revisitation, we aim to find revisitation *patterns* rather than the *amount* of revisitation. The following measures were taken into account:

– the **path length** is the number of pages that the user has requested during a navigation session, including page requests that involved revisits;

- the **relative amount of revisits** is calculated as the probability that any URL visited is a repeat of a previous visit. We adopted the formula that is suggested by Tauscher and Greenberg [17];
- the **page return rate** indicates the average number of times that a page will be revisited. The return rate is calculated by averaging the number of visits to all pages that have been visited at least twice. A more extensive use of navigation landmarks will most likely lead to a limited set of pages that is visited very frequently;
- **back button usage** indicates the percentage of back button clicks among the navigation actions, including backtracking multiple pages at once using the back button;
- **relative amount of home page visits** is a self-descriptive label. 'Relative' refers to a correction of home page visits based on path length.

### View Times

The *average time* that users spend at web pages is reported to be an important indicator for user interest and human factors [16]. Besides the average view time, the *median view time* was also taken into account, as users generally spend only little time on the large majority of pages before selecting a link [3]. The median view time is not affected by the few 'high content' pages that were inspected more carefully, and thus provides a better indicator for the average view time while *browsing*.

### Navigation Complexity

Navigation complexity can be defined as 'any form of navigation that is not strictly linear'. Complexity measures are mostly derived from graph theory and used frequently for assessing hypertext and its usage [8]. Typical measures reflect the cyclical structure of the navigation graph and the length of navigation sequences within the graph. Several commonly used complexity measures were taken into account:

- the **number of links followed per page** ('fan degree') [14] represents the ratio between the number of links followed and the number of distinct pages visited;
- the **number of cycles** [14] is calculated as the difference between the number of links followed and the number of pages visited. As the number of cycles grows with the length of the navigation path, it can only be used for a fixed time window;
- the **path density** [14] compares the navigation graph to the corresponding fully connected graph. A higher path density indicates that a user makes use of short navigation sequences and regularly returns to pages visited before;
- **compactness** [11] is a measure similar to path density. It indicates that users follow a 'shallow' search strategy. In contrast to the path density, it compares the average distance between any two pages in the navigation graphs to a theoretical minimum and maximum;
- the **average connected distance** [3] indicates the average length of a path between any two connected pages in the navigation graph. A higher average connected distance indicates that users do not return to a page very soon, but only after having browsed for a while. They also return using a link rather than using the back

button. In short, the average connected distance measures the users' confidence in that they 'will find their way back later'.

The navigation measures that are described above are labeled *first-order measures* in this paper, because they are derived directly from the raw data, without taking into account that the measures might be correlated, which most likely would be the case. As an example, the *average connected distance* is calculated independently of *back button usage,* without taking into consideration the fact that usually low values on the former measure are associated with high values on the latter and vice-versa. This aspect was dealt with by calculating *second-order measures* – or *navigation styles*, as will be explained in the next section.

## 4 Pilot Study – Navigation Styles and Disorientation

In our pilot study we were interested in what navigation styles occur when users perceive disorientation when performing several goal-oriented tasks. In order to better interpret the outcomes, we also collected several user characteristics – as introduced in section two – as well as users' evaluation of their navigation activities. The experimental setup and the results will be discussed in this section.

### 4.1 Experimental Setup

The study consisted of individual sessions with thirty subjects, all undergraduate and graduate students from two Dutch universities in the age range 19-28, with an average age of 21.5. Participants were selected randomly out of the student lists of both universities, while making sure that males and females were equally presented.

Each session consisted of three stages:

- collection of data on user characteristics;
- the actual navigation session and collection of navigation data;
- evaluation of the navigation session, including a survey on users' perceived disorientation.

Several user characteristics were collected in the first stage. The characteristics that are relevant in the context of this paper are briefly described below. For more details we refer to [9]. *Spatial ability*, *episodic memory* and *working memory* were measured with computerized cognitive tests provided by the Dutch research institute TNO Human Factors. The users' *internet expertise* is composed of self-reported frequencies of internet use and self-assessed level of knowledge. At the beginning of the navigation session the users rated their affective disposition; users who rated themselves high on the states determined, calm and alert, and low on the states sluggish and blue, were considered to be in an *active mood*. *Locus of control* refers to the users' belief in how they contributed to their own success or failure, which was measured with a 20-item scale.

In the navigation session, subjects were asked to perform various tasks in the field of web-assisted personal finance. This field includes using the web to keep a personal budget, to perform financial transactions and decide to save or invest money. The tasks were designed in such a way that it would require a fair amount of navigation to answer or to solve them [9]. Subjects had thirty minutes in total to solve the tasks. Three web sites were used in this study, two of which are dedicated to personal finance. They provide users with advice and tools – such as planners, calculators and educators – to deal with their financial problems. The third site, an online store, was used as a reference.

After the navigation session, the subjects were asked to evaluate their satisfaction with task completion and the usability of the different web sites used. A survey on perceived lostness [1] was also included in the evaluation session.

### 4.2 Results

As it is most likely that patterns in the first order navigation measures occur simultaneously, second order navigation measures – linear combinations of the first order measures – were calculated. Principal component analysis with *equamax* rotation on twenty-two navigation measures resulted in four factors that together explained 86% of the variance. We will focus on two factors, which account for 27% and 23%, respectively, after rotation. We labeled them *flimsy navigation* and *laborious navigation*, based on their correlations with first-order measures and user characteristics. It should be noted that these styles do not exclude one another. All correlations mentioned are significant with $p<0.05$.

High scores on the *flimsy navigation style* are associated with:
- small number of pages visited ($r=-0.80$)
- high path density ($r=0.80$)
- high median view time ($r=0.77$)

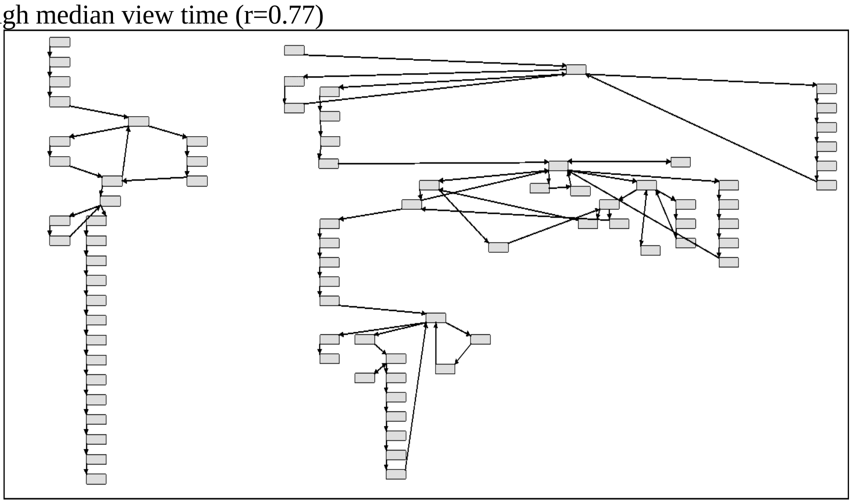

**Figure 1. Flimsy (left) versus sturdy (right) navigation.** From the figure it can be observed that flimsy navigation is characterized by short navigation paths and a low number of cycles in the navigation graph. The page revisits that did take place in the flimsy navigation path were made using the back button

– short average connected distance (r=-0.70)
– low number of cycles (r=-0.53)
– high rate of home page visiting (r=0.48)
– high frequency of back button use (r=0.39).

Flimsy navigation appeared to be a weak navigation style. Most of the navigation takes place around the site's home page and users regularly return to their starting points. Time is mostly spent on processing content instead of actively locating information. The short average connected distance indicates that users return to a page very soon. Users also prefer to return by using the back button instead of by following links. The low number of cycles indicates that users employing this navigation style do not make extensive use of the means for revisitation available within the sites.

High scores on the flimsy navigation style are associated with low scores on Internet expertise, current active mood, working memory and locus of control. Based on these correlations, it is likely that flimsy navigation is mostly employed by inexperienced users who are not able or not inclined to reconstruct their past actions; rather, they continue along the same path or eventually start over again. For these reasons, we might expect that flimsy navigation is related to users' perceived disorientation.

High scores on the *laborious navigation style* are associated with:
– high number of links followed per page (r=0.95)
– high revisitation rate (r=0.94)
– high number of cycles (r=0.79)
– high return rate (r=0.73)
– high frequency of back button use (r=0.71)
– high path density (r=0.43)
– high number of pages visited (r=0.40)
– short average connected distance (r=-0.39).

This navigation style involves intensive exploration of navigational infrastructure provided by the site. Users seem to employ a trial and error strategy; they follow links merely to see if they are useful or not. They figure out quite fast when paths are not leading towards their goal and return. Revisits are numerous but not redundant: once a page is revisited a different link is followed than before, which constitutes another trial.

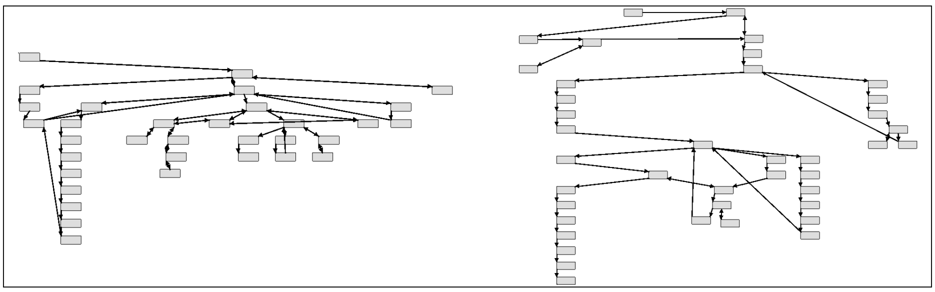

**Figure 2. Laborious (left) versus non-laborious (right) navigation.** From the figure it can be observed that the laborious navigation style is characterized by a high amount of revisits, with some pages clearly functioning as navigational landmarks.

This behavior is particularly observed on navigational hubs, such as menus and index pages.

High scores on *laborious navigation* are associated with high *episodic memory*, and low *spatial ability*. This style indicates a revisitation pattern that does not lead to disorientation; instead, laborious navigation appears to help users in constructing a conceptual overview of the site structure and then to make use of this model.

Multiple linear regression analysis was used to find out which navigation measures and navigation styles performed best in predicting the subjects' perceived disorientation. Including predictors in regression models was based on the *stepwise method*; the predictive power must be seen as the best one can get with the minimum number of predictors. It turned out that the *flimsy* and *laborious* navigation styles together best predicted the user's perceived disorientation ($R^2$=0.29) with a large effect size ($ES^2$ = 0.29/0.71 = 0.41)[1].

**Table 1.** Prediction of perceived disorientation based on navigation styles. The regression model consists of *perceived disorientation* as dependent variable and *flimsy navigation* and *laborious navigation* as predictors. From the regression coefficients (B) one can observe the positive and negative correlations of flimsy and laborious navigation respectively with perceived disorientation. The standardized coefficients (Beta) show a larger relative importance of flimsy navigation as compared with laborious navigation.

| | B | Beta | t | Sig. |
|---|---|---|---|---|
| (Constant) | 40.1 | | 29.66 | 0.000 |
| Flimsy navigation | 3.92 | 0.46 | 2.85 | 0.008 |
| Laborious navigation | -2.38 | -0.28 | -1.73 | 0.095 |

## 5 Discussion

The results of our pilot study suggest that users' vulnerability to experience disorientation in large web sites can be automatically diagnosed with an attractive level of accuracy. We identified two navigation styles, *flimsy navigation* and *laborious navigation*, which proved to be significant predictors with a large effect size.

The area in which these navigation styles have been identified, is rather limited: they apply to situations where goal-directed and performance-oriented tasks are performed on the web. The domain of web assisted personal finance might seem narrow and this is why we used three different web sites and a relatively complex and heterogeneous range of task. By choosing three different websites to be used in the pilot study, we attempted at randomizing factors pertaining to a specific site structure or interface design. Tasks were not only aiming at locating information but also at

[1] The effect size for regression is calculated with the following formula: $ES^2 = R^2/(1-R^2)$. 0.02 is considered a small effect, 0.15 a medium one and 0.35 a large effect size [6].

using this information to solve actual problems. These decisions were intended to constitute premises for ecological validity and generalizability of the results.

The number of subjects (thirty) was rather limited and relatively homogenous, as they were students. New data is necessary to find out in what situations the identified navigation styles are relevant for predicting disorientation. Most likely, other styles will be identified as well that can explain other facets of disorientation.

### 5.1 Implications for Adaptive Navigation Support

Prediction of users experiencing disorientation that is based on navigation measures has important practical consequences. From a usability point of view it is useful to identify those users who are at risk of experiencing disorientation and to assist them by adequate, and possibly personalized, navigation support.

Context information is important for effective navigation, as each navigation process is inextricably tied to the structure of the site. Two types of user context can be distinguished: the *structural context* and the *temporal context* [12]. Structural navigation aids – such as site maps, menus and index pages – describe a user's current location and navigation options; temporal navigation aids – such as the browser's back button, bookmarks and visual navigation histories – describe the way that led to this position.

Users that navigate in a *flimsy* manner appear not to be able to reconstruct their navigation paths and therefore are prone to get stuck. Visual navigation histories might help them out. In contrast, users that do not navigate *laboriously* enough and yet do not effectively exploit the site structure, can better be presented local or global site maps or a list of links to index pages. As these types of add-on navigation support typically consume a large amount of screen estate, it is desirable bother users with tools that they do not need.

### 5.2 Future Perspectives

In this paper we discussed how to address two navigation styles that might indicate or that might lead to users getting disoriented in web sites while working on goal-oriented tasks. The add-on navigation support, as discussed in the previous subsection, aims at improving the way users navigate rather than at forcing users to passively follow some ready-made paths. We believe that this should be the goal of adaptive hypermedia systems in general. Whereas the results of this pilot study might be applicable only in the small domain of web-assisted personal finance, the prospect of adaptive navigation support that fits the user's navigation style is attractive. As an example, users that prefer to extensively explore the sites that they visit, should be supported in doing so, instead of being urged to leave for a different site, unless the system is capable of making clear to the users that the benefit is higher than the cost of altering their strategy.

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# Designing an Adaptive Feedback Scheme to Support Reflection in Concept Mapping

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**Abstract.** In this paper, we present an adaptive feedback scheme, which is incorporated in the “Knowledge Reconstruction + Refinement” process of a web-based concept mapping tool, named COMPASS, in order to support the reflection process in concept mapping. The feedback scheme includes multiple informative and tutoring feedback components and combines a stepwise presentation of these components with a multiple try strategy, aiming to provide personalized feedback. The adaptation of the scheme is based on the learner’s knowledge level, preferences and interaction behaviour. Two pilot empirical studies were conducted in order to investigate whether the design of the feedback components as well as the proposed adaptive feedback scheme can stimulate learners to reflect on their beliefs and appropriately revise their maps. The results revealed from the studies are encouraging, as the feedback provided, led the majority of the students to reconstruct/refine their knowledge and accomplish successfully the concept mapping tasks.

## 1 Introduction

Concept mapping, as a knowledge elicitation technique, stimulates learners to articulate and externalise their actual states of knowledge during the learning process. A concept map is comprised of nodes (concepts) and links (relationships between concepts), organized in a hierarchical structure to reflect the central concept of the map. Meaningful relationships between concepts form propositions. It is important to emphasize the inherently reflective nature of concept mapping, as it requires from learners to reflect on their understanding of concepts and their relationships [9].

Various applications of concept maps in learning and assessment and a number of concept mapping software tools are presented in [1]. During the assessment process, feedback is usually provided to learners according to specific common errors identified on their concept maps [2], [3]. These approaches do not take into account any learner’s individual characteristics or needs. More specifically, in [2], the system analyses the learner’s map by comparing it with the teacher’s map and provides hints (feedback strings defined by the teacher) about specific errors such as missing propositions. In [3], the system gives appropriate hints to the learner in the form of partial propositions. Moreover, to our knowledge, very few studies focus on the adaptation of the provided feedback according to learners' individual differences. In [7], a study was conducted, examining the effects of adaptive feedback (adjusting the amount of feedback based on learners confidence in their answer) on learning outcomes and learning efficiency. In [6], a framework for the provision of feedback, based on the nature of the learning task and the learner's achievement level and prior knowledge, is presented. In [11], the incorporation of adaptive feedback into the proposed system is one of the researchers' plans.

In this context, we are developing a tool, named COMPASS (COncept MaP ASSessment tool) [4], aiming to provide a more flexible and learner-centered approach in the accomplishment of assessment activities based on concept mapping tasks and help learners to reconstruct/refine their knowledge. COMPASS supports the "Knowledge Reconstruction + Refinement" (KR+R) process by providing multiple informative and tutoring feedback components, tailored to the learners' knowledge level, preferences and interaction behaviour, through a stepwise presentation. The provided feedback aims to stimulate learners to reflect on their beliefs and proceed with the appropriate revisions. Two pilot empirical studies were conducted in order to investigate whether the design of the feedback components and the proposed adaptation scheme can help learners in revising their beliefs and refining their knowledge.

The paper is organized as follows. In Section 2, a description of the functionality of COMPASS is outlined. Then, in section 3, the adaptive feedback scheme, incorporated into the "KR+R" process, is presented. The results revealed by the two empirical studies are presented in Section 4 and the paper ends with concluding remarks and some directions for future work.

## 2 The COMPASS Tool

COMPASS is a web-based concept mapping tool aiming to assess the learner's understanding as well as to support the learning process. In particular, COMPASS serves (i) the *assessment process* by employing a variety of activities and applying a scheme for the qualitative and quantitative estimation of the learner's knowledge, and (ii) the *learning process* by providing different informative and tutoring feedback components, tailored to each individual learner, through the "KR+R" process.

More specifically, COMPASS supports the elaboration of assessment activities employing various mapping tasks such as the construction of a concept map from scratch ("free construction" task), the completion and evaluation of a concept map using an available list of concepts/relationships ("concept-relationship list completion/evaluation" task) [4]. After the learner has completed the assessment activity, COMPASS activates the *diagnosis process* for (i) the identification of errors on the learner's map (according to Table 1), based on the similarity of the learner's map to the teacher's one, and the qualitative analysis of the errors, (ii) the qualitative diagnosis of learner's knowledge, which is based on the proposed error categorization (Table 1) and concerns the identification of the unknown concepts, incomplete understanding and false beliefs, and (iii) the quantitative estimation of learner's knowledge level on the central concept of the map and subsequently on the assessment activity, which is assigned to one of the characterizations {Insufficient (Ins), Rather Insufficient (RIns), Average (Ave), Rather Sufficient (RSuf) and Sufficient (Suf)}; this assignment is based on specific assessment criteria defined by teacher [4]. The learner may check/verify his/her map through the "Analysis" tool (Fig. 1). This tool provides the "Visual Feedback" option and the "Interactive Feedback" option. In case learner selects the "Visual Feedback" option, COMPASS graphically annotates the errors on the map, if any, following the proposed error categorization. In case of the "Interactive Feedback" option, COMPASS activates the *"KR+R" process* resulting to the provision of the appropriate feedback for each of the errors identified on the map.

## 3 The Adaptive Feedback Scheme

Feedback is considered as one of the most important sources of information to assist learners in restructuring their knowledge [6]. According to [5], effective feedback provides the learner with two types of information: verification (a judgement of whether the learner's answer is correct/incorrect) and elaboration (relevant cues to guide the learner toward a correct answer). Depending on the levels of verification and elaboration incorporated into the feedback, different types and forms of information may be combined (e.g. explanations for correct/incorrect answers, hints about useful sources of information, the knowledge of response) [6]. As one of the factors that contribute to the informative and tutoring value of feedback is the individual characteristics of the learner (e.g. learning objectives, prior knowledge and skills, motivational prerequisites), many researchers propose to tailor feedback to learner's individual needs and characteristics [10], [8].

In the context of COMPASS, the "KR+R" process aims to provide feedback, tailored to each individual learner in order to support the reflection process, to tutor and guide the learners and subsequently to enable them enrich/reconstruct their knowledge structure. The feedback scheme, adopted in the "KR+R" process, incorporates informative and tutoring feedback components (ITFC) and combines a stepwise presentation of these components with a multiple try strategy (see Activating the "KR+R" process). The ITFC include (i) an initiating question (IQ) consisting of the learner's belief, and a prompt to think of the concepts included in the proposition and to write any keywords describing the concepts, (ii) specific error-task related questions (E-TRQ), (iii) tutoring feedback units (TFU) relevant to concepts/relationship included in the concept map, and (iv) the knowledge of correct response (KCR). The ITFC concerning the E-TRQ and/or the TFU are provided according to the learner's individual characteristics (i.e. learners' knowledge level, preferences and interaction behaviour). Moreover, the stepwise presentation of the ITFC provides gradually the appropriate feedback components that are considered to be necessary in order the learner to modify/enrich his/her knowledge structure. Below, we present the design of the E-TRQ and the TFU, the adaptation of the feedback scheme as far as these specific feedback components are concerned, and the stepwise feedback presentation.

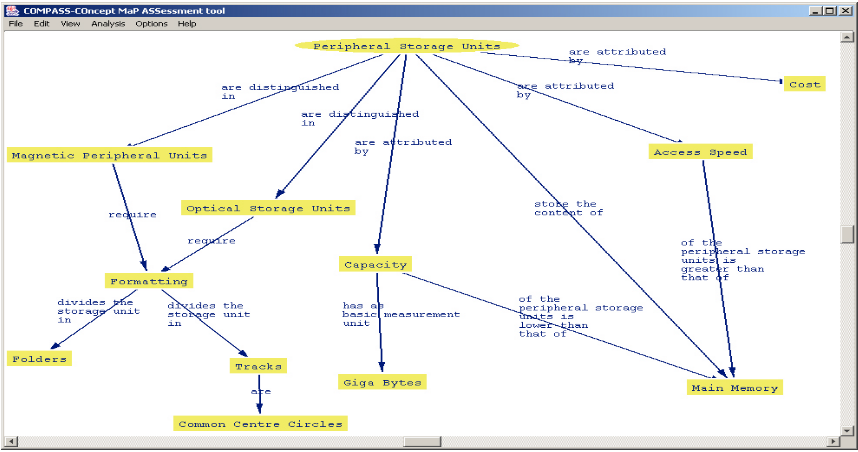


**Fig. 1**. A concept map constructed by a learner for a "concept-relationship list completion/evaluation" task.

**The Design of the E-TRQ and the TFU.** The error-task related questions, incorporated (E-TRQ) into the feedback scheme, aim to redirect the learner's thinking and give a hint for correcting the error and completing the task. In the context of COMPASS, the form of the questions is differentiated according to the error categories that may be identified on the learner's map. The form of the questions that are associated with each error category as well as an example of such a question for the learner's map illustrated in Fig. 1, are presented in Table 1.

The tutoring feedback units (TFU) aim to allow the learner to review educational material relevant to the attributes of the desired/correct response. In the context of COMPASS, the TFU concern: (i) the concepts represented on the teacher's concept map and/or the concepts included in the provided list of concepts (if a list of concepts is provided according to the mapping task) (TFUC), and (ii) specific propositions that the teacher anticipates a learner's false belief (TFUP) [4]. TFUC are organised in two levels, TFUC1 and TFUC2 differing on the level of detail of the feedback information. TFUC1 presents the corresponding concept in general and it is independent of the mapping task (i.e. the same TFUC1 can be provided for different mapping tasks, which include the specific concept). TFUC2 presents the corresponding concept in more detail, focusing on the relationships of the concept with the other concepts of the map. Thus, TFUC2 depends on the concepts that may be represented on the particular concept map. TFUC2 is provided only if the learner insists on his/her belief after providing TFUC1. The feedback units (TFUC1 and TFUP) are associated with educational material consisting of knowledge modules, which constitute multiple representations of the concepts included in the proposition (i.e. a definition/description, an example, and/or an image of the concepts).

**Table 1.** The qualitative diagnosis of learners' knowledge based on different categories of errors and the form of error-task related questions according to the error categorization.

| **Qualitative Diagnosis of Learners' Knowledge** | **Categories of the Learners' Errors** | |
|---|---|---|
| | **Form of E-TQR**<br>[C1], [C2], [C3] … are concepts, while R, R1, R2 … are relationships between concepts | **Example of Error-Task Related Question** |
| **Unknown Concepts** | **Missing concept and its relationships**: specific concepts, which should be represented on a map and have been defined by the teacher as fundamental concepts for the specific task/map [4], are missing. | |
| | *Do you consider that you could add on your concept map the concept of [C1]?* | Do you consider that you could add on your concept map the concept of [Sectors]? |
| **Incomplete Understanding** | **Incomplete relationship**: the relationships between two concepts are incomplete, as several relationships are missing (e.g. concepts [C1] and [C2] are related with m relationships on the teacher's map, while on the learner's map n relationships appear, where n<m). | |
| | *Do the [C1] only R the [C2]?* | Not applicable to the example |
| | **Missing relationship**: the relationship between two concepts that should be related is missing. | |
| | *Do you consider that you could add a relationship between the concepts of [C1] and [C2]?* | Do you consider that you could add a relationship between the concepts of [Cost] and [Main Memory]? |
| **False beliefs** | **Superfluous relationship**: two concepts are related although they should not. | |
| | *Do you really believe that the concepts [C1] and [C2] are related with the specific relationship?* | Do you really believe that the concepts [Optical Storage Units] and [Formatting] are related with the specific relationship? |
| | **Incorrect relationship**: two concepts are related with an incorrect relationship, which should be substituted. | |
| | *The [C1] R [C2]. Do you agree with this?*<br><br>(where R is the correct relationship as represented on the teacher's concept map) | The [Capacity] of the peripheral storage units is greater than that of [Main Memory]. Do you agree with this? |
| | **Superfluous concept**: a superfluous concept appears which should be deleted. | |
| | *Do you want to reconsider the relationship of the concept [C2] with (i) the concept [C1], and (ii) the central concept of the map?* | Do you want to reconsider the relationship of the concept [Folders] with (i) the concept [Formatting], and (ii) the central concept of the map? |
| | **Incomplete propositions**: a concept (presented on the map) is not related to all the required concepts because the related concepts are missing. | |
| | *Do you really believe that [C1] only (i) R1 [C2] and (ii) R2 [C3]?* | Not applicable to the example |
| | **Incorrect concept**: a concept is related to an incorrect concept, which should be replaced with another concept. | |
| | *Do you really believe that the [C1] (correct concept) R [C2] (incorrect concept) [and the concept of [C2] is related with the concepts of [C3] and [C4] ]?*<br>(where the concepts [C3] and [C4] are the children of the concept [C2]) | Do you really believe that the [Capacity] has as basic measurement unit [Gigabytes]*?<br>*: the concept [Gigabytes] has not children, so the rest of the question is not applicable |

**The Adaptation of the Feedback Scheme**. The adaptation of the feedback scheme, regarding the provision of TFU and/or E-TRQ, is based on information concerning the learner's knowledge level, preferences (i.e. preferences on ITFC and on knowledge modules) and interaction behaviour (i.e. knowledge modules of TFUC1 or TFUP more often provided, ITFC more often provided and frequency of errors made) (this information is provided by the learner model). Indicative rules that have been adopted in the adaptation scheme are:

- If the knowledge level of the learner has been evaluated as (Ins) or (RIns) on the assessment activity, then both TFU and E-TRQ are provided (TFU+E-TRQ).
- If the knowledge level of the learner has been evaluated as (Suf) or (RSuf) on the assessment activity, then E-TRQ are provided.
- If the knowledge level of the learner has been evaluated as (Ave) on the assessment activity, then according to the learner's preferences (ITFC preferred) and interaction behaviour (ITFC more often provided and frequency of errors made), E-TRQ or TFU+E-TRQ is provided. For example, (i) if the learner's favourite ITFC is E-TRQ but TFU+E-TRQ is more often provided, then TFU+E-TRQ is provided, (ii) if the frequency of a specific error identified on the learner's map is minimal (e.g. the learner's map includes very few incorrect relationships), then E-TRQ is provided.
- If TFU+E-TRQ is to be provided, then according to the error category, TFUC1 and/or TFUP is provided. TFUP is provided when the error belongs to the categories of "incorrect relationship", "incomplete relationship", "incomplete propositions" and "superfluous relationship". TFUC1 may concern more than one concepts according to the error category (e.g. in case of "incorrect concept", TFUC1 concerns only the incorrect concept of the proposition, while in case of "superfluous relationship", TFUC1 concerns both the concepts [C1] and [C2]).
- If TFUP and/or TFUC1 is to be provided and both types are available for the specific error (e.g. "superfluous relationship"), then TFUP is firstly provided and if the learner insists on his belief and/or asks for more help, TFUC1 is provided.
- If TFUC1 or TFUP is to be provided, then according to learner's preferences on knowledge modules and/or learner's interaction behaviour (types of knowledge modules more often provided), specific types of knowledge modules (i.e. definition/description, example and/or image of the concept) are provided.
- If the learner insists on his/her belief although TFUC1 was provided, then TFUC2 is also provided (in case it is available).

**Activating the "KR+R" Process**. COMPASS incorporates the abovementioned feedback scheme as well as the adaptation mechanism in the "KR+R" process. The "KR+R" process is activated when the learner completes an activity or asks for support/help during the task. The following sequence of interactions is taken place:

- *First Step:* After detecting an error on the learner's concept map, COMPASS indicates the error by providing the learner with an initiating question (IQ). The IQ gives learners the possibility to rethink their beliefs and to identify and check their own errors. This form of feedback may be sufficient for learners with high knowledge level. The applicability of the step depends on the category of error (e.g. for a “missing relationship” error, this step is not applied). Following, the tool enters in a “wait” state, expecting the learner’s action.

- *Second Step*: If the learner insists on his/her belief, then according to the abovementioned rules E-TRQ and/or TFU+E-TRQ are provided. COMPASS enables the learner to think about the feedback and proceed with any changes; the tool enters again in a “wait” state, expecting the learner’s action.
- *Third Step:* If an impasse is reached (learner insists on his/her belief) or the learner asks for the knowledge of correct response, then COMPASS informs the learner about the correct response (KCR feedback component).

It is important to mention that during the interaction between the learner and the tool, the learner has always the option to select the feedback component and the knowledge modules that s/he prefers, ignoring the ones provided by the tool.

## 4 The Empirical Studies

The design of the “KR+R” process was carried out in parallel to two empirical studies that we conducted as a pilot evaluation before proceeding with the implementation of the process in the context of COMPASS. The two studies were carried out during the winter semester of the academic year 2003-2004, in order to investigate whether the design of the feedback components, as well as the adopted adaptation scheme, could stimulate learners to reflect on their beliefs and appropriately revise their maps.

**First Empirical Study.** In order to investigate whether the design of the E-TRQ, as the only source of feedback, can help learners towards the direction of identifying their errors, reconsidering and correcting them appropriately, we conducted an empirical study. Six high school students volunteered to take part. The students had to accomplish a “concept-relationship evaluation” concept mapping task concerning the central concept of “Magnetic Peripheral Storage Units”. After the accomplishment of the activity, the teacher interacted with each one of the students, simulating the stepwise presentation of the “KR+R”. The duration of the empirical study was 2 hours.

For the six students, the percentage of correct responses for each error category, before the provision of feedback and after the stepwise feedback presentation (for the 2$^{nd}$ step only the E-TRQ were provided), is presented in Fig. 2. The reader may notice that all the students improved their performance and the questions helped them to reconsider their beliefs and correct the majority of the errors. However, there are some cases that the questions didn’t help the students to find all the errors (e.g. the case of the 3$^{rd}$ student in the error categories of “incorrect relationship”, “superfluous relationship” and “missing relationship”). As far as any modifications to the form of the E-TRQ are concerned, the study drew implications about the form of the questions posed for the error categories of “incorrect concept” and “superfluous relationship” (the modified versions of the questions are presented in Table 1). Regarding the process (i.e. steps), it is important to mention that in several cases, the application of the first step (i.e. the provision of the IQ) was proved to be adequate and helped students to check for accidental constructions. There were cases that the students weren’t able to correct their errors even if E-TRQ were provided; in these cases, the teacher tried to explain in details the concepts involved in the proposition. This observation led us draw the conclusion that the specific ITFC (i.e. IQ and E-TRQ) are not adequate in all cases; additional feedback should be provided.

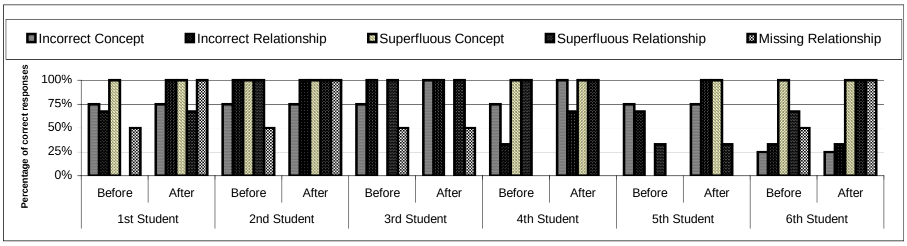


**Fig. 2**. The percentage of the correct responses concerning specific categories of errors.

Summarizing the results, it seems that the form of the E-TRQ can help students, especially those with knowledge level above average, in revising their beliefs and refining their knowledge. In cases of students with low knowledge level, a form of tutoring feedback is required in order to help them identify and correct their beliefs. Therefore it was considered important to incorporate TFU in the feedback scheme.

**Second Empirical Study.** In the second empirical study, the feedback provided to the learners included both the TFU and the E-TRQ. The aim of this study was to investigate whether the design of the proposed adaptation scheme, can stimulate learners to reflect on their beliefs and appropriately revise their maps. Ten high school students volunteered to take part in the study, which lasted 3 hours.

A pre-test was conducted in order to estimate the students' prior knowledge level. The pre-test had the form of open questions such as "Mention keywords that describe the concept of Formatting", "Mention the kinds of Peripheral Storage Units". The pre-test questions address the concepts/relationships that could be represented on the map of the task that the students had to accomplish after the pre-test. The teacher assessed their answers and estimated their knowledge level (1 student as (Suf), 3 as (RSuf), 3 as (Ave), 2 as (RIns), and 1 as (Ins)). The students' preferences concerning the types of knowledge modules (description, example or image) and the ITFC (TFU+E-TRQ and E-TRQ) were also recorded. The task, that the students had to accomplish, was a "concept-relationship list completion/evaluation" task. After its accomplishment, the teacher interacted with each one of the students, simulating the stepwise presentation of the "KR+R". To this end, the learner's interaction behaviour was not considered.

The 1$^{st}$ step of the process (i.e. the IQ feedback component) was adequate only for one student (the 3$^{rd}$ student claimed that he made the errors by accident and was able to recognize and correct them). In the context of the 2$^{nd}$ step of the process, the E-TRQ were used for those students whose knowledge level was characterized as (Suf) and (RSuf). The E-TRQ were proved to be effective in helping the students to identify their errors and correct them appropriately (see Fig. 3). All the students whose knowledge level was characterized as (RIns) and (Ins), improved their performance (see Fig. 3) after the TFU+E-TRQ were provided and they identified and corrected a considerable number of errors. Two of them (5th and 6th student) didn't manage to correct all the errors; in two error cases the KCR was finally provided. In the case of the 7th student, the TFUC1 and TFUC2 were provided, helping him to accomplish correctly the mapping task. For those students whose knowledge level was characterized as (Ave), their preferences concerning the TFU+E-TRQ and E-TRQ (one student selected E-TRQ and two students selected TFU+E-TRQ) were taken into account. All three students, after the provision of feedback, accomplished the task successfully.

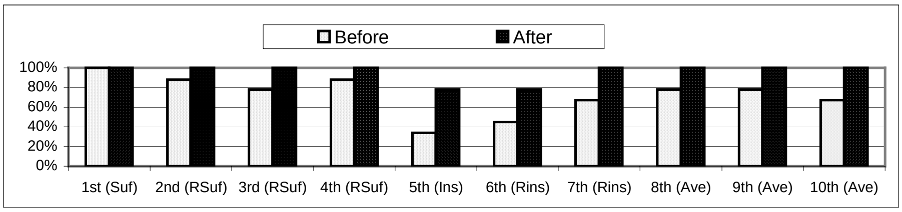


**Fig. 3.** The percentage of correct responses before and after the provision of feedback

Summarizing the results, it seems that the ITFC that were provided, following the stepwise presentation stimulated students to review their maps and reconsider their beliefs, as the majority of them spent some time thinking of them. It has to be mentioned, that the teacher, in all the cases, tried to elicit from students why they proceed with the desired corrections. The impression was that the students had fully understood their errors and refined their knowledge. The adaptive feedback scheme can be characterized as promising as the majority of the students accomplished successfully the mapping task and refined their knowledge. The results revealed from the two studies provided useful indications on the effectiveness of the proposed adaptive feedback scheme. However, data gathered from a larger sample, using COMPASS in real working conditions, under longer periods of time, are considered necessary for the aim of inferring learners' attitudes and evaluating the effectiveness of the adaptive feedback scheme.

## 5 Conclusions and Further Research

In this paper, we presented an adaptive feedback scheme, which is incorporated in the "Knowledge Reconstruction + Refinement" (KR+R) process of COMPASS in order to support the reflection process in concept mapping tasks. The discriminative characteristics of the "KR+R", and in particular of the proposed adaptation scheme are: the adoption of different informative and tutoring feedback components (ITFC) and the stepwise feedback presentation, the adoption of error-task related questions (E-TRQ) based on a categorization of learners' common errors, the adoption of the two levels of the tutoring feedback units (TFU) and the adaptation of feedback to the learner's knowledge level, preferences and interaction behaviour. The results from two empirical studies conducted, even performed on a limited number of subjects and in a simulated environment, are encouraging indicating that the provided feedback support reflection and help students to identify and correct their errors.

The presented research work contributes to the field of adaptive feedback, giving some promising directions for further research. Additional studies need to be conducted in order to compare the efficiency of the proposed informative and tutoring feedback components to other feedback components such as the knowledge of response and the effects of the proposed adaptive scheme to a standard feedback scheme as it is implemented in most learning environments. Our future plans include the enrichment of the informative and tutoring feedback components with additional forms as well as the conduction of a series of empirical studies with a wider group of learners, in order to evaluate COMPASS regarding the effectiveness of the provided feedback components and the adaptive feedback scheme.

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# Adaptation Rules Relating Learning Styles Research and Learning Objects Meta-data

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**Abstract.** This paper investigates the development of adaptation rules which relate individual learning styles characteristics to learning objects characteristics, as the latter are reflected in the IMS Learning Resource Meta-Data Specification. The paper outlines the most well-known learning styles theories and models, some criteria for selecting among them, as well as a number of adaptive web-based learning environments which are utilising learning styles research for facilitating personalised learning. The paper concludes with the set of adaptation rules which are used in the KOD learning environment, which aims to facilitate individualised access to learning material in a re-usable way.

## 1. Introduction

The rapid evolution of Information and Communication Technologies (ICT) and the emergence of the Knowledge Society create numerous new opportunities for the improvement of the quality of education. It can be argued, however, that education has not yet realised the full potential of the employment of ICT: *"there is a shortage of solid evidence to back up the belief that telematic learning systems provide real advantages"* [1]. Besides the apparent benefits of ICT for delivering education to distance learners independently of time, location, etc, several studies question whether there is ***"****a significant difference****"*** with respect to the learning effectiveness when ICT is employed in education [2]. This is mainly due to the fact that the "traditional" mode of instruction (one-to-may lecturing, or one-to-one tutoring) adopted in "conventional" educational technology cannot not fully accommodate the different learning and studying styles, strategies and preferences of diverse learners.

Personalised learning (PL) systems are attracting increasing interest in this context, since they bare the potential to meet the requirements of the knowledge society and knowledge-based economy for high-quality education and training [3]. PL systems can be defined by their capability to automatically *adapt* to the changing attributes of the “learning experience”, which can, in turn, be defined by the individual learner characteristics, the type of the learning material, etc. That is, PL systems can be categorised and differentiated in terms of their *adaptation logic*, which is defined by: (i) PL constituents: the aspects of the learning experience which are subject to adaptations; that is, is the learning material being adapted? and if so, how do we categorise learning material so that we can select different content for different learner? (ii) PL determinants: the aspects of the learning experience which “drive” adaptations; that is, are adaptations based on the learner’s profile? and if so, how is the learner profile defined? and (iii) PL rules: the rules which define which PL constituents are selected for different PL determinants [4]. PL systems can be quite diversified according to their adaptation logics, depending on the requirements of the specific learning context. For example, PL determinants can include learners’ characteristics, which can, in turn, include learner’s background, expertise, prior knowledge, skills, requirements, preferences, etc [5].

This paper addresses the incorporation of learning styles research in the adaptation logic of PL systems. That is, the definition of PL determinants, constituents and rules which are based on, and reflect specific learning styles theories and models. The next section provides a short overview of the most well-known learning styles theories and models, as well as some criteria for selecting among them when developing PL systems. Subsequently, the paper outlines some existing PL systems which utilise learning styles research, with emphasis on PL system which has been developed in the context of the KOD “Knowledge on Demand” European project (see acknowledgements section). The paper concludes with the set of adaptation rules used in the KOD project, which attempt to relate individual learning styles characteristics (as adaptation determinants), and learning objects characteristics (as adaptation constituents), as the latter are reflected in the IMS Learning Resource Meta-Data Specification – LOM [6].

## 2. A Brief Overview of Learning Styles

The term “learning styles” has been attributed with several connotations in the literature. Learning styles can be generally described as “an individual’s preferred approach to organising and presenting information” [7]; “the way in which learners perceive, process, store and recall attempts of learning” [8]; “distinctive behaviours which serve as indicators of how a person learns from and adapts to his environment, and provide clues as to how a person’s mind operates” [9]; “a gestalt combining internal and external operations derived from the individual’s neurobiology, personality and development, and reflected in learner behaviour [10].

Learning styles models can be presented through an onion metaphor (proposed in [11]), consisting of three basic layers which categorise learners in terms of instructional preferences (outermost layer), information processing (middle layer) and personality (innermost layer). Social interaction, a fourth layer placed between Curry’s two outer layers, was proposed in [12]. The most well-known and used learning styles theories and models are presented in Table 1. For each model, the presentation includes: (i) the learner categorisations proposed by each model, (ii) the existence of an assessment instrument for categorising each learner in the above categories, and (iii) indicative references for each model.

**Table 1.** Overview of Learning Styles

| Name | Learners' Categorisation | Assessment Instrument |
|---|---|---|
| Kolb Learning Style Inventory [13], [14] | Divergers (concrete, reflective), Assimilators (abstract, reflective), Convergers (abstract/active), Accommodators (concrete/active) | Learning Style Inventory (LSI), consisting of 12 items in which subjects are asked to rank 12 sentences describing how they best learn. |
| Dunn and Dunn – Learning Style Assessment Instrument [15], [16] | Environmental, Emotional, Sociological, Physical factors. | (i) Learning Style Inventory (LSI) designed for children grade 3-12; (ii) Productivity Environmental Preference Survey (PEPS) – adult version of the LSI containing 100 items |
| Felder-Silverman – Index of Learning Styles [17], [18] | Sensing-intuitive, Visual-verbal, Indicative-deductive, Active-reflective, Sequential-global | Soloman and Felder questionnaire, consisting of 44 questions |
| Riding – Cognitive Style Analysis [19], [20] | Wholists-Analytics, Verbalisers-Imagers | CSA (Cognitive Styles Analysis) test, consisting of three sub tests based on the comparison of the response time to different items |
| Honey and Mumford – Learning Styles Questionnaire [21] | Theorist, Activist, Reflector, Pragmatist | Honey & Mumford's Learning Styles Questionnaire (LSQ), consisting of 80 items with true/false answers |
| Gregoric – Mind Styles and Gregoric Style Delineator [9], [22] | Abstract Sequential, Abstract Random, Concrete Sequential, Concrete Random | Gregoric Style Delineator containing 40 words arranged in 10 columns with 4 items each; the leaner is asked to rank the words in terms of personal preference |
| McCarthy – 4 Mat System [23], [24] | Innovative, Analytic, Common sense, Dynamic | - |
| Gardner – Multiple Intelligence Inventory [25], [26] | Linguistic, Logical-mathematical, Musical, Bodily-kinesthetic, Spatial, Interpersonal, Intrapersonal | an instrument consisting of 8 questions |
| Grasha-Riechmann – Student Learning Style Scale [27], [28] | Competitive-Collaborative, Avoidant-Participant, Dependent-Independent. | 90 items self-report inventory measuring the preferences of both high school and college students |
| Hermann – Brain Dominance Model [29], [30] | Quadrant A (left brain, cerebral), Quadrant B (left brain, limbic), Quadrant C (right brain, limbic), Quadrant D (right brain, cerebral) | 120 questions that refer to four profile preferences codes corresponding to each quadrant |
| Mayers-Briggs – Type Indicator [31], [32] | Extroversion, Introversion, Sensing, Intuition, Thinking, Feeling, Judgement, Perception | (i) MBTI (Myers-Briggs Type Indicator), (ii) Kiersey Temperament Sorter I, and (iii) Kiersey Character Sorter II |

### 2.1 Criteria for Selecting Among Different Learning Style Models in PL Systems

Given the variety of learning styles theories and models that are available in the literature, we need to define a set of criteria for selecting the most appropriate learning style model to be accommodated in a specific PL system.

Of course, the most important criterion, apart from the theoretical and empirical justification of the model, is the suitability of each model for the specific learning context under consideration, the available adaptation technologies, etc, especially from an educational point of view. For example, if all learners of a specific learning context are "experts" in the domain (e.g. an application for aircraft pilots), then it might not be reasonable to select a learning style model which categorises learners as being either "experts" or "novices". Similarly, if all the educational material that is available for a specific case is in textual form, then it is not reasonable to select a model which differentiates content according to its medium.

The following paragraphs summarise some additional selection criteria that need to be considered in this context.

- *Measurability:* We need to be able to "measure" how learners are "classified" into the categories defined by each model. For example, one model may differentiate learners according to their emotions; while this may be reasonable from a theoretical point of view, since emotions may affect learning, it may not be reasonable to select such a model for a PL system, since it may be very difficult to measure learners' emotions. The existence of an assessment instrument (e.g. such as the questionnaires included in Table 1) may help in this direction. Moreover, for adaptive learning environments, this classification needs to be performed at run-time, based on the learners' observable behaviour (i.e. it cannot be based on initial questionnaires).
- *Time effectiveness:* The assessment instrument related to each learning style model needs to include a reasonable number of questions in order to be time effective. For example, if an assessment instrument consists of 200 questions, then the instrument may not be effective time wise. The user may not be willing to dedicate his/her time in order to complete a large questionnaire before starting using the system.
- *Cost:* The cost of a learning style model along with its assessment instrument is another parameter that system designers may need to consider. The situation here varies, as some assessment instruments are only available for use after payment, while others are available to be used free-of-charge. Another type of "cost" related to each learning style model is the type of learning material selected for different (categories of) learners; for example, starting from a text-based learning material, it may not be cost-effective to adopt a visual/verbal learner classification, since this may require that the learning material is enriched with visual multimedia components.

## 3. Some Examples of Accommodating Learning Styles Research in PL Systems

Learning styles research has formed the basis for the development of a number of PL systems, since a number of studies have shown that adaptation to the individual's learning style can have a positive impact on learning effectiveness (e.g. [33]). TrainingPlace.com is a notable example of a commercial PL system which is based on learning styles research. This system is based on Learning Orientation Theory, which categorises learners into transforming, performing, conforming and resistant. Based on this categorisation, the system presents different "learning experiences" to each learner. For example, the system selects "loosely structured environments that promote challenging goals, discovery and self-managed learning" for transforming learners, and "semi-complex, semi-structured, coaching environments that stimulate personal value and provide creative interaction" for performing learners [34].

The INSPIRE system adapts the presentation of the learning material, based on the Honey and Munford's learning styles model, as shown below [35]:

| learner style | selected learning material |
|---|---|
| activist (motivated by experimentation and challenging tasks) | activity-oriented learning material with high interactivity level |
| reflector (tend to collect and analyse data before taking action) | example-oriented learning material |
| pragmatist (keen on trying out ideas, theories and techniques) | exercise-oriented learning material |
| theorist (preferring to explore and discover concepts through more abstract ways) | theory-oriented learning material |

The same learning styles model is used in SMILE, a web-based knowledge support system aiming at promoting intelligent support for dealing with open-ended problem situations [36]; as well as within the 3DE European Project www.3deproject.com), where different courses are developed for each learner from a repository of learning objects.

The AES-CS system adapts the learning environment based on the field dependent/independent learning styles model, as shown below [37]:

| field-dependent learners | field-independent learners |
|---|---|
| provide global approach | provide analytical approach |
| provide information from general to specific | provide information from specific to general |
| program control | learner control |
| provide advance organizer | provide post organizer |
| provide maximum instructions | provide minimal instructions |
| provide maximum feedback | provide minimal feedback |
| provide structured lessons | allow learners to develop their own structure |

The *iWeaver* system adapts the presentation of the learning material, based on the learner's style, following the Dunn & Dunn model, as shown below [38]:

| learner style | recommended representation | representation type |
|---|---|---|
| auditory | PowerPoint-style presentations with synchronous audio, no text | multimedia representation |
| visual (pictures) | diagrams, illustrations, graphs, flowcharts, animations & audio | multimedia representation & text or audio |
| visual (text) | reading, context-aware note-taking tool | text & additional tool |
| tactile kinesthetic | interactive multimedia elements: puzzles, drag-and-drop fill-ins, small games | multimedia representation & text |
| internal kinesthetic | extra examples of real-life relevance, links to prior content | additional text |
| impulsive | try-it button (allows immediate trial) | additional tool |
| reflective | context-aware note-taking tool, questions that encourage reflection | additional tool |
| global | advance organisers or mind maps | additional multimedia representation |
| analytical | sequential lists of key points and components | text (default) |

## 4. Adaptation Rules in the KOD Adaptive Web-Based Learning Environment

The KOD European project aims to promote individualised access to learning material in a re-usable way. This section focuses on the adaptation rules which are used in the KOD project, in order to accommodate learning styles research (the work of the project has been published in [39], [40], [41]).

Following the discussion of the previous section (concerning the selection among the available learning styles theories and models), we should also highlight another important selection criterion: it is important that the selected model describes not only how learners are categorised, but also how instruction should be adapted for each learner category; that it, apart from the descriptive information (e.g. learners are categorised into "active" and "reflective"), the model should provide prescriptive guidelines, which can lead to specific adaptation rules for designing instruction and adaptation (e.g. what types of educational content should be selected for active and reflective learners).

However, learning styles models are usually rather descriptive in nature, in the sense that they offer guidelines as to what methods to use to best attain a given goal; they are not usually prescriptive in the sense of spelling out in great detail exactly what must be done and allowing no variation: "prescription only applies to deterministic or positivistic theories, which are almost nonexistent in the social sciences" [42].

In this context, as part of the KOD project, we "interpreted" the literature on the respective models (presented in Table 1), in order to develop a set of adaptation rules, which are shown in Table 2. Since KOD aims to build on existing learning technologies specifications, the adaptation constituents (i.e. learning objects characteristics)[1] were selected among the LOM elements.

It should be noted that:

- the values of some of the LOM elements included in Table 2 require an extension of the current version of the specification; for example, the value `theoretical` does not belong into the suggested values of the `educational.learningResourceType` element;
- the values for the `technical.format` element have been selected for presentation purposes to be `visual`, `verbal`, etc; according to the specification, these values should be mapped onto MIME types, based on RFC2048:1996 specification (e.g. `image/jpg` or `image/gif`, etc);
- the adaptation determinants of the rules of Table 2 could also be described through learning technologies specifications, and in particular through the Learner Information Package Specification – LIP [43]; since the LIP specification does not include specific elements for maintaining the learner's learning styles characteristics, the adaptation determinants could be maintained within the (extended) `preference.cognitive` element.

**Table 2.** Example KOD Adaptation Rules

**Felder-Silberman Index of Learning Styles**

- `IF learner=sensing THEN LOM.educational.learningResourceType=exercise OR simulation OR experiment`
- `IF learner=intuitive THEN LOM.educational.learningResourceType=problemStatement OR narrativeText`
- `IF learner=visual THEN LOM.technical.format=visual`
- `IF learner=verbal THEN LOM.technical.format=verbal`
- `IF learner=inductive THEN LOM.educational.semanticDensity=0 OR 1`
- `IF learner=decuctive THEN LOM.educational.semanticDensity=3 OR 4`
- `IF learner=active THEN LOM.educational.semanticDensity=exercise OR simulation OR experiment`
- `IF learner=reflective THEN LOM.educational.semanticDensity=problemStatement OR narrativeText`
- `IF learner=sequential THEN LOM.educational.semanticDensity=0 OR 1`
- `IF learner=global THEN LOM.educational.semanticDensity=2 OR 3`

**Riding Cognitive Style Analysis**

- `IF learner=analytic THEN LOM.educational.semanticDensity=0 OR 1`
- `IF learner=wholist THEN LOM.educational.semanticDensity=2 OR 3`
- `IF learner=visual THEN LOM.technical.format=visual`
- `IF learner=verbal THEN LOM.technical.format=verbal`

---

[1] The term "learning object" is used to refer to "any (digital) entity that can be used, re-used, or referenced during technology-supported learning" [6].

| |
|---|
| **Honey and Mumford Learning Styles** |
| • `IF learner=theorist THEN LOM.educational.learningResourceType=theoretical` |
| • `IF learner=activist THEN LOM.educational.learningResourceType=practical` |
| • `IF learner=reflector THEN LOM.educational.semanticDensity=0 OR 1` |
| • `IF learner=pragmatist THEN LOM.educational.semanticDensity=2 OR 3` |
| **Gregoric – Mind Styles and Style Delineator** |
| • `IF learner=abstractSequential THEN LOM.educational.semanticDensity=0 OR 1` |
| • `IF learner=abstractRandom THEN LOM.educational.semanticDensity=2 OR 3` |
| • `IF learner=concreteSequential THEN LOM.educational.learningResourceType=exercise OR simulation OR experiment` |
| • `IF learner=concreteRandom THEN LOM.educational.learningResourceType=problemStatement OR narrativeText` |
| **Learning Orientation Theory** |
| • `IF learner=transforming THEN LOM.educational.interactivityLevel>2` |
| • `IF learner=performing THEN LOM.educational.interactivityLevel>2` |
| • `IF learner=conforming THEN LOM.educational.semanticDensity<2` |

## 5. Conclusions and Future Work

This paper investigates the accommodation of learning styles research in PL systems. It briefly reviews the most well-known learning styles theories and models, as well as some criteria for selecting among them, and also outlines a number of PL systems which utilise this line of research for delivering personalised learning.

The emphasis of the paper is on the PL system which has been developed in the context of the KOD European project, and, moreover, on the adaptation rules which have been used in the KOD system, based on learning styles research.

As it was described earlier, the "rule templates" employed in KOD (shown in Table 2) are the result of an "interpretation" of the literature on the respective models, which was carried out within the project. Part of our current and future work involves the validation of these "prescriptive rules", through the development and testing of adaptive learning material which is based on them. The KOD project, facilitating the interchange of learning material in a re-usable way [40], offers an effective test-bed for this endeavour.


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# Adapting Hypermedia to Cognitive Styles: Is it necessary?

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**Abstract.** Adaptive hypermedia systems traditionally focused on adapting to the user's prior knowledge, but recent research has begun to consider adapting to cognitive style. This paper presents the results of an experiment investigating the learning performance and user-perceptions of 60 undergraduate students using educational adaptive hypermedia interfaces. Participants used two interfaces – one 'normal' and one adaptive – and were randomly matched or mismatched to their cognitive styles. Whilst there was no interface preference for those who were matched to their cognitive styles, those who were mismatched were significantly more likely to prefer the normal interface. The implications of these findings in relation to adaptive hypermedia development are discussed.

## 1. Introduction

Adaptive hypermedia (AH) is hypermedia that can adapt the content presentation and navigation support to the users, to aid the users in their search for the information most appropriate and best suited to them [1]. The purpose of AH, particularly in regard to education, is to provide a learning environment that can match with the needs of each individual, preventing them from being "lost in hyperspace" [2]. A number of AH systems have been created for educational settings and these systems tailor information to the students' level of knowledge such as ELM-ART [3] and InterBook [7]. Such systems adapting to prior knowledge have been found to be beneficial to the user and more effective as a learning tool than traditional hypermedia, in terms of improved learning performance [4], and user-satisfaction [5].

Recently, another human factor, i.e. cognitive style, is being considered in AH systems. INSPIRE [20] and AES-CS [5] are two famous AH systems that take into account users' cognitive styles. In the former, users' cognitive styles are classified based on the model proposed by Honey and Mumford. This model, based on Kolb's theory of experiential learning, identifies learners as Activists, Pragmatists, Reflectors, or Theorists. In the latter, Witkin's Field Dependence is used to identify learners as Field Independent (FI), Intermediate (FM), or Field Dependent (FD). However, since these two systems adapt based on prior knowledge as well as cognitive style, reported benefits cannot necessarily be attributable to the adaptation to cognitive style. In this vein, this study was to examine whether the performance of an AH system can be enhanced by adapting to cognitive styles alone.

### 1.1 Cognitive Style

Cognitive styles refer to the way of how users process information. One of the most widely investigated cognitive styles with respect to hypermedia learning is field dependence. Field dependence refers to an individual's ability to perceive a local field as discrete from its surrounding field [8]. It is a single bi-polar dimension ranging from FD individuals at one extreme to FI individuals at the other.

Research has indicated differences in the way FD and FI individuals browse through hypermedia. For example, FD individuals tend to prefer a more restricted interface [9] and follow a linear route [10], whilst the converse is true for FI individuals. In addition, FD users have been found to prefer a breadth-first navigation path, where overviews of the topics are browsed first, whilst FI users prefer a depth-first path, browsing individual topics separately [12]. Further studies have highlighted differences regarding hypermedia structure and navigational aid preferences. FD users have been found to perform worse than FI users when there is no explicit structure within the interface [14], becoming confused and disorientated [15]. Furthermore, FD students have been shown to prefer using a map as a navigational aid [16], whilst FI users prefer an index [10]. Such studies are consistent with the conceptual differences between FD and FI individuals. Table 1 describes the relationships between the characters of FD and FI users and their navigation preferences.

**Table 1.** Field Independent vs. Field Dependence navigation preferences

| **Field Independent** | | **Field Dependent** | |
|---|---|---|---|
| *Characteristic* | *Preference* | *Characteristic* | *Preference* |
| Active approach | Prefer to use index to locate specific items | Passive approach | Rely on map to impose structure |
| Analytical tendency | Prefer depth-first paths | Global tendency | Prefer breadth-first paths |
| Internally Directed | Prefer non-linear and flexible navigation | Externally Directed | Prefer linear and restricted navigation |

Based on Table 1, we have developed an adaptive hypermedia tutorial, which includes two types of interface: FI and FD interfaces (See Section 2.2). In addition, a normal interface that incorporated characteristics from these two interfaces was created. Comparing learning performance and user-perceptions of these three interfaces can help determine whether it is useful to consider cognitive styles in the development of AH systems. Therefore, this study aimed to examine this particular research question.

## 2. Methodology Design

### 2.1 Participants

64 participants took part in this experiment. All were second year Computer Science students at Brunel University and were each paid £5 for their participation and were

further motivated to take part in the experiment by being told that the tutorial may help them to learn the material from the course.

## 2.2 Materials

### *2.2.1 Web Tutorial*

A Web tutorial was created to teach the students about computation and algorithms. This was split into two parts, one part of which was a standard tutorial with Normal Interface, the other adapted to suit either a FD or FI user. In order for some students to use the adaptive interface followed by the Normal interface, and others to use the adaptive interface followed by the Normal interface six half-tutorials were created (Normal, FD, FI for each half). The Normal interface was designed to be a richly linked hypermedia system to allow for non-linear learning. This meant the tutorial contained rich links within the text, as well as three navigation tools (a map, an index, and a menu) to aid the participants in their use of the tutorial.

**Table 2.** The differences of Field Independent and Field Dependent Interfaces

| FI Interface | Adaptive Hypermedia | FD Interface |
|---|---|---|
| Depth-first path | Link Ordering | Breadth-first path |
| Rich Links | Link Hiding | Disabled Links |
| Alphabetical Index | Adaptive Layout | Hierarchical Map |

Both FI (Figure 1) and FD (Figure 2) interfaces were developed on the basis of findings of previous hypermedia learning research that were summarized in Table 1. To achieve the particular aim of this study, these two interfaces only provided adaptivity and did not consider adaptability. In other words, the system automatically adapted the interface based on the users' cognitive styles; the users were not able to customize the interface. As described in Table 2, three types of AH techniques were applied to develop these two interfaces, and their detailed functionalities are described below:

- *Link Ordering:* the system sorts a list of links according to users' cognitive styles. In the FD interface, the links were sorted based on the Breadth-first path, which gave an overview of all of the material prior to introducing detail. In contrast, the FI interface took the Depth-first path, whereby each topic was presented exhaustively before the next topic, which was presented in the same way.
- *Link Disabling:* Due to the fact that FD users easily become disorientated and prefer to take a linear navigation strategy, the FD interface provided restricted navigation choices whereby links were disabled. On the other hand, the FI interfaces provided rich links, leaving freedom of navigation to the users.
- *Adaptive Layout:* Because FD and FI users process information in different ways, adaptive layout was applied to identify the relationships of the subject topics by providing different tools. The FD interface provided a hierarchical map, which could help the FD users to understand the content structure. Conversely, the FI interface used an alphabetical index to facilitate the location of specific information.

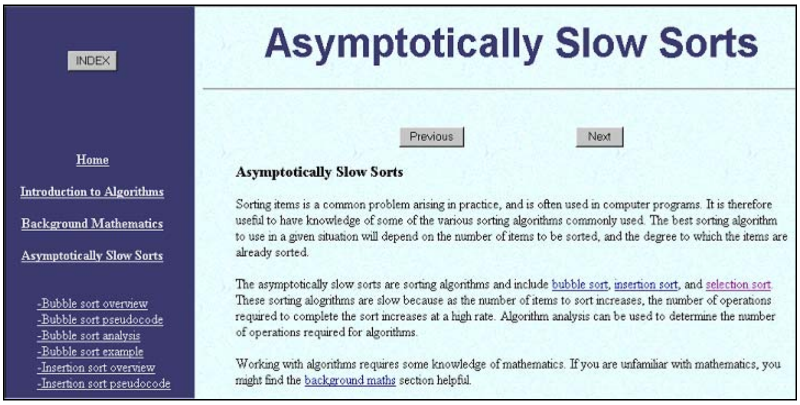


**Fig. 1** Field Independent Interface

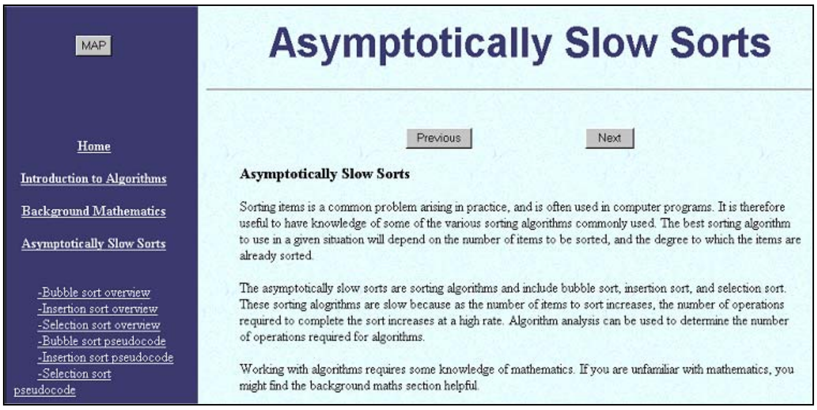


**Fig. 2** Field Dependent Interface

### *2.2.2 Questionnaires*

Two online questionnaires were created. The first of these (Questionnaire 1) asked for background information, such as age and gender, as well as information regarding the students' levels of prior knowledge of the subject domain (computation and algorithms knowledge). It also asked for their experience with, and their enjoyment using, computers, and the Web. Prior knowledge was measured on a 5-point scale to a series of questions related to how familiar with the subject the students were. The second questionnaire (Questionnaire 2) asked the students their perceptions of the Web tutorial. These included various questions regarding interface preference between the Normal and Adaptive interfaces, as well as questions regarding the user's ideal interface. This questionnaire, therefore, allowed for the analysis of a number of user perceptions of the interfaces and preferences between the two across a number of topics relevant to hypermedia learning.

### *2.2.3 Pre- and Post-Tests*

Online pre- and post-tests were written to assess the participants' level of knowledge of the subject domain both before and after using the Web tutorial. Each test contained 20 multiple-choice questions on the subject, 10 of which were related to the first half of the tutorial, and 10 related to the second half of the tutorial. For each question there were five possible responses: four different answers and a "don't know" option. The questions were matched on the pre- and post-tests so that each question on the pre-test had a corresponding similar (but not the same) question on the post-test. Creating similar questions on the post-test was achieved by either re-writing the question or, where appropriate, by substituting different numbers into the questions.

### *2.2.4 Cognitive Style Analysis*

A number of instruments have been developed to measure Field Dependence, including the Group Embedded Figures Test (GEFT) by Witkin et al. and the Cognitive Styles Analysis (CSA) by Riding. The main advantage of the CSA over the GEFT is that FD competence is positively measured rather than being inferred from poor FI capability. In addition, the CSA offers computerized administration and scoring. Therefore, the CSA was selected as the instrument in this study. In terms of the measures, Riding's recommendations are that scores below 1.03 denote FD individuals; scores of 1.36 and above denote FI individuals; students scoring between 1.03 and 1.35 are classed as Intermediate. In this study, categorizations were based on these recommendations.

## 2.3 Design

In order to determine whether or not the adaptive interface was better than the normal interface a within-subjects design was used. This meant that each student used both the normal interface and an adaptive interface. To avoid a learning effect, each of these interfaces covered different topics within the tutorial. Since the interfaces were on different topics within the tutorial it was necessary to create both adaptive and normal interfaces for each of the two half-tutorials, so that half of the students used the normal interface for the first half of the tutorial and the adaptive interface for the second half of the tutorial. Similarly the other half of the students used the adaptive interface for the first half of the tutorial and the normal interface for the second half. This was necessary to avoid any effects of interface preference being related to the content of the interface rather than its presentation.

Finally, in order to show that any effects of interface preference were related to matching with the user's cognitive style rather than just a preference for any adaptive interface, users were randomly matched or mismatched to their cognitive styles: approximately half of the participants used the adaptive interface that was suited to their level of field dependence, whilst the other half used the adaptive interface that was the opposite to the one they were suited to. This meant that for any student there were four possible experimental conditions: FD interface followed by Normal interface, FI/Normal, Normal/FD, Normal/FI.

### 2.4 Procedure

The experiment was carried out over a number of sessions in December 2003. The students took part in one session only. Each session contained a small group of students each working individually. The experiment began by the student taking the CSA to determine their level of field dependence. This was used to automatically provide adaptation of the tutorial interface to suit the user's level of field dependence. Students were randomly assigned to an interface that was either matched with their cognitive style or mismatched with it. After the CSA the students completed Questionnaire 1. This was followed by the Pre-test. This was timed allowing the students a maximum of 15 minutes to complete. Students could submit their test before the 15 minutes was up, but once the time was up the system automatically submitted the test and proceeded to the next section. The Pre-test was followed by using the first interface of the tutorial for 25 minutes, and then the second interface for 25 minutes. This was then followed by the Post-test, again with a 15 minute time limit, before finally with Questionnaire 2.

### 2.5 Data Analyses

The independent variable was the user's level of field dependence as measured by the CSA. The dependent variables were the responses to the various questions about the tutorial from Questionnaire 2, as well as learning performance based on the tests. All questionnaire responses, where appropriate, were scored as 5 for "strongly agree", through to 1 for "strongly disagree". A "gain score" was calculated as the post-test score minus the pre-test score.

SPSS for windows was used for the analysis of the data. Pre- and post-test scores were given as marks out of 20. A significance level of 0.05 was adopted. Chi-square tests were used to analyze interface preference in the matched and mismatched conditions, since this data was in the form of frequencies. Pearson's correlations were used to analyze the relationship between field dependence and questionnaire responses, where field dependence was measured on the continuous score as given by the CSA, as opposed to the discrete categories of FD and FI.

## 3 Results and Discussion

### 3.1 Interface Preference

Analysis of participants' interface preference indicated that there was no significant preference between the Normal interface and the Adapted interface for the participants who were matched with their cognitive style. However, those who were mismatched to their cognitive style were significantly more likely to prefer the Normal interface over the Adapted interface (chi-square = 5.26, df = 1, $p < 0.05$). Figure 3 highlights this finding. This finding suggests that there may be an important interaction between field dependence and interface preference. However, whilst the users were significantly more likely to prefer the Normal interface over the Adapted interface when they were mismatched with their cognitive style, there was no significant preference for the Adapted interface when the users were matched with their cognitive style (with approximately half preferring the Adapted interface and half the Normal interface).

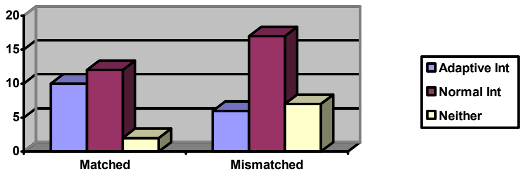


**Figure 3.** Preferences in matched and mismatched conditions

This suggests that whilst a wrongly adapted interface may cause problems for some users, appropriately adapted interfaces may be no more effective than a well-designed interface for all users. This is consistent with other studies adopting a matched/mismatched design (e.g., [12]), which have shown mismatched participants to experience more difficulties than matched participants. It is possible that the Normal interface in this study contained positive aspects for both FD and FI users. For example, the Normal interface provided links within the text that would be suitable for a FI user, whilst also having next/previous buttons to provide direct guidance for FD users. Also, the Normal interface contained both a map and an index. Supporting this conclusion is the fact that 75% of all the participants (including 58 % of FD participants and 77% of FI participants) preferred having a selection of navigation tools. This finding contrasts with previous research indicating that FIs prefer an index and FDs a map (e.g., [10][16]). Whilst it is possible that FDs do prefer a map, and FIs an index, from this study it seems that overall users prefer a selection of navigation tools.

This study, thus, poses the question of whether it is possible to create a single interface that can be suitable for both FD and FI users. Whilst it is possible that the adapted interfaces in this study could be further improved to make them better than the Normal interface, it is important for further studies to determine whether adapted interfaces can be created that are genuinely beneficial above a single interface used by all. With the findings of this study in mind, it is possibly more beneficial for hypermedia system designers to concern themselves with an interface that is easy (and not too restrictive) to use for all users, regardless of their level of field dependence. Trying to create distinct interfaces for different levels of field dependence may do more harm than good. Since field dependence is measured on a continuous scale and is only superficially grouped into distinct categories, it is difficult to decide categorically the preferences of any given user. Whilst some users may prefer an interface that is consistent with the literature regarding their level of field dependence, others may not be. For example, a user at one extreme of the scale may prefer a different interface to a user in the same category, but with a less extreme score. A more suitable interface would be one that was neutral and could support all users, whilst allowing the user to specify any particular changes that they would like (as with the AES-CS [5]). Such an interface would hopefully provide the user with a suitable interface, whilst alleviating any particular difficulties they may have.

Despite the finding that mismatched users preferred the Normal interface, Chi-squared tests carried out between FD/intermediate/FI and six other questions referring to aspects of interface preference showed just one significant finding. FI participants found it easier to get lost using the adaptive interface than the Normal interface (chi-square = 4.8, df = 1, $p < 0.05$). However, since significance was not even approached for FD participants or intermediates, nor for the similar questionnaire responses regarding interface navigation, it seems likely that this result is anomalous. Furthermore, analysis of learning performance as measured by the post-test score minus the pre-test score showed no significant difference on learning performance using the adaptive interface between those who were matched and those who were mismatched. In fact, the results indicated that those who were mismatched performed marginally better (mismatched mean gain score = 1.1, matched mean gain score = 0.96). In this respect this experiment is inconsistent with the majority of reported studies (e.g., [16]). However, it is consistent with those studies that found no significant differences in learning performance (e.g., [17]).

### 3.2 Ideal Interface Perceptions

Pearson's correlations carried out between field dependence score and six questions referring to what the user thought the ideal interface should contain found one significant correlation. Field dependence score was correlated with the statement 'how important do you think the following features are to a tutorial: Providing an example of an algorithm first, before giving more detail' ($r = .267$; $p < .05$). This indicated that FD users found providing an example first more important than did the FI users. This result is consistent with previous research [12], and justifies the FD interface directing the user with an example before giving more detail.

However, it is perhaps surprising that none of the other statements showed any significant correlations, since these were also considered to be characteristic of one or other of the cognitive styles. This suggests that the differences between FD and FI users (as measured by the CSA) in terms of hypermedia preferences may not be as strong as previously believed, at least in terms of subjective preferences. Previous research has suggested that FD users prefer to follow a linear route through hypermedia, whilst FI users prefer to be more flexible (e.g., [9]). Yet, no such correlation was found in this study. Such results would have important implications for designing AH systems to adapt to cognitive style. Since differences may not be clear cut, adaptation to an interface that is too rigidly 'FD' or 'FI' may not be beneficial, and may not suit the preferences of the individual user. In particular, since only one significant difference was found between FD and FI users in relation to ideal interface design, it is important to determine whether the needs of FD and FI users are as clear-cut as are claimed.

## 4. Conclusion

The results from this study suggest that it is possible that adapting to an interface that is too specific may restrict users, who may not necessarily prefer all aspects of the interface that are considered to be useful for a user with that cognitive style. In this study the Normal interface was less restrictive and may have suited users of both cognitive styles. It appears that the Normal interface incorporated enough freedom of navigation to suit those who preferred to navigate freely, whilst also providing a suggested route for those who needed structure. It also provided a range of navigation tools that was found to be preferable by the majority of the users to having just one.

Since this experiment was restricted to the study of field dependence as measured by the CSA, future research should also strive to determine whether the findings from this study regarding adaptation to field dependence apply to other cognitive styles and other cognitive style assessment tools. Furthermore, this study was limited in that it provided adaptation to field dependence and field independence in a way considered appropriate for such individuals based on interpretations of previous research into field dependence and hypermedia learning. Since some findings from this study differ from this interpretation (for example, users preferring a selection of navigation tools as opposed to just one), future studies might consider revising the interpretation used here concerning ideal interfaces. Future research could therefore re-interpret what an ideal interface might be for FD and FI users, and determine whether different interfaces are needed, or whether one could satisfy all users regardless of their level of field dependence.

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