CHAPTER 8 –The Need for Empirical Evaluation of Learner Model Elements

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Introduction

The data stored in a learner model are used by an ITS to adapt and customize instruction based on the learner's state of cognitive and affective knowledge. Ideally, this model would include information about the learner's individual characteristics, past and current competency, performance, cognition, affect, behaviors, etc. The higher the level of functionality and capability of a learner model to interpret and accurately classify the comprehensive knowledge of an individual learner, the better the ITS can adapt to the individualized needs of the learner. For expert human tutors, this process is easy since they have the natural ability to interpret and assess the learner's current and predicted state of readiness for instruction. However, equipping learner models with such capabilities is a computationally complex problem ITS researchers have been trying solve over the last 15 years. The primary sub-research areas of learner modeling research include, but are not limited to, learner state, cognitive modeling, affective modeling, individual differences, behavioral and physiological sensing, and performance assessment.

Most learner modeling research is conducted within academic populations (primarily K–12) and well-defined, domain-specific ITSs, such as mathematics and physics. The next-generation ITSs aim to be more inclusive of adult learners and job-related training; however, little is known about the transferability and validation of previous research findings as well as the investigation of other useful learner aspects that scale beyond academia. While great strides have been made among learner modeling research, there are several factors that limit the future progression/development of comprehensive learner models: (1) the lack of understanding of the impact and interaction effects of learner model elements; (2) the lack of reusability and transferability of learner models between ITSs, domains, and populations; (3) the nonexistence of the measures from user models/modeling of which learner models/modeling is a subset; and (4) the lack of standardization for learner model development and structure.

These limiting factors can be addressed through the process of empirical evaluation in future learner modeling research and learner model development. For years, these issues have been ignored by the user modeling community at large (Adikari & McDonald, 2006; Glavinic & Granic, 2008; Granic & Adams, 2011; Johnson, 1994; Kobsa, 1994) due to the constraints surrounding the needed experimentation. However, GIFT, an experimental testbed that can accommodate such evaluations and comparative analyses, is now available to conduct such experimentation realistically and affordably.

The purpose of this chapter is to provide justification for the need of empirical evaluation by taking lessons learned from the human-computer interaction (HCI) perspective of user modeling research. Moreover, we present guidelines and suggestions on how to conduct such evaluations using GIFT. Specifically, this chapter is divided into three sections: (1) the current understanding of learner model elements; (2) the incorporation of the missing link of HCI user modeling research; and (3) suggestions on how to conduct experimentation using GIFT toward the development of standardizing and generating comprehensive learner models capable of accommodating user and domain diversity.

Current Understanding of Learner Model Elements

The content within learner models is generally categorized in two parts: domain-specific or domain-independent information (i.e., learner-specific characteristics [individual differences]) (Abdullah, 2003; Gonzalez, Burguillo & Llamas, 2006). Domain-specific information reflects the learner's state and level of knowledge or ability within a particular domain. This type of information primarily includes historical competency (domain knowledge and skills measured over time), misconceptions, problem-solving strategies, etc. Most learner models, particularly those of first-generation ITSs, are concerned with modeling this type of information because this allows the model to be more generalized across multiple populations. While this information is useful, it alone is not sufficient for providing the highly adaptive individualized training. Domain-independent information consists of all relevant characteristics of an individual learner and can include, but is not limited to, the following elements: learning goals; cognitive aptitudes; measures of motivational state; learning preferences (including styles and personality); interest; demographics; past performance and competency (non-domain-specific); behavioral/psychological measures; cognitive and affective dimensions; and personal control beliefs (including general self-efficacy; locus of control). These individual difference variables are significantly different between learners and, collectively, are not the same for any two learners.

To accurately classify a learner's state and performance at any given time, the learner models must have all-inclusive understanding of learner's cognition and affective states, influential individual difference characteristics, and performance. One area of learner modeling research is dedicated to understanding the influence of and interrelationship between domain-independent information (e.g., learner-specific characteristics) and how it can be best used in conjunction with the domain-specific information to optimally classify a learner state and performance. Understanding impact and interaction effects of individual learner model elements takes "big data," recurring empirical evaluation and experimentation, and the ability to dynamically incorporate multiple models and modeling techniques simultaneously. However, learner models have limited reusability since they are typically developed standalone and tightly coupled within the specific ITS within which it is integrated. Most of these systems typically can only accommodate one well-defined academic domain (i.e., mathematics, physics, computer science), resulting in the lack of standardization of learner model elements and ideal learner modeling techniques. The review of HCI user modeling research shows the same limitations are present in that area of research. While the approach to user modeling is different, lessons can be learned from the HCI user modeling research area. The next section discusses how ITS learner modeling research can be enhanced by leveraging some of the research of its parent research area, user modeling (from the HCI prospective).

The Missing LINK: The Human-Computer Interaction (HCI) User Modeling Perspective

There are several social and economic factors influencing the evolution of technology; however, technology progression is directly correlated to changes in user requirements. Consider the evolution chain of the personal computer (i.e., desktop to laptops to netbooks to tablets and smartphones) as an example. This progression was accomplished by user's desire to have these devices more portable, faster, and useful to accommodate users with diverse computing purposes. User requirements for the successful and beneficial usage of ITSs are also changing as their need to account for learner and domain diversity increases. Long gone are the days in which user-initiated and user-selected adaptation techniques, such as completing preference menus and editing profile files, are sufficient for personalizing interactive computer systems (Kobsa, 1994). In most cases, especially ITSs, learners (users) do not have the necessary knowledge about the subject area, their own errors, or the system's adaptive abilities to select adaptation preferences. Moreover, adaptation methods in current and future ITSs dynamically occur and are too numerous for learners to customize each potential adaptation path.

User and learner modeling research have the opportunity to significantly enhance the adaptive capabilities of intelligent, interactive interfaces and learning environments; however, there is a rather large disconnect between these two research areas limiting their forward progressions. Learner models and modeling is a subset of user models and modeling (Self, 1988). User models, like learner models, contain the system's assumptions about all user characteristics that are relevant for tailoring system behavior to accommodate the individual user. Furthermore, both user and learner modeling share common tasks including (1) initializing the user or learner model; (2) drawing assumptions about the user or learner based on system interactions and updating the user or learner model accordingly; and (3) supplying other system components with assumptions about the user or learner, as needed. While user and learner modeling share common performing functions, there seems to be a rather large disconnect between these areas. They differ in the following ways:

- **Primary Area of Research**
  - User modeling is a subdivision of HCI
  - System goal is to build useful and usable systems
  - Learner modeling is viewed as a subdivision of AI. This terminology is essentially used for the primary user (i.e., student, learner, trainee, pupil, etc.) of an ITS and other learning environments.
  - System goal is to build systems that portray intelligent behavior
- **Model Content**
  - Both user and learner models can contain personal data associated with a specific user/learner including demographics, past experience, goals, interests and motivation, knowledge and skills, preferences, etc.
  - User models also include and emphasize users' system preferences and dislikes, behaviors and interactions with the system, system acceptance (including perceptions, satisfaction, and usability), and general technology acceptance.
  - Learner models also include and emphasize learner's cognitive and affective states, domain competency and self-efficacy, cognitive aptitudes, etc.
  - There is no current standardization on how to structure and employ these models; therefore, not all current models contain the above information.
- **Adaptation Techniques**
  - User modeling focuses on modifying/adapting the system's interface design based on the user model. Considers other elements of HCI such as usability and user-centered design.
  - Learner modeling focuses on modifying/adapting instruction based on the learner model (not including the change to the physical user interface, but may change the interface feedback via agent, text, audio, etc.).

- **Presence in the Literature:**

    - It is rare to find representation of ITSs and learner models in user modeling research, and it's even more scarce to find reference to user modeling in ITS and learner modeling research. Basically, these two research areas and system development are conducted entirely independently (Johnson, 1994).

      Johnson (1994) suggested that regardless the past neglect of combining the research and development of HCI- and AI-based user models, the two communities will come together in the near future due to the increase of intelligent interface and agents; however, 20 years later, gap and disparities still remain. If both communities understand the importance of optimizing the user's system interactions and have had significant progress within their respected fields, why is the gap between these two areas still as widespread as it was 20 years ago? Why does this issue still matter?

Returning to the notion of technology evolution being driven by user requirements, the need for understanding how an interactive system can dynamically capture/model users' needs and adapt its interaction accordingly has become more vital due to the increase in range and complexity of user requirements for such systems (Granic & Nakic, 2007). In order for ITSs to optimize learning experiences and system intelligent behavior, a greater understanding of the interaction between the learner and system is needed. We can no longer ignore the needed synergy between the learner's learning process (inclusive of individual differences) and the learner's interaction with the learning application (i.e., ITS) (Granic & Adams, 2011; Squires & Preece, 1996). HCI user modeling research can provide the ITS learner modeling community with a potential solution to ascertaining such an understanding, which will directly attribute to better understanding the impact and interactions of currently researched learner model elements.

User Modeling in Human Computer Interaction (HCI) Explained

The general goal of HCI is to facilitate the development of systems that are enjoyable and easy to use. User modeling in HCI research was originally aimed at investigating the different types of user models and their role in supplying information for designers throughout various stages of the system development process (Johnson, 1994). Over the last 10 years, HCI research has realized that understanding users' needs is at the core of successful interactive technology design and adoption. Therefore, this research area has expanded to investigating user-centered, user-sensitive, and learner-centered design approaches toward the development of transparent interfaces and flexible interactions that can account for user diversity (Glavinic & Granic, 2008). Thus, such research has extended its objective to gaining a thorough understanding of the cognitive, perceptual, and motor components of user interactions with interactive systems (Olson & Olson, 2003).

User-sensitive design places equal focus on user requirements and the diversity of such requirements among all intended users (both typical and extraordinary) (Granic & Adams, 2011). Learner-sensitive design (Soloway et al., 1996) expands user-sensitive design by accounting for learner's unique needs, objectives, knowledge, abilities, and other learner-specific characteristics. Since it is known that one single interface design will not satisfy every user, HCI user modeling research looks to intelligent user interfaces (IUIs) as a means of (1) providing more individualized and personalized interactions, (2) enabling adaptation of interface behavior to match user individual characteristics (adaptive systems), and (3) enhancing system acceptance, usability, flexibility, and attractiveness (Granic, 2008b; Hook, 2000).

Adaptive, IUIs rely on the use of user models, which contain a collection of information and assumptions about particular users that guide the adaptation process of the system for an individual (Kobsa, 1995), thus an intelligent system's behavior strongly depends on the impact of user individual characteristics on interaction with the system (Granic & Nakic, 2007; Magoulas, Chen & Papanikolaou, 2003). This is similar to the use of learner models in ITSs. Like ITS research, HCI research has acquired inconsistent results on the impact of individual differences on user performance; however, the underlying cause in HCI research attributing to user performance with a particular system largely depends on the system alone (Granic & Nakic, 2007). In HCI user modeling research, elements of users' acceptance, preferences, usage behavior, perceptions, perceived usability and usefulness, and attitudes toward the system and computers in general are considered as a part of modeling users' system interactions.

ITS learner modeling research can leverage some of these elements to ascertain a clearer distinction between factors influencing a learner's cognitive and affective knowledge during the learning process and factors that are directly linked to system interaction and usage behavior. With this concept in mind, several HCI researchers have investigated the link between users' individual differences and their usage of e-learning applications (as ITSs fall under the same umbrella of educational technology). Adams (2007) evaluated eight hypothetical criteria e-learning systems need to accommodate individualized student learning against five e-learning platforms. Accessibility and student modeling for user diversity were the weakest points among all cases. The Cognitive Tutor Authoring Tool (CTAT) was found to address the most criteria among the five platforms; however, the difficulty and time involved in developing a cognitive model limits its universal usability (Adams, 2007). An experiment conducted to investigate the existence and level of interaction among users' individual differences and learning outcomes through the use of an e-learning application also garnered interesting results. The individual differences that were evaluated within the experiment include both *personal* user characteristics (i.e., intelligence, emotional stability, extraversion, mental stability, experience) and *system-dependent* user characteristics (experience using computers and Internet, motivation to learn programming, expectations from e-learning, and background knowledge material to be learned). The study found significant correlations between mental stability and motivation, and emotional stability and expectations from the system; however, only learner's motivation to learn programming and their expectations of e-learning had a significant impact on the knowledge acquired through their system interaction (Granic & Nakic, 2007). A follow-on study also found motivation to learn and expectations about e-learning (both for e-learning in general and the specific application) to significantly influence learning achievement (Granic & Adams, 2011). These findings support the need for researching the impact and interaction of individual characteristics (inclusive of system-dependent/specific characteristics) and how users' expectations of the system can impact their successful system interactions.

For learners, their interest and motivation to learn pertains to their willingness, direction, intensity, and persistence of learning-directed behavior. It influences their choices during learning activities as well as cognitive engagement during instruction and training (Schultz, Alderton & Bordwell-Hyneman, 2011). The level of a learner's intrinsic motivation, goal orientation, and need for achievement are also directly related to an overall motivation to learn and has been shown to be directly related to learning performance and other learning outcomes (Schultz et al., 2011). Furthermore, learners' self-efficacy beliefs are also related to their motivation to learn, learning, performance, and job performance (Glavinic & Granic, 2008) and have been shown to influence learners' decision making during instruction and training (Soloway et al., 1996). These aspects should be contained within the learner model structure; however, research assessing the influence of learners' motivational characteristics on outcomes and their relationships to other individual difference variables is practically non-existent. Although ITS research has found interrelationships among learner-specific characteristics (for examples, personality and cognitive abilities [(Kobsa, 1994; Schultz et al., 2011)], and learning styles and cognitive traits (Graf, Liu, Kinshuk, Chen & Yang, 2009), current learner models have a limited capability to account for individual differences as explanations of learner's cognitive and affective knowledge. Based on the studies previously mentioned, user models also have limited capabilities for accounting for individual characteristics.

Another important area of HCI user modeling research to consider is end-user technology acceptability and adoption. While technology has been deemed as the "salvation" to education by providing individualized learning, it rarely meets this "broad expectation" (Healey, 1999). Authoring tools and shells, such as CTAT, are designed to accommodate teachers by supporting them in the development of a series of ITSs; however, the ITS adoption and usage for tutoring in real classrooms has been a slow progression. HCI researchers attribute this slow adoption rate to the fact that ITS interaction mechanisms have not been accompanied by an adequate user interface design (Granic, 2008a).

In addition to its focus on user expectations and requirements, technology acceptance also considers user perceptions of a specific technology's usefulness and usability. Liu, Laio, and Peng (2005) found significant evidence that learners of e-learning applications have two identities, one as a system user and the other as a learner, and both identities are influenced by the "flow" (concentration) and perceived usefulness of the e-learning system (Liu, Liao & Peng, 2005). A recent meta-analysis of research found solid evidence that supports perceived usefulness is the strongest predictor of a learner's adoption of an e-learning technology (Sumak, Hericko & Pusnik, 2011). Usability evaluation is an important role in user interface design; however, the number of usability studies on e-learning is limited and the consolidated evaluation methodology for e-learning is non-existent (Ardio et al., 2006; Costabile, Marisco, Lanzilotti, Plantamura & Roselli, 2005; Granic, 2008a). These studies mention the need for further research and empirical evaluation of usability assessment of e-learning applications. Usability assessment and measurement are always among HCI's approach to investigating the interactions between users and the system; determining its value in modeling interactions between learners and ITSs is a valuable factor to consider. Squires and Preece (1996) affirm that "there is a need to help evaluators consider the way in which usability and learning interact" (Squires & Preece, 1996); Costabile et al. (2005) also argue that the usability of an e-learning application can directly affect learning (Costabile et al., 2005).

Usability evaluation can be measured by objective performance metrics of efficiency and effectiveness as well as the user's subjective assessment of the system usage. These objectives quantify user performance, satisfaction, and terms by which they find the system acceptable. Adikari and McDonald (2006) constructed a science-oriented research design to test the value of incorporating conceptual user modeling and usability modeling into product requirement specifications for improving design (Adikari & McDonald, 2006). For authoring shells and ITSs, such evaluations can help identify the exact problems of a particular system (Granic, 2008a) and help separate problems/issues pertaining to the learning process.

The ITS and learner modeling community can benefit from these aspects of HCI user modeling research. By combining the same evaluated user modeling elements of perceptions toward learning, learner models could potentially increase explanation of states, performance, and system behavior. Little ITS research has been done in this area; however, preliminary findings have shown that there is a significant relationship between learners' acceptances of pedagogical agents, or virtual tutors, embedded within a learning environment and the learners' acceptances of the learning environment itself (Adams, 2007). A prior study also identified links between students' behaviors with a tutor and their attitudes and perceptions (Healey, 1999). Research blending these areas will also be beneficial to HCI user modeling as both HCI and ITS user modeling research areas have the same issues of no standardization, the inability to accommodate individual differences, and the need for empirical evaluations to validate modeling elements. HCI user modeling has expresses the need for empirical research over the last 20 years, but this is a concept that has become more apparent recently within the ITS community.

Recommendations and Future Research: Towards the Development of Reusable and Standardized Learner Models

While much research is needed to investigate the transferability of previous findings, future ITS researchers and developers should consider the following: model development and evaluation of a few elements at a time to identify interrelationships between elements and their influences on learner state; controlled experimentation (including sensor validation and comparisons to self-reported data and user-experience post-experiment interviews); and increased collaboration and data sharing.

Practical Implications for Researchers

The field of ITS learner modeling research has close ties with other adaptive computing in fields such as user modeling, HCI, and AI. A common problem among these fields is the limited amount of empirical evaluation associated with the adaptive systems that they produce (Chin, 2001; Mulwa, Lawless, Sharp & Wade, 2011; Weibelzahl & Weber, 2002). One of the main reasons for this is the inherent difficulty of separating out the pieces of an adaptive system. Many of the existing ITSs are tied to one specific domain (e.g., physics, mathematics) and the learner model used within it is closely tied to the system. The cost, time, and difficulty that goes into developing these systems results in inflexibility and an impracticality of many experimental evaluations. In many cases, a non-adaptive, or control, group may make very little sense or be difficult when trying to evaluate the impact of differing adaptations in an empirical manner (Mulwa et al., 2011).

An additional challenge to ITS research is that it is difficult to separate out the user's learning outcomes from their ability to understand and use the system. One approach that has been taken to studying adaptive systems and user models has been to layer evaluations. Rather than trying to examine the entire system, individual pieces are evaluated and empirical studies are run at each part to make sure that it is effective (Mulwa et al., 2011). This approach is a step in the right direction for making it more practical to effectively evaluate the impact of adaptations and information stored in user or learner models.

It is of great importance to researchers, specifically in the field of ITSs, to ensure that information that is contained in the learner model and to which it is being adapted to actually provides a benefit. One way to do this is by examining the specific content of what is included in individual learner models and its impact on learning outcomes. Presently, each individual ITS uses its own combination of domain-independent components in the learner model (e.g., motivation, personality scores, cognitive measures). Many learner models may not even include information pertaining to computer familiarity and system acceptance, which have previously been found to be heavily correlated to overall performance in HCI and user modeling research (Granic, 2008b). Therefore, one of the next necessary and useful steps in ITS research is to empirically evaluate the impact and interactions of specific learner model elements. Through this empirical research, a set of useful and standardized domain-independent learner model components can be developed.

As it stands now, when researchers do examine the individual difference elements within their learner models, it is within specific domains with limited generalizability (Granic, 2008b). Studies such as those reported by Granic (2008b) have begun to examine which learner model elements have an impact on performance outcomes in a specific ITS system. The next step is to continue generating empirical studies that examine the learner model elements and their utility, and then build a body of knowledge, which can be examined as a whole looking for commonalities in the useful elements between domains. This examination can then lead to a generalizable learner model, which will contain useful information that can be applied in ITSs of varying domains.

While many of the components included in learner models have been shown to impact performance in traditional and classroom environments, they may behave differently when computer delivery is added to the equation. Therefore, it is important to conduct studies on these individual difference components within a computerized tutoring environment to see which one impact learning outcomes.

Experimental Design Recommendations

In general, there is a need for more empirical evaluations of learner model elements. There are a number of different steps that can be taken to increase our knowledge about the impact and interactions of learner modeling elements:

> *Literature review and meta-analysis*. A thorough and formal literature review of current empirical research into learner model elements is necessary. It can provide an overview of the different techniques that are used to assess ITSs and learner model elements. It may also lend insight into which elements are commonly included in learner models and which ones have been found to be effective. A meta-analysis could give researchers a better picture of the types of domains that have been examined (e.g., algebra, physics), the number of tutors that have been assessed in each area, and what elements were included in those user models. The meta-analysis would show which elements of learner models were consistently helpful between these domains and which ones are domain specific. This would then give researchers a direction to take when generating specific experiments to test what elements matter in what situations. It also would give researchers a better understanding of potential interactions that exist between learner model elements. The meta-analysis and literature review will also highlight specific gaps in the literature and areas that have not received much attention.

> *More empirical evaluations*. Granic (2008b) examined the different components of a learner model used in a computer programming tutor. Correlations were found between certain elements of the model (e.g., motivation to learn programming) and performance. However, personality factors did not have many correlations with performance (Granic, 2008b). More research of this type should be done with different domains, and different ITSs. Once a large body of empirical evaluation literature has been built up it, can be further examined to see what elements have utility throughout varying domains and which ones appear to be less generalizable. By expanding research in this manner, it will move our learner models to be more consistent with each other, and more easily comparable. GIFT is an ideal experimental testbed to use for such experiments.

Advantages of Using GIFT as an Experimental Testbed and Design Recommendations

A majority of learner modeling research has not focused on examining the same learner model in multiple domains. Since GIFT is a domain-independent framework, it allows teachers and researchers to design their content to work with it, rather than having to develop their own delivery system. One of the main benefits of designing content in this manner is that it will significantly reduce the amount of time and effort that would go into developing an ITS. This also allows for consistency between generated ITSs.

One of the intentions behind GIFT is to be able to easily interchange the pieces of a system, and even, components of the learner model. Further, an additional capability would be to provide a consistent structure for the development of ITSs. Therefore, GIFT is an ideal system to use for the development of ITSs and the empirical evaluation of learner model elements. A researcher can design a tutor with GIFT, and then use the architecture to plug in and hold constant the elements of the learner model to be tested (for instance, testing one condition where motivation level is adjusted, another where personality type is adjusted, and finally, one where both motivation level and personality type are adjusted, and measuring performance). This allows for the examination of the impact of individual learner model elements, and the possible interactions between them. In a custom system that is tied tightly to its content and learner model, these types of experiments would either be extremely difficult or impossible to complete. As GIFT's features continue to develop in the future, it will provide even more flexibility and granularity in the types of manipulations that researchers can conduct in their experimental evaluations of the components of learner models.

Conclusions

The learner model is a vital part of an ITS. The learner model often contains domain-independent information (such as individual differences) about the specific learner, and then adjusts instruction based on these differences. However, there has been very little research on the individual difference components that have been included in learner models, and there is no standardization of the models between systems. It is important for research in the ITS field to (1) examine the impact and interaction effects of learner model elements; (2) increase the reusability and transferability of learner models into different domains; (3) look to fields such as HCI for guidance into elements that may be useful within the learner model; and (4) begin to move toward standardization of learner models. GIFT provides an ideal testbed to use for affordable and efficient experiments into the impact and interaction effects of different learner model elements. Through further empirical evaluations and the use of GIFT as a research tool, the ITS field can move toward generating more comprehensive and consistent learner models that are highly generalizable between domains

References

Abdullah, S. (2003). Student Modelling by Adaptive Testing - A Knowledge-based Approach. Unpublished Disseration. The University of Kent at Canterbury (Dissertation).

Adams, R. (2007). *User Modeling for Intelligent Interfaces in E-Learning*. Paper presented at the Unversal Access in HCI, HCII.

Adikari, S. & McDonald, C. (2006). *User and Usability Modeling for HCI/HMI: A Research Design*. Paper presented at the International Conference on Information and Automation, Shandong.

Ardio, C., Constabile, M., De Marsico, M., Lanzilotti, R., Leviald, S., Roselli, T., et al. (2006). An Approach to Usability Evaluations of E-Learning Applications. *Universal Access in the Information Society,* 4, 270-283.

Chin, D. N. (2001). Empirical evaluation of user models and user-adapted systems. *User modeling and user-adapted interaction*, 11(1), 181-194.

Costabile, M., Marisco, M., Lanzilotti, R., Plantamura, V. & Roselli, T. (2005). *On the Usability Evaluation of E-Learning Applications*. Paper presented at the 38th Annual Hawaii International Conference on System Sciences, Hawaii.

Glavinic, V. & Granic, A. (2008). HCI Research for E-Learning: Adaptability and Adaptivity to Support Better User Interaction. In A. Holzinger (Ed.), *HCI and Usability for Education and Work* (pp. 359-376). Berlin Heidelberg: Springer-Verlag.

Gonzalez, C., Burguillo, J. & Llamas, M. (2006). *A Qualitative Comparison of Techniques for Student Modeling in Intelligent Tutoring Systems*. Paper presented at the 36th ASEE/IEEE Frontiers in Education Conference.

Graf, S., Liu, T., Kinshuk, Chen, N. & Yang, C. (2009). Learning Styles and Cogntive Traits - Their Relationship and Its Benefits in Web-based Educational Systems. *Computers in Human Behavior,* 25, 1280-1289.

Granic, A. (2008a). Experience with Usability Evaluation of E-Learning Systems. *Universal Access in the Information Society,* 7, 209-221.

Granic, A. (2008b). Intelligent Intefaces for Technology-Enhanced Learning. In S. Pinder (Ed.), *Advances in Human-Computer Interaction* (pp. 143-160).

Granic, A. & Adams, R. (2011). User Sensitive Research in E-Learning: Exploring the Role of Individual User Characteristics. *Universal Access in the Information Society,* 10, 307-318.

Granic, A. & Nakic, J. (2007). *Meeting User Individual Characteristics Through Adaptive Interface of an E-Learning System: An Empiracle Study Design*. Paper presented at the 29th International Conference on Information Technology Interfaces, Cavtat, Croatia.

Healey, D. (1999). Theory and Research: Autonomy in Language Learning. In J. Egbert & E. Hanson-Smith (Eds.), *CALL Environments: Research, Practice, and Critical Issues* (pp. 391-402). Alexandria, VA.

Hook, K. (2000). Steps to Take Before Intelligent User Interfaces Become Real. *Journal of Interacting with Computers,* 12, 400-426.

Johnson, H. (1994). Relationship Between User Models in HCI and AI. *IEEE Computers and Digital Techniques Proceedings,* 141(2), 99-103.

Kobsa, A. (1994). *User Modeling and User-Adapted Interaction*. Paper presented at the Computer-Human Interaction (CHI).

Kobsa, A. (1995). *Supporting User Interfaces for All through User Modeling*. Paper presented at the 6th International Conference on Human-Computer Interaction (HCI International).

Liu, S., Liao, H. & Peng, C. (2005). Applying the Technology Acceptance Model and Flow Theory to Online E-learning Users' Acceptance Behavior. *Issues in Information Systems,* 6(2), 175-181.

Magoulas, G. D., Chen, S. Y. & Papanikolaou, K. A. (2003). *Integrating Layered and Heuristic Evaluation for Adaptive Learning Environments*. Paper presented at the 2nd Workshop on Empirical Evaluation of Adaptive Systems held at the 9th International Conference on User Modeling.

Mulwa, C., Lawless, S., Sharp, M. & Wade, V. (2011). The evaluation of adaptive and personalised information retrieval systems: a review. *International Journal of Knowledge and Web Intelligence*, 2(2), 138-156.

Olson, G. M. & Olson, J. S. (2003). Human-Computer Interaction: Psychological Aspects of Human Use of Computing. *Annual Review of Psychology,* 54, 491-516.

Schultz, R., Alderton, D. & Bordwell-Hyneman, A. (2011). *Individual Differences and Learning Performance in Computer-based Training* (Technical note 1 Apr 2010-28 Feb 2011): NAVY PERSONNEL RESEARCH STUDIES AND TECHNOLOGY MILLINGTON TN

Self, J. (1988). Student Models: What use are they? In P. Ercoli & R. Lewis (Eds.), *Artificial Intelligence Tools in Education* (pp. 73-86). North Holland: Elsevier Science Publishers.

Soloway, E., Jackson, S., Klein, J., Quintan, C., Reed, J., Spitulnik, J., et al. (1996). *Learning Theory in Practice: Case Studies of Learner-Centered Design*. Paper presented at the SIGCHI Conference on Human Factors In Computing Systems: Common Ground, Vancouver, British Columbia, Canada.

Squires, D. & Preece, J. (1996). Usability and Learning: Evaluating the Potential of Educational Software. *Computing and Education,* 27, 15-22.

Sumak, B., Hericko, M. & Pusnik, M. (2011). *Factors Affecting the Adoption of E-Learning: A Meta-analysis of Existing Knowledge*. Paper presented at the The 3rd International Conference on Mobile, Hybrid, and On-line Learning.

Weibelzahl, S. & Weber, G. (2002). Advantages, opportunities and limits of empirical evaluations: Evaluating adaptive systems. *KI*, 16(3), 17-20.