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Personality and its effects on learning performance: Design guidelines for an adaptive e-learning system based on a user model

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ABSTRACT

An increasingly widespread interest in developing fully adaptable e-learning systems (e.g., intelligent tutoring systems) has led to the development of a wide range of adaptive processes and techniques. In particular, advances in these systems are based on optimization for each user's learning style and characteristics, to enable a personalized learning experience. Current techniques are aimed at using a learner's personality traits and its effect on learning preferences to improve both the initial learning experience and the information retained (e.g., top-down or bottom-up learning organization). This study empirically tested the relationship between a learner's personality traits, analyzed the effects of these traits on learning preferences, and suggested design guidelines for adaptive learning systems. Two controlled experiments were carried out in a computer-based learning session. Our first experiment showed a significant difference in the learning performance of participants who were identified as introverts vs. those who were identified as being extroverts, according to the MBTI scale. As the distinction between extroverted personality types vs. introverted personality types showed the strongest correlation in terms of different learning styles, we used this criteria in our second experiment to determine whether design guidelines for appropriate content organization could reinforce the aforementioned correlation between personality type and learning experience.

Relevance to industry: The findings from this article provide how one can practically apply personality traits to the design of e-learning systems. The structure and level of extraversion could be the features to be examined in this regard.

1. Introduction

The technological landscape of modern e-learning applications (e.g., adaptive e-learning systems) has advanced due to the availability of new artificial intelligence (AI) algorithms that allow for effective and efficient learning experiences (e.g., Vandewaetere et al., 2011, Papatheocharous et al., 2012). A variety of issues, such as the customization of learning content in computer-based learning activities, serve as the driving forces behind the wide range of adaptive capabilities. Many e-learning applications have been developed to accommodate a certain level of adaptability to an individual's performance based on their usage data, such as how many times they had visited for a particular learning module or which learning process patterns were seen. Machine-learning algorithms have thus been proven to enhance learner satisfaction (e.g., Gerjets et al. 2009), and many studies have now turned their attention to the intrinsic natures of learners (e.g., learning goals, interests, personality, and knowledge level) in order to achieve the best learning experiences (e.g., Brusilovsky, 2001, Germanakos et al., 2008; Vandewaetere, et al., 2011). Pre-emptive algorithms, as compared to reflective machine-learning algorithms, have been widely thought to be promising 21st-century e-learning techniques, as they quickly adapt to a student's learning activities. What is still unknown, however, is which learner characteristics (i.e., the learner's user model) should be collected and how these characteristics should be addressed when designing computer-based learning systems.

Early studies (e.g., Riding and Rayner, 1999; Piombo et al., 2003) on learners' usage models claimed that learners have three ontologically distinct features: (i) *Personality features*, which dictate the student's learning attitude; (ii) *Overlay features*, which denote the student's current domain knowledge level; and (iii) *Cognitive features*, which represent the student's information processing

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characteristics. The last two features have been well studied in instructional design (Graesser et al., 2007; Graf et al., 2008). It has been postulated that the effects of personality are negligible, since it is the weakest organized set of characteristics possessed by an individual, but primarily because it is thought to be already cemented in his or her cognitive features. However, extensive studies on personality effects (e.g., Germanakos et al., 2008; Honey and Mumford, 1986) have indicated that personality does affect the attitudes and behaviors that determine an individual's preferred way of learning. Therefore, a learner's experience may be significantly altered if the instruction style of an e-learning system were to match their learning style as derived from personality features.

Personalization in online education not only facilitates learning through different strategies to create various learning experiences, but it also enables computer-based learning systems to include varied teaching or instructional packages. For example, some studies (e.g., Carver et al., 1999; Vincent and Ross, 2001; Kinshuk and Lin, 2004) identified learner's attitudes, learning goals, interests, and knowledge levels as critical adaptive parameters in personalizing learning content. These researchers assumed that the aforementioned items could be used to determine each learner's cognitive style (Kogan, 1971; Messick, 1970, 1976). Therefore, it is necessary to determine a systematic method of determining a user's cognitive style in advance using relevant attributes. At the same time, the issue of usability has been continually investigated in order to improve e-learning system quality. For example, Barcellini et al. (2009) empirically demonstrated use of a user participatory method in the design process of an e-learning system called 'Python'. In addition, recent articles have proposed design criteria and objective evaluation scales dedicated to e-learning platforms, including research by Hsu et al. (2009) and Oztekin et al. (2010).

More comprehensively, Brusilovsky (2001) proposed seven attributes for use in user models of adaptive e-learning systems, as shown in Fig. 1: learners' backgrounds, knowledge, goals/tasks, previous learning experience, preferences, interests, and interaction style. This model showed a significant impact on subsequent user modeling activities for personalizing adaptive e-learning systems.

However, Jungian-based psychologists have contended that people's personality preferences influence the way they may or may not want to become more actively involved in their learning activities, as well as whether they take responsibility for self-direction and discipline (e.g., Felder et al., 2002; Soles and Moller, 2001). Following a similar line of thought, several researchers (e.g., Gilbert and Han, 1999; Kwok and Jones, 1985; Papanikolaou et al., 2002; Moallem, 2003;) tried to integrate learning style into an adaptive application, matching personal learning style with an appropriate instruction design in order to adapt to that person's strengths and preferences; however, these researchers did not attempt to examine personality effects.

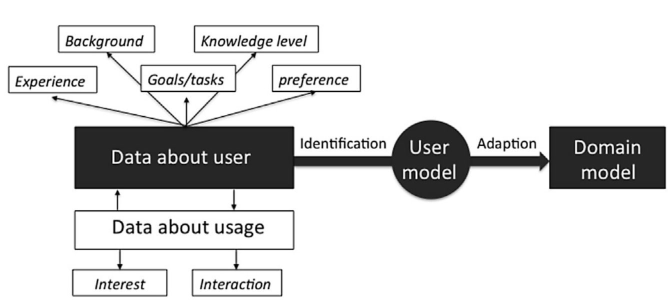

Fig. 1. The user model of an adaptive e-learning system, extended from Brusilovsky (2001).

Therefore, the goal of this study was to examine the inclusion of a learner's personality features in a user model. The findings were then applied to learning materials, which were empirically tested. This paper is organized as follows. In Section 2, we reviewed the possible relationships between a learner's personality and the learning styles included in the user model of adaptive learning systems. In Sections 3 and 4, we examined the personality effect in adaptive e-learning systems. Our first experiment explored the relationship between different personality traits and their effects on learning performance. The second experiment determined whether personality differences can serve as an appropriate criterion for designing an e-learning system that best suits a learner's strengths and preferences, thereby connoting the personality effect in the user model. Finally, in Section 5, we discuss our empirical findings, as well as several design guidelines for adaptive learning systems.

2. Personality effect in adaptive e-learning systems

2.1. Personality effects and learning styles

As briefly discussed above, many Jungian-based educational psychologists (e.g., Bayne, 2004; Corno and Snow, 1986; Keirsey, 1998; Kwok and Jones, 1985; Soles and Moller, 2001) have claimed that personality influences the way learners may or may not want to become more actively involved in their learning processes. There seem to be significant variables for determining learning performance; however, they have not yet been fully examined. The aforementioned researchers argued that personality is closely tied to preferences for learning materials in that a particular format reflects a person's preferences for taking in information and making decisions. Very few adaptive e-learning systems have considered these features in their user models, because there is no easy way to model personality effects. The only method thus far is AHA! (Stash et al., 2004), which specifies the learner's style as "Activist/Reflector", based on a self-rated personality type.

There are many different schemes of personality types, e.g., Kersey's temperament theory (Keirsey, 1998), the Learning Style Inventory (LSI; Kolb, 1984), the Big Five framework (Costa and McCrae, 1992), and the MBTI (Myers, 1993). In their extensive empirical studies, Keirsey (1998) demonstrated that there are four personality types that are highly relevant to learning style: the *Rational type* (NT – the intuitive thinking type focuses on the strategic intellect), the *Idealist type* (NF – the intuitive feeling type focuses on the diplomatic intellect), the *Artisan type* (SP – the sensory perception type focuses on the tactical intellect), and the *Guardian type* (SJ – the sensory judgment type focuses on the logical intellect). Personality types would thus intrinsically reflect the learner's preferences for taking in information and making decisions, which may be defined by one's learning style. For instance, SJ-type learners would prefer procedural organization of learning content over declarative organization. Indeed, the LSI (Kolb et al., 2000) classified personality types according to practical learning styles: conversing, accommodating, diverging, and assimilating. While LSI is highly effective for determining the learning style of each student and is of great use in the development of appropriate lesson preparation, the four LSI classifications have not been widely used in e-learning design. In an empirical sense, it is not easy to determine each individual's personality in such a relatively exclusive and exhaustive manner.

2.2. MBTI learning styles

By comparison, the Myers-Briggs Type Indicator (MBTI) has been widely used and validated in the education domain (DiTiberio,