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Effective Adaptive E-Learning Systems According to Learning Style and Knowledge Level

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Abstract

Aim/Purpose	Effective e-learning systems need to incorporate student characteristics such as learning style and knowledge level in order to provide a more personalized and adaptive learning experience. However, there is a need to investigate how and when to provide adaptivity based on student characteristics, and more importantly, to evaluate its value in learning enhancement. This study aims to bridge that gap by examining the effect of different modes of learning material adaptation and their sequences to the learning style and knowledge level of students in e-learning systems.
Background	E-learning systems aim to provide acceptability and interactivity between students, instructors, and learning content anytime and anywhere. However, traditional systems are typically designed for generic students irrespective of individual requirements. Successful e-learning systems usually consider student characteristics such as learning style and knowledge level to provide more personalized and adaptive student-system interaction.
Methodology	A controlled experiment was conducted in a learning context with 174 subjects to evaluate the learning effectiveness of adaptivity in e-learning systems.
Contribution	The main contributions of the paper are threefold. First, a novel adaptive approach is proposed based on a specific learning style model and knowledge lev-

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	el. Second, the approach is implemented in an e-learning system to teach computer security, the application domain. Third, a rigorous experimental evaluation of the learning effect of the adaptive approach is offered.
Findings	The results indicate that adaptation according to the combination of learning style and knowledge level produces significantly better learning gains, both in the short-term and medium-term, than adaptation according to either trait individually.
Recommendations for Practitioners	Practitioners should consider the combination of learning style and knowledge level when delivering and presenting learning material to their students.
Recommendation for Researchers	Researchers should consider sound educational models when designing adaptive e-learning systems. Also, rigorous and careful experimental design evaluations should be taken into consideration.
Impact on Society	Universities and e-learning industries can benefit from the proposed adaptive approach and the findings in designing and developing more personalized and adaptive e-learning systems. The incorporation of student characteristics, especially learning style and knowledge level, may be used to enhance learning.
Future Research	The experiment might be duplicated with a focus on longer-term learning gains by including more subjects and more learning resources. Also, the study might be expanded to application domains other than computer security. Moreover, other variables such as student satisfaction, motivation, and affective state might be explored to further the understanding of the effect of adaptivity on learning gains.
Keywords	adaptivity, e-learning, learning style, evaluation, computer science education

INTRODUCTION

A driving force behind the development of modern e-learning systems is the provision of appropriate learning content mediation to enhance the effectiveness of the learning process. Current approaches to the evolution of e-learning systems are designed to overcome previous limitations of traditional e-learning systems, avoid information overload, aid students in selecting learning material, and maintain student interest (Rodrigues, Almeida, Figueiredo, & Lopes, 2019). A primary issue realized in the development of adaptive e-learning systems is the fulfillment of student requirements while delivering adaptive learning experiences and appropriate learning resources (Truong, 2016).

Adaptation, also referred to as adaptivity, is the ability of a specific system to modify its output and responses according to student needs (Brusilovsky, 2001). Adaptive E-Learning Systems (AESs) vary instruction based on student characteristics such as learning style, motivation, personality, and knowledge level in order to personalize system features and deliver relevant learning material. For instance, an AES might offer sequenced learning material, modify user interface elements, or highlight important information based on student characteristics.

Student characteristics of learning style and knowledge level are acknowledged as vital influences in learning, and are often used as a foundation to generate personalized learning experiences (Felder & Silverman, 1988; Klasnja-Milicevic, Vesin, Ivanovic, & Budimac, 2011; Normadhi et al., 2019; Özyurt & Özyurt, 2015). Many educational theorists argue that accounting for learning styles when delivering learning material enhances learning (Coffield, Moseley, Hall, & Ecclestone, 2004; Felder, Felder, & Dietz, 2002; Labib, Canós, & Penadés, 2017). Further, in order to improve learning, instructional material should match the learning style of students, especially if they have strong tendencies to a specific style (Felder & Silverman, 1988; Labib et al., 2017). Well-known learning theories, such as behaviorism, cognitivism, and constructivism, stress the significance of knowledge level as an essential factor of instruction (Ertmer & Newby, 1993). Knowledge level is the recall, understanding, and application of certain information relevant to a specific topic (Brusilovsky & Millán, 2007).

Adaptive learning has emerged as a fundamental concept and paradigm for modern e-learning systems (Rodrigues et al., 2019), and is rising in prevalence in educational technology research (Xie, Chu, Hwang, & Wang, 2019). However, the implementation of adaptation is not always apparent in e-learning systems, especially adaptation that takes into consideration both learning style and knowledge level (Brusilovsky & Millán, 2007; Truong, 2016). Studies in this area are limited, mostly due to research design issues and small sample size (Akbulut & Cardak, 2012; E. J. Brown et al., 2009; Xie et al., 2019). Consequently, more empirical research on the effect of adaptation is needed (Akbulut & Cardak, 2012; E. J. Brown, Brailsford, Fisher, & Moore, 2009; Brusilovsky & Millán, 2007; Labib et al., 2017), and research in the area of adaptivity based on learning style and knowledge level is warranted (Brusilovsky & Millán, 2007; Chrysafiadi & Virvou, 2013; Klasnja-Milicevic et al., 2011; Normadhi et al., 2019).

This paper presents an innovative approach to adaptivity that incorporates both learning style and knowledge level in an e-learning system and examines its impact on learning effectiveness. The approach is based on an interpretation of the information perception dimension of the Felder-Silverman model (Felder & Silverman, 1988). Information perception can be found in many models of learning style (Coffield et al., 2004; De Ciantis & Kirton, 1996; Felder et al., 2002; Kolb, 1984). In addition, information perception has a relationship with other factors such as management styles, behavior characteristics, learning style, and career aptitudes (Feldman, Monteserin, & Amandi, 2014). Adaptive features in an e-learning system involve the operation of adaptive ordering, generation and hiding of links to learning material, and adaptive feedback. An evaluation of the proposed approach in terms of its effect on learning gains in an AES is provided via a carefully and well-designed controlled experiment.

BACKGROUND

ADAPTIVITY IN E-LEARNING SYSTEMS

Adaptive systems or user-adaptive systems are defined as systems that modify their behavior and output according to different user characteristics or features such as preferences, personality, emotion, and skills. Adaptive systems can be described as "the technological component of joint human-machine systems that can change their behaviour to meet the changing needs of their users, often without explicit instructions from their users" (Feigh, Dorneich, & Hayes, 2012, p. 1008). Jameson also defines an adaptive system as "an interactive system that adapts its behavior to individual users on the basis of processes of user model acquisition and application that involve some form of learning, inference, or decision making" (Jameson, 2009, p. 106). Several illustrations of adaptive systems exist. Adaptivity in the area of Human-Computer Interaction (HCI) involves adjusting a system, a graphical user interface, or content to meet a user's requirements (Brusilovsky, 2001; Hauger & Köck, 2007; Klašnja-Milićević, Ivanović, & Nanopoulos, 2015). Learning strategies can be matched and adapted to the learning styles and abilities of students. The term personalization is also relevant to adaptivity; to personalize means to design an object following the needs of a specific user.

Adaptive technologies can be applied to a wide variety of different domains such as e-commerce, e-health, and e-learning. For example, in the e-commerce domain, the AEADS system delivers advertisements based upon a given user's preferences and behavior (Qaffas, Cristea, & Mead, 2018). Adaptivity applied to user interfaces represents another application domain. The CHAIN approach assists users accomplish tasks by incorporating adaptive help and assistance as part of a user interface (Akiki, 2018).

Adaptivity is a critical component of modern e-learning systems (Rodrigues et al., 2019). Adaptivity facilitates student learning by recommending suitable learning strategies, offering relevant instructional materials, and guiding navigation through the material (Brusilovsky, 1996). Adaptive and personalized learning based on knowledge level, preferences, and learning style is always an important educational consideration (Xie et al., 2019). Multiple factors involved in developing effective e-learning systems, such as student characteristics, the complexity of matching learning material and their sequences to specific characteristics, and the need for such systems to follow sound instructional models create challenges for researchers.

AESs are considered an improvement to the 'one size fits all' approach in the design and development of e-learning systems. Areas including Intelligent Tutoring Systems (ITSs), adaptive hypermedia and Web-based educational systems (Park & Lee, 2003) represent advances in AESs. ITSs are adaptive learning systems that employ artificial intelligence concepts in order to simulate the instructor's role in providing individualized teaching (Self, 1999). In the 1990s, as student access to personal computers increased and advances were realized in Internet and Web-based technologies, adaptive hypermedia and Web-based learning emerged.

The goal of AESs is to adapt instructional material to meet the requirements of students in order to enrich the learning experience. AESs take into account student characteristics such as knowledge level, affective state, skills, and learning style in order to afford more personalized features and deliver relevant instructional material (Brusilovsky, 2001; Chen & Sun, 2012; Chrysafiadi & Virvou, 2013; Essalmi et al., 2015; Normadhi et al., 2019). An AES may emphasize important learning content fragments, offer feedback on what should be studied, or construct personalized sequences of learning resources.

There are different workstreams in AESs. The development of adaptive models and frameworks represents one such workstream (Feigh et al., 2012; Knutov, 2012). Student modeling represents a more focused stream that involves the representation, storing, and maintenance of student characteristics such as learning style, knowledge level, and motivation (Chrysafiadi & Virvou, 2013; Normadhi et al., 2019). Another stream is related to content domain modeling and the development of authoring tools for AESs (Hsu , 2012; Stash, Cristea, & De Bra, 2004; Weller, 2007). The development of adaptive methods and techniques is also considered an important research area (Brusilovsky, 1996; Klašnja-Milićević et al., 2015).

Many AESs have been designed and deployed by focusing on different workstreams (Akbulut & Cardak, 2012; Brusilovsky & Millán, 2007). An adaptive framework was proposed to facilitate the design of adaptive hypermedia systems. This adaptive framework includes three modules, the user model, the domain model, and the adaptation model (De Bra, Houben, & Wu, 1999). Related to the user or student model, Normadhi et al. (2019) conducted a systematic review that assessed how student characteristics are identified, used, and evaluated in AESs. Simko and Bielikova (2019) proposed an approach for automatic domain modeling in a way that enables the system to account for different modes of adaptation that deliver personalized and adaptive learning material.

Regarding adaptive methods and techniques, a simplified example is adaptive link annotation. This technique associates a metaphor to hyperlinks such as changing the font color, size, or icon of a link to make the student aware of the page or lesson behind that link (Brusilovsky, Schwarz, & Weber, 1996). Another example, the LS-Plan modifies the sequence and arrangements of learning resources based on both the knowledge level and learning style of students (Limongelli, Sciarrone, Temperini, & Vaste, 2009). The e-Teacher system focuses on clustering students into different groups according to their learning styles whereby the system offers suitable instructional strategies to each group of students (Schiaffino, Garcia, & Amandi, 2008). Another example is the Protus system that incorporates both knowledge level and learning style attributes to teach computer programming (Klasnja-Milicevic et al., 2011). An adaptive approach that matches learning resources from the domains of science and art to students based on learning style has also been proposed and initial assessments yield promising results (Dorça, Araujo, De Carvalho, Resende, & Cattelan, 2016). Most recently, the

APELS system was introduced. APELS was designed to freely adapt Web-based learning resources to students based on prior knowledge and learning style preference (Aeiad & Meziane, 2019).

There have been many attempts to build and evaluate AESs. However, there is a shortage of studies that take into account detailed, carefully designed, and controlled experimental evaluations that assess learning effectiveness (Akbulut & Cardak, 2012; Normadhi et al., 2019; Özyurt & Özyurt, 2015; Rodrigues et al., 2019; Truong, 2016; Xie et al., 2019). Further, while there are a number of research studies based on learning style, these studies typically are short-term in nature, focus on a specific model or theory, and utilize small samples of subjects (Akbulut & Cardak, 2012; E. J. Brown et al., 2009; Klasnja-Milicevic et al., 2011; Marković & Jovanović, 2011). Moreover, integrating learning style characteristics into AESs to provide adaptive and personalized learning is challenging because of the large number of learning style models. Furthermore, when learning style is considered in AESs, it is seldom integrated and carefully evaluated with other student features or characteristics (Chrysafiadi & Virvou, 2013; Klašnja-Milićević et al., 2015; Klašnja-Milićević, Vesin, Ivanovic & Budiman, 2011; Labib et al., 2017; Normadhi et al., 2019; Tseng, Chu, Hwang, & Tsai, 2008).

Previous efforts to develop and evaluate AESs differ from the work provided in this paper in terms of learning style dimensions, adaptive features, and application domain. Also, previous studies tend to focus on the technological perspectives of AESs, irrespective of learning style and knowledge level. However, there is a need to carefully investigate whether adapting to specific student characteristics enhances learning and leads to better student satisfaction. Therefore, this study aims to answer the following research question:

How does the learning gain of students vary when they interact with an AES that is based on the following student characteristics:

- learning style
- knowledge level
- both learning style and knowledge level?

LEARNING STYLE

The concept of learning style represents an important issue in learning (Honey & Mumford, 1989; Keefe, 1979; Klasnja-Milicevic et al., 2011). Despite some disagreements on the impact of learning style in terms of enhancing learning (Curry, 2000; Pashler, McDaniel, Rohrer, & Bjork, 2008), many have put forward the view that learning material should match to the learning style of students, and others have shown this has promising results (Akbulut & Cardak, 2012; Chrysafiadi & Virvou, 2013; Felder & Silverman, 1988; Klasnja-Milicevic et al., 2011; Labib et al., 2017; Marković & Jovanović, 2011). Paying closer attention to students' learning styles by instructors and course designers is an idea that has strong intuitive appeal (Coffield et al., 2004).

Keefe (1979) puts forwards that learning style is an emerged characteristic influenced by two main factors, affection and cognition, that determine how an individual student recognizes, understands, and interacts with elements involved in a learning environment. Honey and Mumford (1989) define learning style as the preferred approach to learning of an individual student. The terms of 'learning style' and 'cognitive style' are often used interchangeably; however, cognitive style is generally considered a subset or specific learning style dimension. Many learning style models and theories exist. Dimensions described in some of these models overlap with those defined in other models while other dimensions can be distinctive to a specific model. Popular examples of learning style models include the Felder-Silverman model (Felder & Silverman, 1988), Honey and Mumford (Honey & Mumford, 1989), and Kolb learning style model (Kolb, 1984).

Even though many learning style models exist, a complete learning style model has yet to be developed (Coffield et al., 2004). However, the Felder-Silverman learning style model is commonly used particularly in online-learning research (Akbulut & Cardak, 2012; Alshammari, Anane, & Hendley, 2014). The dimensions of the model are comprehensively detailed, and each dimension is associated with one or more teaching strategies (Felder & Silverman, 1988). The model consists of four dimensions including information processing, input modality, information understanding, and information perception. The Index of Learning Style (ILS) tool that can be used to identify learning styles is also built upon this model (Felder & Spurlin, 2005).

According to the Felder-Silverman model, the information processing (active-reflective) dimension details the technique that students use in order to process information. Active students learn by interacting with and manipulating something as well as by communicating with their peers. Reflective students think deeply about something before acting. AESs can support active and reflective students by integrating collaborative and interactive learning activities that incorporate problem-solving features (Jeong & Lee, 2008).

The input modality (visual-verbal) dimension is concerned with the presentation of information. For example, visual students learning can be enhanced by using pictures, videos, graphs, and diagrams. Verbal students can be supported by offering spoken information and written details. A large body of research examined the learning effect when taking this dimension into account; most reported no significant or positive learning outcomes (Kollöffel, 2012; Massa & Mayer, 2006).

The information understanding (sequential-global) dimension deals with the desired structure of information. Sequential students better understand learning material if the materials are delivered linearly and logically with each learning step outlined in detail. Global students are reported to learn best when they are provided with the big picture and overview of information before being given details. This dimension has been incorporated in an AES without yielding significant results, raising the concern of the feasibility of this dimension in enhancing learning (Brown et al., 2009).

The information perception (sensory-intuitive) dimension is concerned with favored or preferred types of information. Concrete learning resources are more beneficial for sensory students, while abstract resources help intuitive students develop understanding of the concept being studied. Facts, examples, simulation, and interactive lessons are examples of concrete information. Abstract types of information include, theories, definitions, and mathematical notations. An application of the information-processing dimension was developed in a game-based AES, where the objective was to ascertain the information perception style of the student based on observed behavior (Feldman et al., 2014). The results showed that students differ in their preferred types of information matching and their information perception styles. However, the learning effectiveness when incorporating this dimension was not measured.

The information perception of learning style is the most applied dimension of the Felder-Silverman model (Coffield et al., 2004; De Ciantis & Kirton, 1996; Felder et al., 2002; Kolb, 1984). Moreover, this dimension has a relationship to other factors such as management style, behavior characteristics, learning style, and even career competencies (Feldman et al., 2014). On the contrary, information perception has received the least consideration in the research (Akbulut & Cardak, 2012). As a result, the question remains unanswered in relation to its applicability to adaptation in AESs, and, thus needs to be further evaluated.

Proposed Adaptivity Approach

In previous work, we validated the usability of an AES that we developed (Alshammari, Anane, & Hendley, 2015a). Figure 1 presents an abstract representation of the AES. This representation is comprised of three major components: the student model, the domain model, and the adaptation model. The student model stores and maintains student characteristics (to what we adapt?). The domain model involves the representation and storage of learning resources in a way that enables the AES to offer adaptation (what can we adapt?). The adaptation model fetches information represented in the student model and the domain model and then applies some rules to offer relevant learning resources in an appropriate sequencing for each student (how can we adapt?).

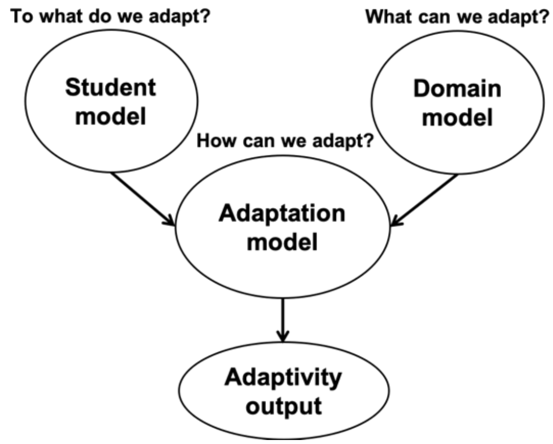

Figure 1. Abstract architecture of the AES

The student model of the AES mainly deals with the information perception dimension of learning style and with the knowledge level of students. The learning style can be identified using the ILS tool (Felder & Spurlin, 2005), while a pre-test is used to identify the prior knowledge of students. This initialization enables the system to provide adaptation quickly. The domain model incorporates the application domain of the learning material for a course on computer security. The system can be manipulated to offer adaptation based on learning style, knowledge level, or both.

The following sub-sections detail the adaptation approaches based on each characteristic.

Learning Style Adaptivity

The information perception dimension of the Felder-Silverman model is implemented in this adaptive approach. This dimension groups students as intuitive or sensory. In the adaptive approach, this is translated into two sequences. Intuitive students follow an abstract-to-concrete sequence by first studying abstract learning material and then moving to concrete learning material. Sensory students follow a concrete-to-abstract sequence by first dealing with concrete learning material and then dealing with abstract learning material.

The learning material was implemented as Learning Objects (LOs), where a LO is defined as a self-contained component of instruction (Anane, 2014). The ordering of links to LOs is produced for each student depending on their information perception dimension of learning style. The main feature of the adaptive order technique is the customized sequencing and arrangements of LOs.

Figure 1 presents a simplified example of how the adaptive order, according to the information perception dimension of learning style, is applied to a subset of the computer security course, the application domain of the AES (Alshammari, Anane, & Hendley, 2015b). For example, the learning unit of symmetric key encryption (i.e., one element of the course) contains four LOs (concept, mathematical notation, an example, and an interactive tool), which are classified as either concrete or abstract objects. Intuitive students interact with each LO as delivered by the AES in the order of concept, mathematical notation, example, and then the interactive tool. Sensory students are offered the learning path in the order of example, interactive tool, concept, and mathematical notation. The important point is that students study the same LOs in both paths, but the order differs based on learning style preference.

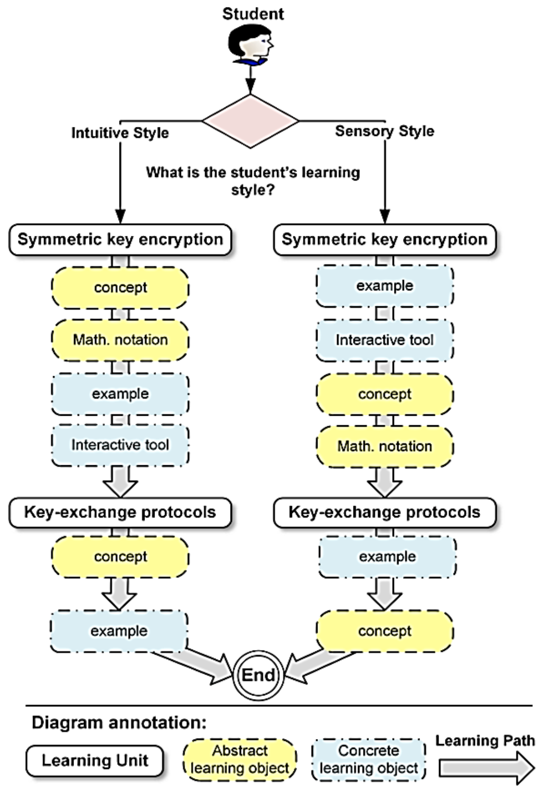

Figure 2. Learning paths for intuitive and sensory students (Alshammari et al., 2015b).

KNOWLEDGE LEVEL ADAPTIVITY

The student knowledge level is also taken into consideration. Links to relevant learning material can be generated, ordered or hidden as appropriate based on the knowledge level of each student. The AES offers links to learning material in a specified sequence (e.g., from basic through intermediate to advanced). Accordingly, for example, if the AES detects the initial knowledge level of the student to be intermediate, the basic learning units will be omitted from the learning path.

The system can also deactivate links to learning material that is ascertained not suitable to the knowledge level of an individual student. For example, when a student successfully completes a specific LO and the knowledge level associated with that LO is also completed satisfactorily, the LO will be then hidden from the learning path. Links to individual LOs can also be activated when the AES determines that the LOs are relevant to student progression.

The construction of learning paths is continuously generated by the AES until the the main learning objectives of the course are met. There are two critical conditions in this process. First, completeness and interaction with all LOs is required. Second, achievement of a satisfactory learning level for each LO is guaranteed. When both conditions are fulfilled, the AES arrives at the optimum situation and no more learning paths are constructed.

In addition to the provision of relevant learning material, the AES provides adaptive feedback based on knowledge level. Adaptive feedback presents the student with timely content recommendations based on recent student-LO interaction data. The AES employs tests/quizzes for each LO as formative assessment techniques (Gikandi, Morrow, & Davis, 2011). Therefore, quiz results are processed by the system as the primary source of interaction data. Each LO is augmented with a quiz and failed attempts to specific questions are incorporated into the adaptive feedback. Supplementary material related to failed questions are retrieved and presented to the student. Figure 3 illustrates an example of supplementary learning material as offered by the system. Another key feature of the adaptive feedback component of the AES is the provision of recommendations highlighting individual LOs for further study and specifying the order in which LOs might best be studied.

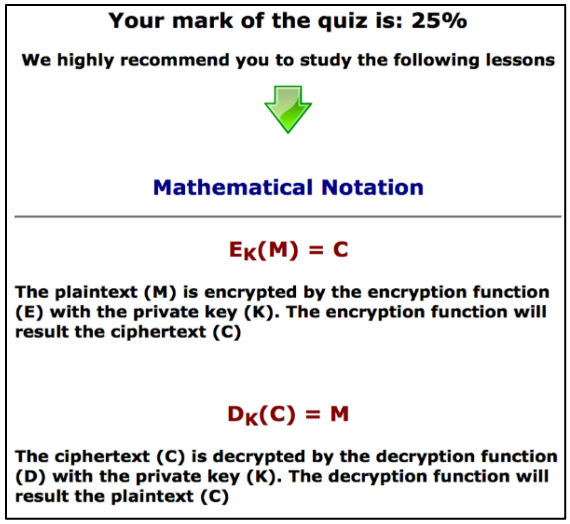

Figure 3. Recommendation example of supplementary material related to a particular LO.

EXPERIMENTAL EVALUATION

This section outlines the methodology, the experimental evaluation of the proposed approach, and the hypotheses that the experiment is designed to test. The experiment aims to evaluate the effects of the two adaptations (learning style and knowledge level), both individually and in combination. This experiment is also designed to evaluate the persistence of the learning effect through short-term and medium-term post-tests.

The information perception dimension of the Felder-Silverman learning model was used in conjunction with knowledge level as the basis for adaptation. This learning style dimension was selected because it is considered to be the most applicable dimension of the Felder-Silverman model, and its prevalence in various learning style models (Coffield et al., 2004; De Ciantis & Kirton, 1996; Felder et al., 2002; Kolb, 1984). Also, information perception has a relationship to other factors such as management style, behavior characteristics, learning style, and career competencies (Feldman et al., 2014).

A controlled experiment was managed in a learning setting in order to evaluate the proposed adaptive approach. The experiment was carried out through twelve learning sessions, each lasting 120–180 minutes. The design of a between-subjects experiment was utilized where each subject is assigned to only one condition. The main reason for adopting this design is to prevent carryover and learning effect from one condition to another. The design of a within-subjects experiment, in which each subject is assigned to more than one condition, was deemed inappropriate to this study.

As the application domain was computer security, the targeted sample included students studying information and computer science in the College of Computer Science and Engineering, University of Hail, Saudi Arabia. In addition, targeted students were students who did not have computer security as part of their core curriculum. Students were randomly selected to participate in the study.

HYPOTHESES

In order to carefully control the experiment, learning gain was identified to be the primary variable of interest. Two types of learning gains were measured. First, 'immediate learning gain' was assessed using a pre-test and post-test taken by the subject right after the study of a specific set of Los delivered via the AES. Second, 'delayed learning gain' was assessed using a pre-test and a delayed post-test (follow-up test) taken by subjects a few weeks after completing the experiment.

In this experiment, two student characteristics were considered: the information perception dimension of Learning style (L) and Knowledge level (K). The combination of the two student characteristics is referred to as L+K. There are four main hypotheses.

- **Hypothesis 1**. Interacting with the AES based on L+K by students produces significantly better 'immediate learning gain' than interacting with the AES based on K alone.
- **Hypothesis 2**. Interacting with the AES based on L+K by students produces significantly better 'immediate learning gain' than interacting with the AES based on L alone.
- **Hypothesis 3**. Interacting with the AES based on L+K by students produces significantly better 'delayed learning gain' than interacting with the AES based on K alone.
- **Hypothesis 4**. Interacting with the AES based on L+K by students produces significantly better 'delayed learning gain' than interacting with the AES based on L alone.

Three experimental conditions/groups were proposed in order to validate these hypotheses:

- **L:** A condition where subjects interact with a version of the AES according to the information perception dimension of learning style (L) alone.
- **K:** A condition where subjects interact with an AES version according to the knowledge level (K) alone.
- **L+K:** A condition where subjects interact with an AES version according to the combination of learning style (L) and knowledge level (K).

Several steps were followed in this experiment. The first step was the identification of the learning style of the subjects. The second step was the random assignments of subjects to one of the experimental conditions. The third step was the administration of the pre-test. This was followed by the fourth step, the beginning and the end of the learning process. The final step was the completion of the post-test and the follow-up test.

Measurement Tools

Subject learning style was identified using the ILS questionnaire based on the Felder-Silverman model (Felder & Spurlin, 2005). The ILS includes 44 items, each with two possible options. As the Felder-Silverman model has four dimensions, each dimension is identified by 11 items. Therefore, the 11 items related to the information perception dimension of learning style were used in this study. Acceptable reliability related to the items of the information perception dimension in the conducted experiment was evaluated using a Cronbach's alpha test ($\alpha > 0.70$).

Learning gain is measured by the following tests: a pre-test, a post-test and a follow-up test. Each test contained 22 multiple choice items. Each item has five answer options including one answer being 'I do not know!'. This specific choice is added to avoid random selections of answers by subjects. The tests were related and similar except for the formulation of some items, their sequence, and the offered multiple choice answers. The tests were carefully created and reviewed by three experts who checked the expression of each item and their related multiple-choice answers, assessed content validity, and insured the tests measured different learning abilities, including recall, understanding, and application (Ertmer & Newby, 1993). Moreover, the tests had sufficient reliability; Cronbach's alphas for the items of the pre-test, post-test, and follow-up test were 0.91, 0.76 and 0.74, respectively.

To identify initial knowledge level, subjects took the pre-test before interacting with the AES. The post-test was offered immediately after completing the experiment. The idea of the follow-up test is akin to the post-test but is offered after some time has elapsed to assess sustained knowledge of subjects.

Learning gain was assessed using a pre-test and post-test. The variable used in this experiment to report on learning gain was the '$\text{LearningGain}_{\text{immediate}}$'. This variable is computed based on the difference between the post-test score and the pre-test score of each subject. Learning gain can also be assessed using a pre-test and a delayed post-test, which is called a follow-up test, that is taken after some weeks have elapsed. The variable 'LearningGain$_{delayed}$' refers to this type of learning gain. LearningGain$_{delayed}$ is calculated based on the difference between the score of the pre-test and the follow-up test.

EXPERIMENTAL PROCEDURE

Figure 4 simplifies the experiment procedure. The subjects were first presented with the main objectives and process of the experiment after signing consent forms. Subjects were requested to access the AES through an Internet browser and to submit demographic information and complete the ILS questionnaire. Subjects then took the pre-test to assess their initial knowledge level. Then, the system randomly assigned subjects to one of the experimental conditions, either being in the L group, the K group, or the L+K group.

Subjects then engaged with the AES in the application domain area of computer security. The course consisted of three main learning units including nine learning lessons. Subjects studied these lessons as recommended by the AES according to their assigned experimental condition. At the end of the learning session, subjects completed a post-test. The same subjects also completed a follow-up test two to three weeks later.

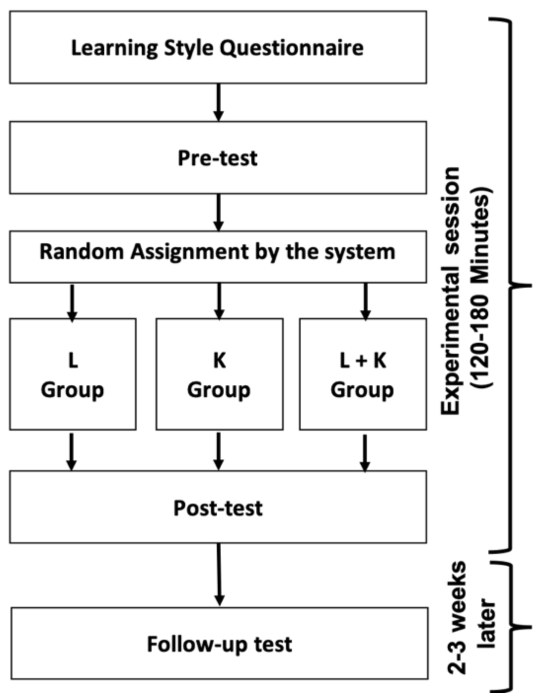

Figure 4. The experimental procedure

RESULTS

Study subjects were 174 undergraduate students, comprised of 102 Males (58.6%) and 72 Females (41.4%), from the College of Computer Science and Engineering, University of Hail, Saudi Arabia. The mean age of the subjects was 21.07 (SD = 1.48), the maximum age was 25 and the minimum age was 19. All three experimental conditions (L, K, L+K) were balanced in terms of group size, with 58 subjects each, and in gender (34 Males and 24 Females).

Table 1 shows pre-test results. The experimental groups (L, K and L+K) had approximately the same pre-test mean. There was no statistically significant difference between the experimental groups according to the one-way ANOVA test. This test is typically used to determine whether statistically significant differences exist between means of three or more independent groups. The results suggest that the subjects in the experimental groups had similar prior knowledge on the subject. Therefore, useful comparisons can be accomplished between the experimental groups eliminating the effect of prior knowledge as a confounding factor.

Table 1. Mean, standard deviation (SD), F-value($df_{between}$,df_{within}), P-value according to the results of one-way ANOVA relating to the experimental groups (L, K and L+K) measuring the pre-test variable. df=degree of freedom.

Condition/Group	Mean	SD	F(2. 171)	P
L	5.97	8.64	0.38	0.68
K	7.41	10.19		
L+K	6.53	8.07		

Post-test mean was highest for the L+K group followed by the K group and the L group (L+K > K > L). Statistically significant differences between these groups, as shown in Table 2, were also evidenced. The effect size, as measured by the partial eta squared test (η_p^2) for the post-test results, was between small and medium. Reporting on the effect size is helpful to indicate how important the findings might be.

Table 2. Mean, standard deviation (SD), F-value($df_{between}$,df_{within}), P-value, partial eta squared (η_p^2) according to the results of one-way ANOVA relating to the experimental groups (L, K and L+K) measuring the post-test variable. *P <0.0005.

Condition/Group	Mean	SD	F(2. 171)	P	η_p^2
L	59.47	17.05	32.17	0.000*	0.27
K	72.16	14.90			
L+K	82.02	13.35			

Follow-up test results followed a similar pattern, as shown in Table 3. The L+K group had the greatest mean score followed by the K group and the L group and statistically significant differences were found between the groups. The effect size for the follow-up test was between medium and large.

Table 3. Mean, standard deviation (SD), F-value($df_{between}$,df_{within}), P-value, partial eta squared (η_p^2) according to the results of one-way ANOVA relating to the experimental groups (L, K and L+K) measuring the follow-up test variable. *P <0.0005.

Condition/Group	Mean	SD	F(2. 171)	P	η_p^2
L	35.52	16.27	87.05	0.000*	0.51
K	54.59	14.58			
L+K	72.43	14.26			

The results related to the $LearningGain_{immediate}$ variable (i.e., post-test score – pre-test score) showed that the L+K group had the highest mean in comparison to the results for the K group and the LS group. Also, the K group had better ‘immediate learning gain’ results than the L group. In addition, statistically significant differences between these groups were found, and the effect size was between small and medium, as presented in Table 4.

Table 4. Mean, standard deviation (SD), F-value($df_{between}$,df_{within}), P-value, partial eta squared (η_p^2) according to the results of one-way ANOVA relating to the experimental groups (L, K and L+K) measuring the $LearningGain_{immediate}$ variable. *P <0.0005.

Condition/Group	Mean	SD	F(2. 171)	P	η_p^2
L	53.50	18.92	22.89	0.000*	0.21
K	64.74	18.94			
L+K	75.48	14.18			

The pattern of the results related to $LearningGain_{delayed}$ (i.e., follow-up test score – pre-test score) were similar to the pattern of the results of $LearningGain_{immediate}$ but with different mean values with the observations of statistically significant findings between the experimental groups. However, the main difference was in the effect size of the $LearningGain_{delayed}$ variable; it was found to be between medium and large. Table 5 summarizes the results of the $LearningGain_{delayed}$ variable.

An interesting finding was that the effect size (i.e., an indication of how important the findings are) for the results related to the follow-up test and $LearningGain_{delayed}$ was between medium and large. This finding emphasizes the importance of adapting learning material according to both learning style and knowledge level to enhance not only the short-term learning effect but also to enhance medium-term learning effect.

Table 5. Mean, standard deviation (SD), F-value($df_{between}$,df_{within}), P-value, partial eta squared (η_p^2) according to the results of one-way ANOVA relating to the experimental groups (L, K and L+K) measuring the $LearningGain_{delayed}$ variable. *P <0.0005.

Condition/Group	Mean	SD	F(2. 171)	P	η_p^2
L	24.55	16.61	68.96	0.000*	0.45
K	47.17	18.68			
L+K	65.90	14.43			

The one-way ANOVA test indicated significant differences between the three experimental conditions (L, K, L+K) in terms of the experimental variables (post-test, follow-up test, $LearningGain_{immediate}$, $LearningGain_{delayed}$). However, the results do not indicate where the significance between two experimental conditions lies. This requires further analysis. A Tukey post hoc test was carried out. The results showed statistically significant differences in the comparisons between each pair of experimental groups for each variable. One exception was related to the pre-test. For instance, there was a statistically significant difference for the post-test, follow-up test, $LearningGain_{immediate}$, $LearningGain_{delayed}$ between the L+K group and the K group, p = 0.000 (<0.0005); between the L+K group and the L group, p = 0.000 (<0.0005); and between the K group and the L group, p = 0.000 (<0.0005). Based on the findings, the four hypotheses, outlined earlier, are confirmed.

DISCUSSION

The experiment conducted in this study varies in comparison to previous work on learning gains in AES in that it examines two distinct student characteristics: the information perception dimension of learning style and knowledge level. Other studies have been limited by study design and small sample size (Akbulut & Cardak, 2012; Brown et al., 2009; Xie et al., 2019). This study is unique in that it reports on the execution of a carefully designed and controlled experiment involving a reasonably large number of subjects.

This study contributes to current research on adaptation in AESs. The findings of this study are not confined to a single pre-test post-test evaluation. Using a delayed post-test, sustained knowledge was also measured. Few studies have been reported that assesses both immediate and delayed learning gains in AESs. Further, this study examined both learning style and knowledge level in isolation and in combination. This study found that adaptation based on the combination of the information perception dimension of learning style and knowledge level significantly improved learning gains in both the short-term and the medium-term.

Although several studies report varying results in terms of learning gains (Akbulut & Cardak, 2012; Brown et al., 2009; Dorça et al., 2016), the results of this study are supported by studies that report significant learning gains obtained from a combination of learning style and knowledge level (Akbulut & Cardak, 2012; Klašnja-Milićević et al., 2015; Limongelli et al., 2009). Tseng et al. implemented three versions of an AES based on two characteristics (learning style, learning behaviors and the combination of the two), and evaluated learning outcomes of each version (Tseng et al., 2008). Achievement of learning outcomes was greater when adaption was based on two student characteristics.

Peña, Marzo, & de la Rosa (2017) reported the results of perceived usefulness of adaptivity of an AES utilizing adaption based on learning style and knowledge level from a small study comprised of five instructors and 25 students. However, this study did not employ statistical testing for learning effectiveness given the small sample size. The results of the evaluation of an AES called OSCAR CITS were similar (Latham, Crockett, McLean, & Edmonds, 2012). Limongelli et al. adopted a different methodology for evaluating an AES and obtained promising findings in terms of learning gain (Limongelli et al., 2009). Nevertheless, this study also had a small sample size of 30 subjects. The Protus system was evaluated with a larger sample; the results related to course completion and student satisfaction were encouraging but learning effectiveness in the long term was not measured (Klasnja-Milicevic et al., 2011). Dorça et al. proposed and evaluated an adaptive approach to the recommenation of relevant learning objects (Dorça et al., 2016) via an AES, but did not evaluate learning gain. Similarly, the APELS system was evaluated by domain experts for content validity but not for student learning (Aeiad & Meziane, 2019).

In this study, the ability of subjects to control the learning process was limited. A downside to this is that these restrictions do not facilitate a constructivist approach to learning (Ertmer & Newby, 1993). Student controllability means that students are responsible for their decisions to enable them to approach learning in the way and order of their choice. Student controllability is similar to self-directed learning, an instructional strategy where students decide what and how they will learn rather than adhering to direct and compulsory guidance from instructors. Because of the nature of controlled experiments, subjects in this study were requested to follow system recommendations precisely.

General issues related to learning must be emphasized. While knowledge level and learning style have been integrated as factors of adaption in the AES, other factors such as culture, behavior, personality traits, emotion also contribute to learning effectiveness (Martin & Briggs, 1986; Normadhi et al., 2019) and should be explored in future studies (Chen & Sun, 2012; Gao, 2003; Klašnja-Milićević et al., 2015; Leontidis & Halatsis, 2009). These studies are needed as the provision of adaptivity is not straightforward, and as Brown et al. (2007) state, "the nature of learning is obviously very complex, with a large interplay of factors" (p. 65). As a result, more high-quality AESs research is needed that is built upon sound models of educational theory.

CONCLUSION

This paper presented a specific approach to adaptation based upon learning style and knowledge level. The adaptive approach was implemented in an AES employing an interpretation of the information perception (sensory-intuitive) learning style dimension. Relevant techniques based on knowledge level included operations such as adaptive ordering, generation and hiding of links to learning material, and adaptive feedback. The study was conducted with 174 undergraduate students; the experiment produced significant results regarding learning gain. Adaptation according to learning style alone or knowledge level alone can be beneficial. However, taking both characteristics into account as means of adaptation produces significantly better learning gains. To summarize, adaptation based on learning style and knowledge level produces significantly better short-term and medium-term learning effects than adaptation based on knowledge level alone and or on learning style alone.

Further research will include a longer-term evaluation with more subjects, and a more extensive set of learning resources. In addition, the same methodology can be extended to studies in other application domains. Moreover, different variables such as student satisfaction and motivation can be incorporated to further extend understandings of the effect of adaptive and personalized student-system interaction.

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