

An E-Learning Investigation into Learning Style Adaptivity

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Abstract

Traditional e-learning systems are typically designed for generic learners irrespective of individual requirements. In contrast, adaptive e-learning systems take into account learner characteristics such as learning style and level of knowledge in order to provide more personalised learning. The contribution of this paper is threefold. First, a generic adaptive framework aimed at enhancing learning is proposed. Second, a specific approach to adaptivity based on learning style is put forward within the framework. Third, the framework is validated and the approach is evaluated in order to determine their effectiveness in learning provision in an adaptive e-learning system. An experiment conducted with 60 participants produced positive results. They indicate that adapting instructional material according to learning style yields significantly better learning outcome and learner satisfaction than without adaptation.

1. Introduction

Teaching has shifted from an instructor-centric approach, which focuses mainly on transmitting knowledge from expert to learner, to a learner-centric approach, in which knowledge is constructed by learners who are actively involved in the learning process and who engage in collaborative work with their peers [1]. E-learning systems are expected to support better learner-centric instruction and enable more self-paced and self-directed learning [2].

In e-learning systems, learners may be overwhelmed by the large amount of information they encounter. This could lead to poor decisions on what and how to study. The learning process can be time-consuming, confusing, frustrating and less effective. One of the key challenges in developing e-learning systems is to meet the different needs and preferences of learners and to provide more personalised learning and more relevant instructional material.

Adaptation is often put forward as a way of tailoring a system to the user's requirements [3].

Adaptive e-learning systems integrate learner characteristics such as learning style and level of knowledge to provide personalised services and to recommend relevant instructional material. For example, a system may highlight relevant information, recommend to a learner what to study or construct personalised learning paths.

Amongst learner characteristics, learning style is recognised as an important factor [4]. Many educational theorists agree that recognition of learning style can improve learning [4]–[7]. It is also argued that if a learner has a strong affinity with a particular learning style, the instructional material should match this style to enhance learning [4].

It is not always evident how to implement adaptation in e-learning systems in general and, more particularly, adaptation based on learning style [8]. Moreover, the lack of empirical research on learning style effectiveness is a key issue in the deployment of adaptive e-learning systems [8]–[11]. Accordingly, learning style adaptivity and its effectiveness in learning is seen as a challenging area of research [3], [8]. The main corollary of adaptation in learning is the promotion of a teaching style that fits the specific learning style of a learner.

This paper is part of an investigation into learning style adaptivity in e-learning systems, supported by an empirical evaluation. A generic adaptive framework aimed at enhancing learning is presented. In addition, a specific approach to learning style adaptivity is proposed within the framework. The approach provides personalised learning paths for each learner based on their learning style.

An evaluation of the approach in terms of its effectiveness in learning provision and learner satisfaction in an adaptive e-learning system is also provided. The system implements a restricted version of the learner model by carefully producing a sequence of the learning objects to meet the learning style of each learner. This also facilitates the conduct of controlled experiments.

The remainder of the paper is structured as follows. Section 2 presents the theoretical foundations. Section

3 describes the proposed generic adaptive framework. Section 4 details the learning style adaptivity approach. Section 5 highlights the evaluation approach. Section 6 presents the results of the experimental evaluation. Section 7 offers a critical discussion of the work, and Section 8 concludes the paper.

2. Theoretical foundations

The theoretical foundations of this work relate mainly to adaptive e-learning systems and learning style.

2.1. Adaptive e-learning systems

Adaptation in the context of e-learning systems can be defined as an action or process of tailoring instructional material to the learner's needs [3]. Meeting the learner's needs, providing relevant instructional material and supporting the learner's interaction goals are increasingly important concerns in e-learning systems [12]. Learner modelling, domain modelling and adaptation modelling are often considered when developing adaptive e-learning systems [3], [13]. This perspective has shaped the structure of many adaptive systems. They often include three major components: (1) a learner model, (2) a domain model and (3) an adaptation model [12]. An effective adaptive e-learning system requires a strong commitment to these components. Their characteristics are described below.

2.1.1. Learner model. Learner modelling has been an important subject of research in intelligent tutoring systems (ITS) since 1970 [14]. According to Self a learner model is "what enables a system to care about a student" [14]. Systems may include a learner model that incorporates various learner characteristics, such as learning style and knowledge, to support adaptation [15]. Overlay and stereotype models represent two of the several widely used approaches to learner modelling. An overlay model assumes that the knowledge of the learner is a subset of the knowledge of the expert or of the entire knowledge domain [8]. A stereotype model categorises a group of learners with the same characteristics into different classes and devises different treatments for each class [16]. The maintenance of learner models is a key challenge. Building accurate and useful learner models depends upon the availability of valid learner-system interaction data [17]. The data might be provided explicitly by learners or implicitly through the learners' behaviour.

2.1.2. Domain model. A domain model is defined as an abstract representation of part of the domain of

discourse. Domain modelling is a process of capturing, classifying and structuring knowledge related to a specific application domain [3]. Knowledge is usually categorised into two types: (1) declarative (i.e., the what) and (2) procedural (i.e., the how). Knowledge elements (e.g., learning objects) are usually classified and annotated following specific approaches (e.g., IEEE Learning Objects Metadata) to support adaptation and to facilitate the retrieval of learning objects. Domain modelling plays an important role in the fields of ITS, hypermedia systems and expert systems [3]. For example, a hierarchical network representation (i.e., a tree-like structure) is frequently used in adaptive e-learning systems [8], [18].

2.1.3. Adaptation model. The adaptation model and the introduction of new adaptive methods and techniques represent another research perspective [18], [19]. An adaptation model may, for example, deal with the optimisation of the structure of learning material and how a learner studies it in a limited period of time. It may also underpin the construction of personalised learning paths and provide appropriate hints and feedback to learners when needed. It takes into account the learner model and the domain model mainly by matching relevant instructional material, or sequences of learning objects, to the needs and characteristics of individual learners. According to Brusilovsky an adaptive technology may take three forms: adaptive content, presentation and navigation [12], [15]. Adaptive content and presentation techniques are concerned with various operations, such as content inserting and modifying or interface zooming and layout alteration [20]. Adaptive navigation involves the recommendation of selective learning paths, curriculum sequencing, link generation, direct-guidance, link hiding and link sorting [21].

2.2. Learning style

Learning style is recognised as an important factor in e-learning frameworks. There is a general consensus that taken into account an individual's learning style can improve learning [4]–[7]. Learning style is defined as a composite of cognitive and affective factors that indicate how a learner perceives, interacts with and responds to the learning environment [5]. A number of learning style models and frameworks have been introduced, mainly by Dunn and Dunn [7], Honey and Mumford [22], Kolb [23], Myers-Briggs [24] and Felder-Silverman [4]. These models differ in their main focus and content, but they also exhibit some overlap. For example, the information perception dimension of the Felder-Silverman model [4] is found

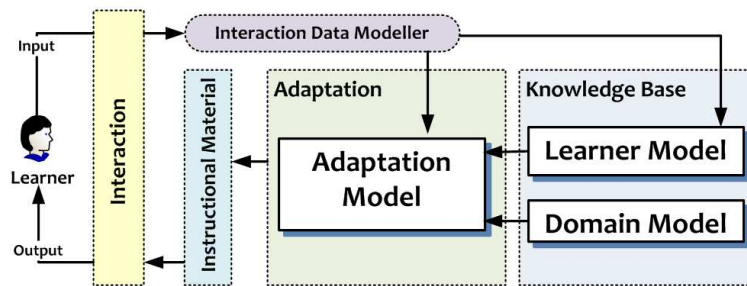


Figure 1. A generic adaptive framework.

in the Myers-Briggs Type Indicator (MBTI) [24] and is also part of the Kolb model [23].

Although a comprehensive and clear learning style model has yet to be identified [6], the Felder-Silverman model is widely used as the preferred learning style model, particularly in online-learning research [9], [13]. The model is particularly relevant to this study. It consists of four dimensions: information perception, input modality, information processing and information understanding [4]. It provides comprehensive details on its dimensions and identifies a teaching style for each dimension [4]. It is also augmented with a reliable and validated assessment tool [25], [26].

The information perception dimension (sensing-intuitive) concerns the most suitable type of information to be perceived by individual learners. Sensing learners may benefit more from concrete information such as facts and examples; intuitive learners may perform better with abstract concepts such as theories and mathematical models. The input modality dimension (visual-verbal) involves the presentation of information. Visual learners may learn well with pictures, graphs and diagrams; verbal learners may grasp spoken and written information quickly. The information processing dimension (active-reflective) involves the way the learners process information. Active learners learn by trying something out and interacting with peers; reflective learners learn by thinking deeply about the information independently before acting. The information understanding dimension (sequential-global) refers to the way information is organised. Sequential learners gain understanding by linear and logical steps; global learners learn on the basis of large and random leaps through sets of information.

3. Adaptive framework

A generic adaptive framework aimed at enhancing learning is depicted in Figure 1. It incorporates the three different facets of adaptivity. The framework

consists of three main components: the learner model, the domain model and the adaptation model. As mentioned earlier these components are common to many adaptive e-learning systems. However, the framework allows for different characteristics such as affective state and knowledge level to be considered in the learner model.

The framework also includes two auxiliary components: an interaction module and an interaction data modeller. The interaction component is responsible for facilitating communication between learner and system. The interaction data modeller monitors learner-system interactions; it feeds into the learner model and into the adaptation model for updates.

The framework is generic and can be used as a reference for adaptive e-learning. It may also be extended to include additional components. The framework and its components are presented in the following sections.

3.1. Learner model

A wide variety of learner characteristics, such as knowledge, learning style, affective state, goals, motivation, skills and context can be integrated into the learner model [13]. The proposed framework supports both static and dynamic learner modelling. The TANGOW system, for example, uses a static learner model in which learners complete a questionnaire to identify the learning style at the beginning of their interaction with the system; the learning style characteristics are stored in the learner model and kept unchanged [27]. A dynamic approach to learner modelling is applied by the eTeacher system, which monitors learner-system interactions continually to maintain a running update of learning style characteristics in the learner model [28].

Adaptive e-learning systems may draw upon explicit learner feedback (e.g., rating and bookmarking), implicit learner feedback (e.g., page visits and time spent) or hybrid learner feedback (a combination of explicit and implicit feedback) to build

and update learner models. The INSPIRE system uses a questionnaire to identify individuals' learning styles—an example of explicit learner feedback [18]. The Protus system uses implicit feedback (in the form of page visits) to maintain learner models [29].

The learner model in the framework is not limited to specific learner characteristics, a specific learner model representation or a specific method. It implies that relevant techniques and methods can be applied to meet the requirements of the adaptive e-learning system.

3.2. Domain model

The domain model may contain the learning resources, instructional material or learning objects of any application domain. Different representations, such as network and hierarchy models can also be used. The content of the domain model may be classified and annotated to facilitate the retrieval of learning resources and to support adaptation.

The application domains of adaptive e-learning systems are usually related to computer science topics. For example, the INSPIRE system teaches computer architecture [18], the eTeacher system offers an introduction to artificial intelligence [28] and the Protus system provides a Java programming course [29]. However, the domain model in the proposed framework is flexible in terms of content, representation and management.

3.3. Adaptation model

The adaptation model takes into account the learner model and the domain model in order to adapt and recommend relevant instructional material. The adaptation model of the framework can provide two types of adaptation: short-memory-cycle and long-memory-cycle adaptation.

Short-memory-cycle adaptation can be achieved by processing only the most recent information elicited from learner-system interactions. For example, when a learner completes a quiz, the adaptation model immediately processes answers by learners to provide adaptive feedback, hints or other instructional guidance.

Long-memory-cycle adaptation processes past and recent learner-system interaction data to recommend appropriate instructional material continually until the goals of the learning activity have been met. For example, if a learner rates a specific learning object as difficult, the adaptation model evaluates this recent interaction in view of past ratings of similar learning

objects, and then processes the data to recommend more relevant learning objects.

The adaptation model can incorporate different adaptive methods and techniques to support adaptation. For example, the Protus system adapts instructional material by providing different media formats based on learning style [29]. Link generation and annotation techniques are applied by the eTeacher system to recommend relevant instructional material [28].

4. Framework implementation

In this section, a specific approach to adaptivity is proposed as a way of validating the framework. In order to evaluate the approach, an adaptive e-learning system is implemented within the framework. The system includes three components: a learner model, a domain model and an adaptation model. The system implements a restricted version of the learner model in order to carefully adapt the sequences of learning objects and to conduct a controlled experiment. The learner model is restricted to learning style only as a key learner characteristic, whereas the domain model contains instructional material related to cryptography.

In the approach, all learners study the same learning objects. However, the different sequences of learning objects are provided for individual learners based on learning style. The adaptation model constructs a personalised learning path for each learner by matching instructional material and learning style. The approach requires the identification and classification of learning objects according to a teaching style which corresponds to a specific learning style. The components of the system are described below.

4.1. Learner model

Due to its completeness the Felder-Silverman learning style model is used in the learner model [4]. In this learning style model, the information perception dimension has received the least attention in published research [9], [17]. It is argued by some researchers that the information perception dimension is the most important learning style dimension [30], [31]. Its effectiveness in e-learning systems offers a lot of scope for research. It is therefore integrated in the learner model as a single dimension.

The information perception dimension categorises learners into two types: sensing and intuitive. Felder and Silverman describe sensing and intuition as follows: "Sensing involves observing, gathering data through the senses; intuition involves indirect perception by way of the unconscious—speculation,

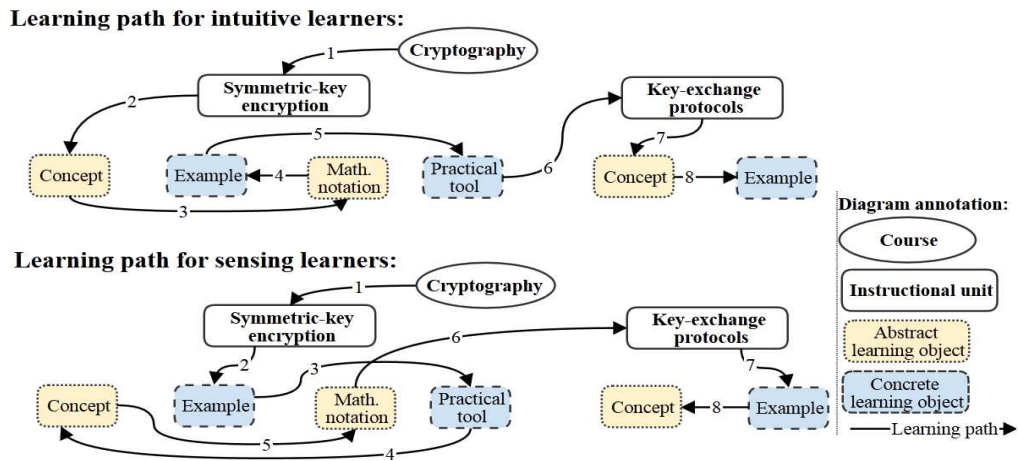


Figure 2. Constructed learning paths for intuitive and sensing learners.

imagination, hunches. Everyone uses both faculties, but most people tend to favour one over the other” [4]. Sensing learners prefer facts, data, experimenting and real-world examples; intuitive learners prefer principles, theories and mathematical models [4]. Sensing learners may learn better with concrete information, whereas intuitive learners may benefit more from abstract concepts.

The approach is implemented by building a static learner model for each learner. Each model contains data about the information perception dimension of the learning style. The system provides a registration page at the beginning of the interaction with the system, which contains the index of learning styles (ILS) questionnaire based on the Felder-Silverman model [26]. A subset of the questionnaire containing 11 questions related to the information perception dimension is used. When the learner completes the questionnaire, the system computes the learning style value in the dimension, determines the learning style type (sensing or intuitive) and stores them in the learner model.

4.2. Domain model

The domain model is based on either a hierarchical or a network-based representation. It contains two instructional units related to a cryptography course, as the application domain. Each instructional unit contains a set of interrelated learning objects. The first unit consists of four learning objects (concept, example, mathematical notation and practical tool) related to symmetric key encryption. The second unit has two learning objects (concept and example) that describe key exchange protocols.

Following the Felder-Silverman model, the learning objects are classified and annotated according to the teaching style that corresponds to the information perception dimension. The teaching style aims to provide a combination of concrete (more suitable for sensing learners) and abstract (more appropriate for intuitive learners) instructional material. Examples and practical tools are classified as “concrete” learning objects, whereas concepts and mathematical notations are classified as “abstract” learning objects.

The domain model incorporates concrete and abstract learning objects, which will ensure that sensing and intuitive learning styles are equally supported and that a combination of concrete information and abstract concepts can be generated.

4.3. Adaptation model

The adaptation model constructs personalised learning paths by taking into account the domain model and the learner model. Learners are categorised into sensing and intuitive. The key feature of learning paths is the customised sequencing of learning objects based on the information perception dimension.

Figure 2 depicts the personalised learning paths that are constructed by the adaptation model for intuitive learners and for sensing learners. Intuitive learners study “abstract” learning objects first and then interact with “concrete” learning objects (abstract→concrete). In contrast, sensing learners interact with “concrete” learning objects first and then study “abstract” learning objects (concrete→abstract).

For example, the “symmetric-key encryption” instructional unit contains four learning objects (concept, mathematical notation, example and practical

tool), which are classified as either concrete (example and practical tool) or abstract (concept and mathematical notation). The adaptation model constructs personalised learning paths based on the proposed approach. Intuitive learners study each learning object as provided in the sequence: concept, mathematical notation, example and practical tool. Sensing learners follow the learning path: example, practical tool, concept and mathematical notation. In both learning paths, the learners interact with the same learning objects, but the order of learning objects is adapted according to the learning style.

The next section presents the evaluation of the proposed approach in terms of learning effectiveness and learner satisfaction.

5. Evaluation

A controlled experiment in a university learning environment was conducted in a computer laboratory to evaluate the learning style adaptivity approach and to validate the proposed framework.

Eight experimental sessions were conducted over a period of five days. Each session lasted for about 75 minutes. The participants were encouraged to take part in the experiment in order to learn new topics related to cryptography, which was not part of their curriculum.

A between-subject design in which each participant experiences only one condition, was used. This is considered a more appropriate design than a within-subject design because it avoids the problems of carryover and learning effect from one condition or factor to another. In a within-subject design each participant experiences more than one condition. A between-subject design, however, requires a large number of participants, and the variances between experimental and control groups may occur. Variances between groups should be eliminated, and some variables, such as prior knowledge of the application domain, learning style characteristics and age, should be carefully controlled.

A precise formulation of research hypotheses, an identification of the data-collection instruments and a detailed account of the experimental procedure are prerequisites for any well-conducted and controlled experiment.

5.1. Hypotheses

Two hypotheses are put forward for this study. They are based on the information perception dimension of the Felder-Silverman model [4]. The hypotheses are formulated as follows:

Hypothesis 1: Matching information perception learning style and instructional material in an adaptive e-learning system yields significantly better learning outcome than without matching.

Hypothesis 2: Matching information perception learning style and instructional material in an adaptive e-learning system yields significantly better learner satisfaction than without matching.

5.2. Data collection

Three data collection instruments were used in the experiment. Learning style was identified by the ILS questionnaire based on the Felder-Silverman model [4], which contains 44 questions linked to the four learning style dimensions. As the dimensions are independent of each other [25], [26], [32], 11 questions related to the information perception dimension were selected. The tool is considered reliable and valid for identifying learning styles of learners [25], [26], [32].

Pre-test and post-test are commonly used to measure learning outcome, and they were subjectively evaluated by three experts. The reliability of the pre-test and post-test scores were also acceptable, as the Cronbach's alpha for the pre-test scores was 0.71 and for the post-test scores was 0.73. The following equation was used to compute learning outcome:

$$Learning_outcome = Post_{test} - Pre_{test}$$

Learner satisfaction was measured by the conceptualisation of e-learner satisfaction (ELS) tool. It has 17 questions with 7-point Likert scale with anchors ranging from "strongly disagree" to "strongly agree", and it can be found in [33]. It includes four components: learner interface, learning community, learning content and personalisation. The tool is applicable to a wide variety of e-learning systems, and it can be adapted to fit specific research needs [33]. Questions related to the learning community component (i.e., 4 questions) were omitted, since this has limited applicability to the implemented system and since this requires an integration of collaborative features that are not addressed in this study. The tool is considered reliable and valid [33], and a Cronbach's alpha test was also conducted to measure its reliability in this study. It was found to be highly reliable ($\alpha = 0.94$).

5.3. Experimental procedure

Participants were first welcomed, introduced to the main objectives of the experiment and informed of the procedure. They were asked to access an adaptive e-learning system through an Internet browser. They

completed a demographic data form and the ILS questionnaire [4] using the system. Then, the system randomly assigned participants (i.e., it made double-blind assignments) to experimental (matched) or control (mismatched) groups and directed them to complete a pre-test. The pre-test involved answering a set of questions related to cryptography. The next step involved the study of instructional units on cryptography. At the end of the learning session, they completed a post-test, followed by the conceptualisation of ELS tool [33]. This ended the procedure.

6. Results

The experiment was conducted with 60 male participants (matched group = 29, mismatched group = 31). They were undergraduate students in a Computer Science degree programme. The mean age of the participants was 25.27 ($SD = 5.49$), the maximum age was 39 and the minimum age was 18. The IBM SPSS statistics software package (version 21 and 32-bit edition on Windows) was used for the data analysis.

6.1. Learning style

With regard to the distribution of learning style characteristics amongst participants, there were more sensing learners (71.67%) than intuitive learners (28.33%). The majority of the participants had mild to moderate characteristics of learning style, and very few participants had strong characteristics for both sensing and intuitive categories. Figure 3 presents the percentages of participants in the subcategories (mild, moderate and strong) of the information perception dimension.

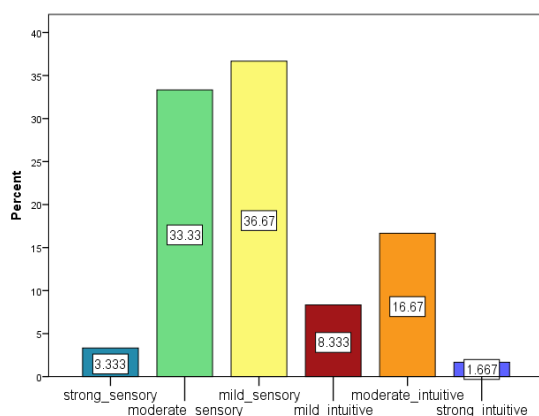


Figure 3. Distribution of participants in the information perception dimension.

6.2. Learning outcome

The first hypothesis was tested. Figure 4 shows that the post-test and the learning outcome of the matched group were higher than those of the mismatched group. It indicates that there was a positive effect in matching instructional material with information perception learning style.

An independent sample t -test was conducted using an alpha level (α) of .05 to test the significance of the finding. An examination of the learning outcome means indicates that the matched group ($M = 33.38$, $SD = 19.41$) had significantly higher learning outcome than the mismatched group ($M = 20.16$, $SD = 26.64$), $t(58) = 2.18$, $p < .05$, $d = .57$. The effect size ($d = .57$) of the finding was between medium and large.

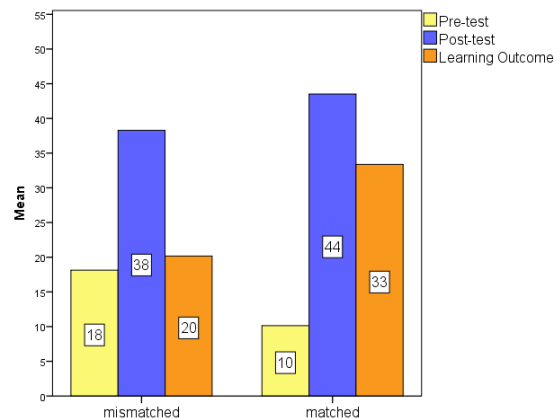


Figure 4. Results of pre-test and post-test and learning outcome for the matched and mismatched groups.

There was a difference between the matched and mismatched groups in terms of their prior knowledge (which was measured by the pre-test). This difference may have negatively affected the findings. However, participants were asked before interacting with the system to evaluate their current level of knowledge about the topic of cryptography in general, and 95.45% of the participants indicated that the topic was new to them. For better accuracy, further analysis was carried out to test whether the difference between matched and mismatched groups in terms of pre-tests was significant. An independent sample t -test was conducted and showed that the matched group ($M=10.14$, $SD=14.35$) and the mismatched group ($M=18.13$, $SD=18.33$) did not differ in terms of pre-test results, $t(58)=1.87$, $p > .05$. This suggests that there was no significant difference between the two groups in terms of their prior knowledge. Hence, the effect

was caused mainly by the learning style adaptivity approach.

Hypothesis 1 is therefore confirmed, and it can be concluded that matching information perception learning style and instructional material in an adaptive e-learning system yields significantly better learning outcome than without matching.

6.3. Learner satisfaction

The second hypothesis was also tested. Figure 5 shows that the matched group had better learner satisfaction regarding learning content, the interface and personalisation than the mismatched group.

General learner satisfaction was measured using an independent sample Mann-Whitney U test. The result indicates that the matched group ($n = 29$) reported significantly higher satisfaction than the mismatched group ($n = 31$), $U = 302.5$, $p < .05$, with the sum of the ranks equal to 35.57 for the matched group and 25.76 for the mismatched group.

Hypothesis 2 is therefore confirmed, and it can be concluded that matching information perception learning style and instructional material in an adaptive e-learning system yields significantly better learner satisfaction than without matching.

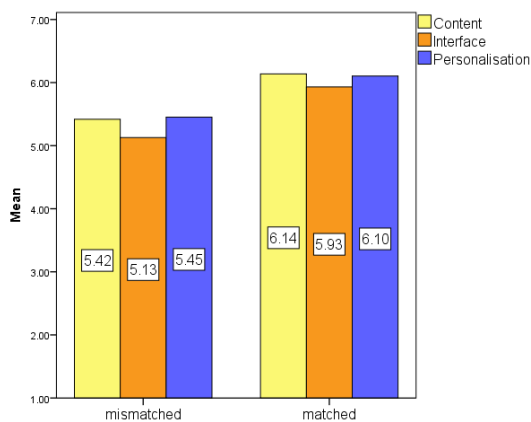


Figure 5. Learner satisfaction in the matched and mismatched groups.

An analysis of the correlation between learning outcome and learner satisfaction variables was also carried out. It was found that the relationship between these two variables was non-monotonic. Therefore, a correlation test was not performed, it can be stated that there is no clear correlation between learning outcome and learner satisfaction.

7. Discussion

The experiment was conducted with 60 participants, and the group of participants was homogeneous in terms of culture, gender, spoken language and specialisation. Future experiments should target a larger sample, and a heterogeneous group of participants in order to generalise the results. Although the difference between participants in terms of prior knowledge (i.e., pre-test) may affect the findings, post-test results of the matched group are still higher than those in the mismatched group. However, a more careful assignment of participants to study groups should be considered.

The distribution of the participants in the information perception dimension (sensing-intuitive) shows that there were far more sensing learners than intuitive learners, and that the majority had mild to moderate characteristics. A few learners had strong characteristics. The findings are mostly in agreement with several studies [25], [26], [32]. However, due to the random approach of assigning participants in the study groups, balanced groups across the learning style dimension could not be accurately achieved. This is difficult to control and it may take a long time before balanced groups can be completed.

This study contributes to current research on adaptivity by providing more evidence on learning effectiveness and on the importance of learning style in adaptive e-learning systems. It is argued in this work that matching instructional material and information perception preferences significantly enhances learning outcome, with a medium to a large effect. Although some studies have led to the conclusion that adapting instruction based on learning style does not have a significant effect on learning outcome [11], [34], the findings of this study conform to the results of many related studies [34], [35]. However, this study is one of the few that explicitly deals with the information perception dimension of the Felder-Silverman model.

The findings also shed more light on the information perception dimension. The study involved an adaptivity approach based on this dimension by constructing personalised learning paths, in which learners study learning objects in customised sequences. In addition, the approach is independent of the domain and context, as most topics usually have different types of learning objects, including examples, concepts, theories, case studies, practical tools, exercises and theories. A combination of concrete and abstract material can be generated.

Another important finding was that learners' satisfaction is higher when instructional material matches their learning style. These results match those

of other studies that conclude that adapting instruction based on learning style yields better learner satisfaction [10], [18]. However, this study found no correlation between learning outcome and learner satisfaction. This suggests that learning style can also be effective in enhancing the learning experience and motivation of learners [9], [10]. It may also be used as a guideline for designing adaptive e-learning systems and instructional content.

In the experiment, the application domain was cryptography. Other domains of study would be investigated in future experiments to generalise the results. The domain model consisted of six learning objects with a learning process that lasted about an hour. More learning objects would be taken into account, and long-term studies should be performed.

It is important to consider instructional design models when developing effective learning objects to support both sensing and intuitive learners in adaptive e-learning systems. For example, an interactive and animated cryptographic learning object that could be suitable for sensing learners was presented in [36]. Nevertheless, because intuitive learners prefer abstract material such as theories and mathematical models, researchers should invest some time in authoring more creative and novel instructional material. Additionally, a more refined approach should be used for a better fit with the sub-categories of the dimension. For example, it may be more effective to treat learners differently according to their affinity with the mild, moderate or strong characteristics of a particular learning style.

Importantly, the findings cannot be generalised to other learning style dimensions and other learning style models. They are closely linked to the information perception dimension of the Felder-Silverman model and the proposed adaptivity approach. However, this dimension can also be found in the Kolb model [23] and MBTI [24]. Although the information perception dimension is recognised as the most important learning style dimension [30], [31], other dimensions may also be incorporated in the proposed approach to further enhance the learning process.

The system implemented a restricted version of the learner model in order to customise the sequence of learning objects based on the proposed approach and to evaluate the approach by carefully controlling the experiment. However, more advanced features and tools should be included to fully automate the system and to provide adaptation in response to learner-system interaction on the fly. A possible avenue of research is to investigate learner controllability over the learning process. For example, a comparative evaluation could be made between an adaptive e-learning system that affords learners some control over the recommendations and the learning process, and one

that provides recommendations without any control over the learning process by the learner. Additionally, in order to develop cognitive and meta-cognitive skills and abilities of the learners when providing adaptivity, an e-learning system may allow learners to inspect their learner models and associated learning style. Learners may become aware of their weaknesses and strengths when the learner models are open to them. This may also enhance transparency and trust between the learner and the adaptive e-learning system.

A more advanced learner model that monitors learner-system interaction and makes updates accordingly is desirable. Such a model would come with a price; evaluation may be more difficult for dynamic models, and learners have to interact with systems over a long period of time before accurate and useful learner models can be established.

Although it may be the case that adapting instruction based only on learning style yields better learning outcome and learner satisfaction, other important learning factors should not be ignored. Further customisation can be achieved by incorporating a combination of different learner characteristics such as the level of knowledge and learning style. However, such customisation may require more sophisticated and novel forms of adaptation.

8. Conclusion

This paper has presented a generic adaptive framework which can be used as a reference model for designing adaptive e-learning systems. In addition, a specific approach to learning style adaptivity was proposed within the framework. The approach provided personalised learning paths in an adaptive e-learning system based on the information perception dimension of the Felder-Silverman learning style model. The framework was validated and the approach evaluated by conducting a controlled experiment with 60 participants. The experiment produced positive results regarding learning outcome and learner satisfaction when matching instructional material and information perception learning style.

The experiment had, however, some limitations. It was based on a short-term study with a relatively small and homogeneous group of participants. In addition, a limited number of learning objects were used. Other learning style dimensions may also be incorporated in the proposed adaptivity approach besides the information perception dimension to produce better results. Future research will extend the learner model to incorporate knowledge and learning style and will involve a long-term evaluation.

9. References

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