

# LEARNING STYLES FOR K-12 MATHEMATICS E-LEARNING

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**Keywords:** e-Learning, Learning Styles, Adaptive Learning, K-12 Mathematics.

**Abstract:** This review paper analyzes significant studies in learning style and e-Learning fields in order to synthesize an answer to the question “Does considering learning styles improve e-Learning performance especially for K-12 mathematics education?”. Included studies can be categorized into the following topics: learning style models, learning style detection methods, considering learning styles in traditional education and e-Learning, considering learning styles in K-12 mathematics education. The review shows that applying different teaching methods for different learning styles could actually help a K-12 student understand a mathematics subject better.

## 1 INTRODUCTION

Computer supported education environments offer a significant alternative to traditional learning methods. Among other benefits, they also allow specializing or adapting according to learners’ needs. Herein, designing an e-Learning application that is capable of detecting user’s learning style and teaching a subject by accommodating itself to that style is an interesting research area. However, it is necessary to investigate the impact of learning styles on e-Learning environments before launching out such a research.

This paper aims to review the existing literature for teaching mathematics to K-12 students in an e-Learning environment according to students’ learning styles. Reviewed papers were selected according to their significance and relevance. Significance is measured by the quantity and quality of citations while relevance is decided according to the the applicability of the study to K-12 mathematics e-Learning. Although we tried to cover as many papers as possible, we are aware that we may have left out some significant and relevant papers.

The paper is organized as follows: section 2 provides a summary of notable learning style models, while in section 3 methods for detecting them are explained. To justify the positive effect of considering learning styles, studies considering e-Learning and face-to-face learning in general are given in section 4. Then, in section 5 other studies focussing on K-12 and mathematics education are considered. Finally, section 6 summarizes the findings and comments.

## 2 LEARNING STYLE MODELS

Learning style or cognitive style is the preferences or methods of a learner in his/her learning activities (Felder and Silverman, 1988). Different people have different methods to understand a subject better. Some individuals may prefer visual learning while others may find auditory or verbal approaches more useful. Yet, some may succeed by only studying the theory while experimenting may be essential for others. Learning style models aim to specify and designate general preference categories similar to these examples. They also classify learners according to their approaches in learning and understanding subjects by means of various measures (Felder and Silverman, 1988).

Learning styles have aroused interest of researchers from various fields through the years. As a result, many different models have been proposed by theoreticians and made use of by educational specialists. According to a relatively recent and extensive report (Coffield et al., 2004), at least 71 learning style models are present and 13 of them are considered major or more influential than the others. They mainly differ from each other according to the extent that they may change over time for an individual.

In his Mind Styles Model (MSM) (Gregorc, 1985) Gregorc considered learning styles as unchangeable and inborn. He stated that each individual can be strong in one or two of the four styles defined by two dual dimensions: Abstract-Concrete and Sequential-Random. Similarly, there are two dual dimensions in

Ridings Cognitive Styles Analysis (CSA) (Riding and Rayner, 1998): Holist-Analytic and Verbaliser-Imager. Unlike the former, learning strategies are regarded changeable in this model, however learning styles are still fixed.

Some models such as Kolb's Learning Style Inventory (LSI) (Kolb and Kolb, 2005) and Felder-Silverman learning style model (LSM) (Felder and Silverman, 1988) did not consider learning styles constant. According to them, learning preferences may change slightly depending on time and situation. Kolb proposed two dimensions (Abstract-Concrete and Active-Reflective) and four styles (Converging, Diverging, Assimilating and Accommodating) while the Felder and Silverman introduced four dimensions (Active-Reflective, Sensing-Intuitive, Visual-Verbal and Sequential-Global).

Different from the approaches above, Dunn and Dunn (Dunn and Griggs, 2003) included other preference factors such as environmental factors (sound, temperature, light), emotional factors (motivation, responsibility), physical factors (learning preferences, intake and time of the day) and sociological factors (such as learning groups, parental motivation). Visual, Auditory, Kinesthetic and Tactile learning are proposed as physical learning preferences.

### 3 LEARNING STYLE DETECTION

Before trying to teach a subject using a method that matches the learning style, challenge of determining the learning style stands. There are both traditional and computerized approaches trying to solve that challenge.

#### 3.1 Questionnaires

Custom designed questionnaires are the most common method of learning style determination. Nearly all of the models mentioned above have their own questionnaires, surveys or inventories. Some questionnaires contain less than 15 items such as Gregorc Mind Style Delineator (MSD) or Kolb's LSI while some of them contain more than 100 items such as LSI for the Dunn and Dunn model or Vermunt's Inventory of Learning Styles (ILS) (Vermunt, 1998).

Questionnaires also differ by the type of their items. In Gregorc MSD and Kolb's LSI, respondents should rank 4 alternative responses for each item according to how much it fits them. An example item of that type can be "I learn best from..." while the responses to be ranked are: "rational theories", "per-

sonal relationships", "a chance to try out and practice" and "observation". Each of these responses contributes to a different learning style for the respondent (Coffield et al., 2004).

Another quite common type of question is the 3 or 5 point Likert scale in which the respondents are asked in what level they agree to the given statement. This scale is used in Felder and Soloman's Index of Learning Styles (IXLS) (Soloman and Felder, 2001), LSI for the Dunn and Dunn model, and Vermunt's ILS. An example item is "I dislike things uncertain and unpredictable" where the possible responses are "true", "uncertain" and "false" (Coffield et al., 2004).

Distinct from the ones above, Riding did not employ a self-report measure in his CSA for his model of cognitive style. Instead, he developed a "computerised assessment method" where the respondents are presented with "matching tasks" and "embedded figures tasks" on a computer where their response times are saved and used to determine learning style (Coffield et al., 2004). Although Riding's method is not a questionnaire and the respondent is not aware of how his/her preferences are measured, it cannot be considered as an automatic detection method either, because; user is still tested on a custom-engineered setting instead of natural learning environment.

Questionnaires designed for some models provide valid and reliable classifications in ideal situations; however, there are problems with the questionnaire approach, because; it is not realistic to assume that learners are aware of their learning style and motivated to answer the questionnaire properly (Graf, 2007). This awareness and motivation problem is especially evident in the case of younger children in K-12 level and it puts the validity and reliability of the questionnaires in question.

#### 3.2 Automatic Detection

Learning indicators (Papanikolaou and Grigoriadou, 2004) are the observable and quantifiable behavior of the learners and they can be grouped into three categories: (i) navigational indicators; (ii) temporal indicators; (iii) performance indicators. As an alternative to traditional questionnaires, learning indicators are proposed in a web based learning environment (Bousbia et al., 2009). This method proposes a track based system called "Indicators for Detection of Learning Style" which logs learner behavior. Then the system analyzes the logs mainly focusing on navigational and temporal indicators and suggests learning styles.

Another approach (Graf and Kinshuk, 2006) based on Felder-Silverman LSM, presents a generic tool to detect learning style by extracting it from the

learning management system database. They use the same approach as the IXLS questionnaire developed for Felder-Silverman LSM. Similarly, yet another approach (Graf, 2007) aims to automatically assign Felder-Silverman learning styles by applying Bayesian Networks on indicators such as percentage of time spent on certain pages, percentage of performed self-assessment questions, percentage of correctly answered questions about certain subjects, time spent in the forum or percentage of times a learning object is skipped via the navigation menu.

Although automatically detecting learning style according to user behavior offers a more natural and unnoticeable solution to the detection problem, there is not as much research as questionnaires demonstrating its validity and reliability. Moreover, logging detailed user behavior and deducing a meaningful model from the data to guess a learning style is not an easy task. There are enormously many user actions and it is required to decide which action contributes to which learning style and in what level. Automatic detection functionality is also hard to implement afterwards, unless the e-learning system is natively developed with logging capabilities.

There are also detection methods making use of wearables and video/audio sensors which are not examined here as we focus mainly on methods that do not require any additional hardware other than a personal computer on the user side. Nevertheless, it is worth mentioning the affective tutoring system for mathematics called "Easy with Eve" (Sarrafzadeh et al., 2008) which successfully evaluates primary school students' emotional states.

## 4 LEARNING STYLES AND PERFORMANCE

When developing an application that considers learning styles, it is important to understand whether designing different learning processes for different learning styles actually affect learning performance positively. Intensive research has been devoted on the impact of learning style models for both traditional learning and e-Learning environments.

### 4.1 Traditional Learning Performance

Learning style models and effects of educating students in methods matching their learning styles have been thoroughly researched for traditional learning environments. For example, in a research (Riding and Grimley, 1999), eighty 11-year-old students were assessed for their learning style applying 3 different ed-

ucation methods. It was observed that students of certain learning styles perform better learning achievement using certain education methods.

On the other hand, surveys were conducted in (Ballone and Czerniak, 2001) on K-12 teachers. They were inquired about applying different instructional strategies to match students of different learning styles. Results demonstrate that science teachers believe doing so will "increase student success, motivate students, meet all student needs, make science a good learning experience for all students, encourage participation, and create interest in science".

Another interesting analysis (Cafferty, 1980) determined the learning styles of both students and their teachers. Then, the students were grouped into four categories with gradual amount of match of elements on their profile with that of their teachers. Performance evaluation showed that, greater degree of match between the teacher's and students' learning styles will result in higher Grade Point Average for that group of students.

### 4.2 e-Learning Performance

Studies that examine the effect of learning styles in e-Learning environments can be grouped roughly in two categories: (i) studies that do not consider adaptive systems and experiment how e-Learning suits on certain learning styles; (ii) studies that experiment the effects of adapting the e-Learning system for different learning styles. Studies in the first category provide the same content using the same methods to all learners and measure the effect of e-Learning on different learning styles. While in the second category, a specific method is applied for each learning style and the performance improvement with respect to the same method for all case is measured.

A study (Manochehr, 2006) from the first category used Kolb's LSI to measure learning styles and compared performance of learning style groups for traditional and e-Learning methods. Their research indicated that undergraduate students from certain learning styles (namely, assimilator and converger) achieved better results with the e-Learning.

Another research (Shrestha et al., 2007) conducted face-to-face interviews to 43 Undergraduate students to detect both their learning styles and their usage preferences on a Virtual Learning Environment (VLE). Results revealed the influence of learning style preferences on VLE performance and demonstrated that VLE is particularly supportive for certain types (namely, activist and reflective).

As an example to the second category of studies, (Ford and Chen, 2001) explored the relation between

matching and mismatching teaching styles with students learning style by asking them to create web-pages after giving instructions either matching or mismatching their learning style. Performance of the students in matching group was superior in the multiple choice test that is applied afterwards.

On the other hand, (Moallem, 2007) designed multiple instructional materials using Felder-Silverman LSM for an online course. Their results suggest that although learning performance does not show major difference, developing specific materials for people of different styles results in higher motivation and more interaction with the course content.

Another study (Papanikolaou et al., 2003) presented an Adaptive Hypermedia prototype called INSPIRE that focuses on learning style differences. It dynamically generates “learner-tailored lessons” through “curriculum sequencing, adaptive navigation support, adaptive presentation, and supports system’s adaptable behavior”. Their results supported the hypothesis that learners of different styles discover and prefer resources of INSPIRE that are beneficial for their learning style.

### 4.3 Overview of Studies

We draw two conclusions from the studies on both traditional teaching methods and on e-Learning: (i) When the same teaching method is applied to all learners, there is a correlation between learning performance and learning style. Learners of certain styles perform better while some others fail to improve. Although, this outcome is suggested as a drawback of e-Learning in some studies such as (Ross and Schulz, 1999), it can be considered primarily as a drawback of just the methods where the same content and methods are applied to all learners regardless of their learning styles. (ii) When a learning method which is compatible with the learner’s learning style is used, learning achievement significantly increases. Both conclusions support the claim that: in an ideal learning environment each learner should be treated differently depending on his/her learning style.

## 5 LEARNING STYLES IN K-12 MATHEMATICS TEACHING

In this section, we cover the details on the learning performance effects of learning styles and adapting teaching style according to learning styles. We focus only on mathematics teaching for K-12 students and examine the effects in two cases: traditional (face-to-face) learning and e-Learning, respectively.

### 5.1 Traditional Mathematics Teaching

Literature on the relationship of learning style and K-12 mathematics education is not broad. One of the few studies in the area (Riding and Agrell, 1997) investigated the relationship between learning style, intelligence and school achievement of 205 age 14-16 students in 5 core subjects including mathematics. Riding’s CSA was chosen as the learning style model while mathematics performance was measured by the end of year marks. Results of the study demonstrate that in mathematics, students with wholist-verbaliser style perform best among the high intelligence group, while analytic-verbalisers are most successful among the low intelligence group. They also find no correlation between learning style and intelligence.

Another approach (Kopsovich, 2001) tried to understand whether “a positive correlation between students’ learning styles and their achievement test scores in mathematics” exists for fifth grade students. 500 students were tested for their learning style using LSI for the Dunn and Dunn model. Mathematics achievement was measured using Texas Assessment of Academic Skills Test (TAAS) that is an accountability system for all public schools in Texas, United States. Results revealed that significant differences exist in the mathematics test scores of fifth grade students with different learning styles.

We were not able to find a study on K-12 mathematics teaching where adaptive methods were applied to children of different learning styles. Even so, a study on 108 college students (Chamberlin, 2011) that analyzes the impact of differentiated instruction on mathematics teaching, is worth mentioning at this point since those students were prospective teachers of K-12, and a purpose of the study was to “assist them with implementing differentiated instruction in their future mathematics teaching”. Instructors attending the experiment were taught differentiated and traditional courses of 5 sections each. Mean scores of the experimental group were significantly higher showing that to meet diverse learning style needs of the students is a factor for mathematics performance.

### 5.2 Mathematics Teaching through e-Learning

In the evaluation of adaptive e-Learning performance in K-12 mathematics teaching, little research that we are aware of has been carried out. One of the few studies to mention is the A-MathS Multimedia Courseware (Zin, 2009) which is an adaptive system for teaching mathematics, based on learning styles. The system detects learning styles (in global/analytical

and visual/verbal scales) in the diagnostic module and provides one of the four instructional modules accordingly. They applied pre- and post-tests in order to evaluate the performance of courseware on 35 secondary school students. Their findings indicate that adaptability resulted in significant post-test score increase. Experimental group with matching learning styles achieved 10.5 points mean gain of score while the control group with mismatching learning styles only achieved 1.8 points. Moreover, in the questionnaire presented to students to rate the usability of the courseware, control group rated the interface design much lower than the experimental group showing that they had difficulty in using and navigating in an environment incompatible with their learning style.

Carnegie Learnings Cognitive Tutor is a differentiated mathematics instruction software for learners including middle school students that features multiple representations of problems for different abilities and learning styles. Some evaluations for Cognitive Tutor are summarized in (Ritter et al., 2007). In one example, performances of two classes using Cognitive Tutor and a textbook they had been previously using are compared. Results show that, students using Cognitive Tutor get higher grades as well as reporting greater confidence in their mathematical abilities and usefulness of these abilities in real life. Another evaluation demonstrate that among more than 6000 high school students, ones who use Cognitive Tutor outperformed others significantly in a state exam. Performance improvement is especially obvious for some groups of students such as receiving Exceptional Student Education or having limited English proficiency.

We also would like to mention adaptive, web-based learning environment called ActiveMath which generates interactive mathematics courses adapted to the student's preferences (Melis et al., 2001). Although we were not able to find any published paper on its performance, it is asserted that summative evaluations continue in 10 German schools as well as universities of Edinburgh, UK and Malaga, Spain.

### 5.3 Overview of Studies

In the case of K-12 mathematics education there is not an adequate number of studies on either traditional learning or e-Learning to enable reliable deductions. However, the small number of studies considered above create an impression that similar positive outcomes in other age groups and other subjects can also be obtained for K-12 mathematics. More research should be devoted especially on adaptive teaching methods based on learning style to understand its impact on K-12 mathematics performance.

## 6 CONCLUSIONS AND FUTURE WORK

Our literature review shows that the research in learning style models and their application to e-learning environments is quite adequate both theoretically and empirically. There is a potent and detailed background for learning style models despite of some minor differences among them. Moreover, there are many publications suggesting that, considering learning styles appropriately enhances the learning experience. On the other hand, amount of studies on the effects of learning styles in younger learners (K-12 in our case) and in specific school subjects (Mathematics in our case) are not proportionally intensive, although a few available studies are encouraging.

Besides, almost all of the learning style detection/determination methods are either questionnaires or automated systems that track user behavior in an e-Learning environment. Those are not quite suitable for K-12 students due to lack of learner self-awareness and motivation in the case of questionnaires and due to highly sophisticated infrastructure and decision algorithm requirements and lack of reliability/validity experiments in the latter case.

Our aim is to develop an educational game which detects learning style of a K-12 student (especially 3 to 5 graders), then tries to teach a simple mathematics subject in accordance with his/her learning style and finally measures the level of cognition. We would like to give an example for how learning style differences could be used for easier multiplication table learning. This subject is chosen due to the difficulty that students have in learning it as well as its applicability to multiple teaching styles on a computer. For instance, multiplication table can be taught through a game with numbers, spoken explanations and applying speech recognition to learner responses for verbal learners or using symbols, animations or images of real-life objects such as fruits for visual learners. User interaction can be emphasized by allowing dragging and dropping symbols or numbers to the multiplication equations in order to support kinesthetic learners who prefer to learn by getting involved and carrying out a physical activity.

Learning style can be detected via a separate game presented beforehand or concluded from learner's performance in abovementioned games. Alternatively, these two approaches can be combined in a system where initially detected learner and game profiles change over time based on how students perform on various games.

We expect to observe that, games which are natural ways of learning for students of these ages, can

accurately detect learning style and increase learning performance when suitable teaching methods for learning style are employed. Results of that study will hopefully contribute to the quest of filling in the gap of reliable empirical analysis in the area.

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