ASSESSMENT OF PREDICTIVE POWER OF THE FELDER & SILVERMAN LEARNING STYLES MODEL ON STUDENTS' PERFORMANCE IN AN INTRODUCTORY PHYSICS COURSE

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Abstract

According to the Felder and Silverman Learning Styles Model (FSM), students have learning preferences regarding how information is obtained, processed, perceived and understood. The Index of Learning Styles (ILS) is an online questionnaire created by Felder and Soloman to classify students according to their learning styles. With a priori knowledge of students' learning styles, one might hypothesize that the instructor could adapt his/her class to support, and even improve, students' learning. Still, one question that remains open is whether it is possible to individualize the FSM, *i.e.,* if students of determined learning styles perform different (better or worse) on questions mapped to different styles. In this work, we assessed the correlation between students' performance and their learning styles in an Introductory Physics course. We designed a Learning Styles Classification Method (LSCM) and implemented it online (LSQuiz) to predict individual students' performance on pre-class questionnaires (N = 63). We found that, in general, the ability of the ILS to predict individual student performance on pre-class questionnaires was not better than random, with no significant correlation between students' performance and their learning styles, indicated by a Pearson's correlation coefficient of 0.54. Nevertheless, when independently analyzing the learning styles dimensions, we have identified heterogeneous data between the dimensions, with a greater correlation in the Sequential-Global dimension, with a 0.76 coefficient, followed by a coefficient of 0.50 in the Visual-Verbal and 0.35 in the Sensory-Intuitive. We found, however, that the results related to the Sequential-Global dimension are not supported by the internal consistency of that dimension in the ILS (Cronbach's alpha of 0.30). We conclude suggesting that the adoption of customized learning practices in the Visual-Verbal dimension have potential and could be the focus of further studies.

Keywords: Physics, student, learning, peer instruction, understanding, learning styles.

INTRODUCTION

As explained by Önder & Silay (2016), each person has his/her own way or preferred way of learning, like watching, listening or even touching. These differences are determined by what is defined in literature as learning styles. Several learning styles models were developed to explain and document such learning particularities, such as the Hall and Moseley (2005) model, the VAK (Visual, Auditory and Kinesthetic) model (Geake, 2008), the Kolb model (Kolb, 1981), the Dunn, Dunn and Freeley model (1984), the Herrmann (2000) model and the Felder & Silverman (1988) model.

Also, Önder & Silay (2016) defend that these differences – *i.e., the learning styles* – must be considered to support an effective learning environment. In the fields of Physics Education Research (PER), several initiatives have been conducted to study the impact of learning styles in the students' learning.

For example, Önder & Silay (2016) organized a study related to the adoption of the cooperative learning approach, supported by learning styles, in college physics classes. The researchers divided the students into groups composed of students of different learning styles (experimental group) and students with different academic grades (control group). Results indicate that students in the experimental group had a better performance than the control group.

In the same vein, Larkin (2000), Larkin & Budny (2000) and Larking & Budny (2003) proposed teaching approaches and learning techniques supported by learning styles for introductory physics courses, with positive impact in students' interest and motivation to learn.

Bawaneh, Zain & Saleh (2011) investigated the effects of learning styles approaches – specifically, the Herrmann While Brain Teaching Method (Herrmann, 2000) – over conventional teaching in electric circuits classes. When compared to the control group, students related to the learning styles approach had a better understanding of the topic than the other students, therefore suggesting the adoption of learning styles approaches in higher education curricula and textbooks.

Additionally, there are initiatives to employ educational strategies supported by learning styles to secondary level physics education, as proposed by Zajacova (2013).

The Felder & Silverman Model

Among all existing learning styles models, one that stands out – both for theoretical foundation and adoption in literature – is the Felder & Silverman (1988) model. The Felder and Silverman model (FSM) supports the idea that each student has learning preferences related to how information is obtained, processed, perceived and understood. The approach to assessing students' preferences was proposed some years later (Felder & Soloman, 2015), based on an online questionnaire known as Index of Learning Styles (ILS) (Felder & Soloman, 2000).

The ILS is composed of 44 questions that aim to classify students according to four learning styles dimensions: 1) from Sensory to Intuitive; 2) from Visual to Verbal; 3) from Sequential to Global, and 4) from Active to Reflective. As stated by its authors (Felder & Soloman, 2000), every year hundreds of thousands of people answer the ILS questionnaire.

According to Felder and Spurlin (2005), the goal of the FSM is to "capture the most important learning style differences among (...) students and (to) provide a good basis for (...)

instructors to formulate a teaching approach that addresses the learning needs of all students". The authors (Felder & Spurlin, 2005) also mention they do not believe that the ILS should be used to predict the students' performance individually, as the learning styles would reflect only preferences. This is supported by the empirical study performed by Zwanenberg, Wilkinson & Anderson (2000), which analyzed the correlations between the ILS dimensions and the students' grades (end-of-year performance data), not finding statistical significance.

For instructors, however, the opportunity to employ the ILS information to deliver the content to each student that best fits his/her learning styles could represent an exciting approach. For example, problems with pictures and diagrams could improve learning from a student who is predominantly visual. Similarly, a student who is predominantly sequential would consider easier to learn through a sequence of small exercises, each one addressing a particular topic. As explained by Larkin & Budny (2003), the need to identify individual learning styles through formal assessment has never been more important than it is at present.

Thus, even if studies like Zwanenberg, Wilkinson & Anderson (2000) point out that there is no correlation between the learning styles and the students' final grades, a still open question is whether **students of a certain learning style will perform better on questions of that same style**. If true, specific and individual active learning practices could be designed, providing customized content and exercises to these students (*e.g.* focusing on questions compatible to their learning styles, or the opposite, in learning styles that students are not accustomed to, forcing them out of the comfort zone).

Also, even if one assumes that it is possible to use the students' ILS data to deliver individualized content to each student, this approach might not enhance the learning process at all. Therefore, it might be relevant to question whether there might be a correlation between the students' performance on questions associated with each style and their own learning styles.

In this study, we analyzed whether students' performance could actually be improved by delivering individual content based on each student's learning style, as measured by the ILS. We argue that for the ILS to be useful in this scenario, it must predict the performance of students when confronted with different types of questions. Our hypothesis is that students would have a better performance when dealing with questions related to their own learning styles preferences.

The experiment was performed with students enrolled in an undergraduate Introductory Physics course. The course was designed based on the Active Learning approach (Bonwell & Eison, 1991; Chickering & Gamson, 1987; Caceffo, Rocha & Azevedo, 2011) which employs several techniques to motivate students' collaboration, participation, and motivation. Specifically, we employed Peer Instruction (PI) (Araujo & Mazur, 2013; Watkins & Mazur, 2013; Zingaro & Porter, 2014; Caceffo, Gama & Azevedo, 2018), a method that applies Just in Time Teaching principles, asking students to study in advance the lesson content, answering and submitting an online quiz before each class (Novak & Patterson, 2004). Instructors can thus analyze in advance the answers, adjusting their classes to meet students' needs.

We consider that if there is a correlation between students' learning styles and performance, it would also be possible to extend the Active Learning approach and some of its techniques (as PI) and systems, as the LSQuiz (Caceffo & Azevedo, *2014*), to individually support learning styles features. This would also be in line with the emerging Ubiquitous Computing (Weiser, 1999;

Caceffo & Rocha, 2011; Caceffo & Rocha, 2012) field, that advocates a more pervasive and personalized way of the interaction with technology.

This paper is organized as follows: the next section describes the **Related Work,** focusing on studies about the Felder & Silverman Model, and also arguing that the ILS's internal consistency cannot be considered fully established by existing art; then in the subsequent section we detail our experimental **Methodology**; the following section presents the **Results** obtained for both extrinsic consistency measure and internal consistency measures and; finally, we have the **Discussion and Conclusion**s section, which discusses the results and points future directions.

Related Work

The Felder and Silverman Model (FSM) suggests that students' learning styles may be measured along four independent dimensions: 1) the information perception dimension (which ranges from Sensory to Intuitive); 2) the sensorial input dimension (Visual-Verbal); 3) the scope of understanding (Sequential-Global), and; 4) the processing preference (Active- Reflective). For each dimension, students can be classified into one of the two possible learning styles, according to their learning preferences. In addition, Felder & Silverman (1988) suggest a teaching style for each dimension by describing how instructors could perform to outreach different types of learners.

One shortcoming of the model is that its descriptions are general and subjective, which poses challenges in applying the FSM to specific teaching practices, such as the pre-class questionnaires of Active Learning environments (Araujo & Mazur, 2013; Watkins & Mazur, 2013; Novak & Patterson, 2004). For example, the criteria to classify a question between abstract or concrete are neither detailed nor accurate. The same problem arises with questions with diagrams, which might not necessarily be classified as visual. Because FSM rules are contingent on subjective interpretation, different subjects might disagree on the classification of the same question, which raises doubts about its applicability and validity.

The FSM reliability, specifically its internal consistency, is also a problem. Felder & Soloman (2000) developed an online questionnaire known as the Index of Learning Styles (ILS). The ILS is composed of 44 questions, divided into four groups of 11 questions each. The ILS attempts to measure the preference expressed by students along the four dimensions of the FSM. As mentioned by Felder & Spurlin (2005), several studies have been gathering and analyzing data from the ILS questionnaire. The ILS internal consistency is usually measured by the Cronbach's alpha.

Table 1, which was compiled by Litzinger, Lee, Wise & Felder (2005), shows that the Cronbach's alpha reported in the literature for the ILS ranges from 0.41 to 0.77. Currently, there is no consensus in the literature about whether or not these values indicate internal consistency. As pointed by Lance, Butt & Michels (2006), studies involving Cronbach's alpha usually quote previous studies (Nunally, 1978) to justify a minimum alpha of 0.70. Lance et al. (2006) propose a cut-off of 0.7 as a "rule of the thumb" for the early stages of research, while 0.8 is indicated for later stages of basic or applied research. Even more strict values could be required for real-world applications. Because of that, Zwanenberg, Wilkinson & Anderson (2000) support that the ILS has

low internal reliability and suggest using the questionnaire to assist students in becoming aware of their learning preferences, and not beyond that point.

Table 1. *Cronbach's alpha of ILS for each dimension of FSM, as reported by five independent studies, and compiled by Litzinger et al. (2005). Only 5 out of 20 values are above 0.7 (indicated in bold), the minimum acceptable alpha suggested by many researchers. All values are below 0.8*

Source	Active- Reflexive	Sensory- Intuitive	Visual- Verbal	Sequential- Global	N
(Litzinger et al. 2005)	0.6	**0.77**	**0.74**	0.56	572
(Livesay, Dee, Neuman & Hites, 2002)	0.56	**0.72**	0.60	0.54	242
(Felder & Spurlin, 2005)	0.62	**0.76**	0.69	0.55	584
(Zwanenberg et al., 2000)	0.51	0.65	0.56	0.41	284
(Zywno, 2003)	0.60	**0.70**	0.63	0.53	557

On the other hand, Tuckman (1999) proposes that while achievement tests must have a minimum alpha of 0.75, attitude tests are acceptable with alphas of 0.5 and above. Based on that opinion, Felder & Spurlin (2005), Litzinger et al. (2005) and Zymno (2003) argue for the internal consistency of ILS, with the argument that the alpha found in previous studies is within the attitude category.

Our hypothesis is that, if the ILS has a minimally satisfactory internal consistency – at least in one of its dimensions – it would be possible to verify the existence of a correlation between the students' learning styles and their performance on questions classified/mapped to these styles. In this study, we propose the use of not only internal consistency measures but also an extrinsic consistency measure on how FSM predicts students' performance in an Introductory Physics course. To accomplish that, we measured the ILS results against the actual performance of students when solving the PI's pre-class questionnaires.

METHODOLOGY

As briefly explained on the previous section, to measure whether the FSM is a valid tool to predict the students' performance in Introductory Physics courses, we compared the students' learning styles through two different methods: the ILS questionnaire website (Felder & Soloman, 2000) and the LSQuiz (Caceffo & Azevedo, 2014).

Figure 1 shows how the methodology employed in this study is organized. Briefly, the students' learning styles identification through the ILS Questionnaire was a direct and almost immediate process, as Felder & Soloman (2000) have made available a website[1] that automates this process. On its turn, on the LSQuiz front, we initially designed a Learning Styles Classification Method (LSCM), to formalize the classification process. Then a set of questions of an Introductory

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[1] Available at https://www.webtools.ncsu.edu/learningstyles/ Accessed: April 2019

Physics course was classified through the LSCM. Finally, the students' performance in these questions allowed the LSQuiz to infer the students' learning styles. In the data analysis step, statistical techniques were employed to compare the learning styles identified through the ILS questionnaire and the LSQuiz. The interested reader can read Caceffo & Azevedo (2014) and Caceffo (2015) for more information on the statistical techniques employed for the identification of the learning styles.
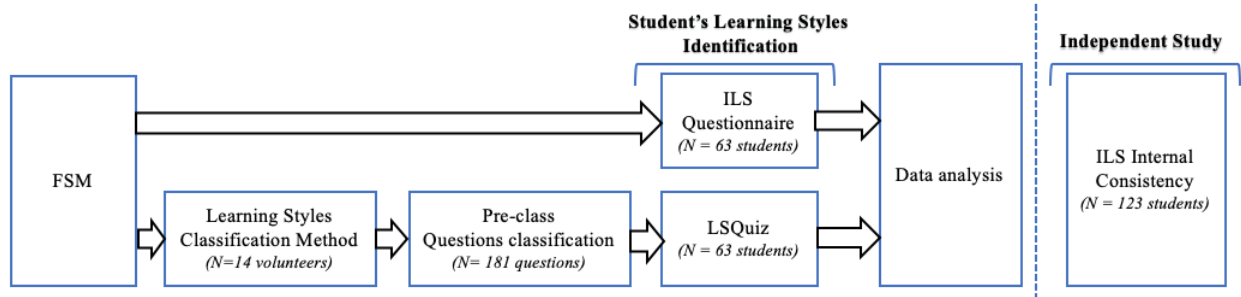

Figure 1. Methodology steps employed in this study

The following subsections describe each one of the methodology steps.

General Sample Data Information

In order to perform the study, we recruited students from a first-year, calculus-based, Peer Instruction supported, Introductory Physics course at the University of Campinas[2], Brazil. The course is mandatory for all freshman engineering and natural science students in the university. Topics covered in the course include Newton's laws, energy, and conservation of energy, systems of particles and dynamics of rigid bodies. The study was previously approved by the local Ethics Committee[3], identification number 30245214.4.0000.5404.

The Active Learning through Peer Instruction may support students' learning of Physics courses (Novak & Patterson, 2004; Araujo & Mazur, 2013; Watkins & Mazur, 2013; Caceffo, Gama & Azevedo, 2018). In this context, students are required to complete reading assignments and answer online multiple-choice questions previous to class. The questions are used by instructors to adapt their class according to students' needs, which involves choosing adequate conceptual tests to be discussed during class.

Also, the course was chosen because its main audience is engineering students, and the FSM was initially developed to measure the learning styles of engineering students.

Initially, we sent an email inviting all students enrolled in the course (N = 647) to participate in this research. They were informed their participation would be completely optional, not counting or interfering with the course grading, as well as no compensation, in any form, would be provided.

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[2] The course's name is "General Physics I". Additional information can be found (in Portuguese) at https://sites.ifi.unicamp.br/f128/ementa/ Accessed: April 2nd, 2019

[3] Available at https://www.prp.unicamp.br/pt-br/cep-comite-de-etica-em-pesquisa
Accessed: April 1st, 2019

In addition, students have informed the prerequisite for participation was the ability to read and understand texts in English. Overall, 63 students accepted to participate.

Learning Styles Classification Method (LSCM)

Related to the identification of students' learning styles through the LSQuiz, we designed a Learning Styles Classification Method (LSCM) in order to minimize the influence of subjective interpretation of the FSM in this process, supporting a more formal and standardized process.

In this study, 14 volunteers participated in the LSCM experiment. All volunteers were graduate students in either Computer Science (9) or Physics (5). The volunteers were recruited by email and did not receive any form of compensation for their participation. All of them had successfully completed the same Introductory Physics course at some time in their academic history. All volunteers from Physics were also teacher assistants (TAs) of that course.

The experiment was performed in three sessions, with distinct participants in each one of them (*i.e.* each volunteer only participated in a single session). The first 2 sessions had 5 participants each, and the 3rd session had 4 participants. Each session lasted around 2 hours each.

Each LSCM session consisted of five steps:

- **S1 (Read):** volunteers (N=14) were asked to read the original FSM paper (Felder & Silverman, 1988). Each participant received a printed copy of the paper and was able to make annotations on it;

- **S2 (Criteria Decision):** volunteers filled out a form to indicate, based on their interpretation of the FSM, which criteria should be considered for the classification of questions along the four dimensions of learning styles;

- **S3 (Classification):** volunteers classified a set of sample questions (N=53), extracted from the pre-class questionnaires. Volunteers were oriented to classify each question using the criteria defined in step S2;

- **S4 (Discussion):** for each question, the results from each participant (*i.e.* how that question was classified) were presented and discussed. Any disagreement during classification was debated.

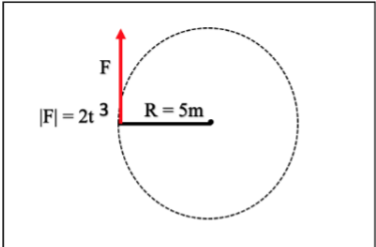- **S5 (Revision):** volunteers were asked to revise the classification made in step S3.

Except for step S4, all steps were performed individually (i.e., without communication between participants). All 5 steps were mediated by a researcher (one of the authors of this work). Figure 2 shows the criteria form, adapted and translated to English[4], used in step S2:

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[4] The actual criteria form was presented and filled by participants in the Portuguese language.

Figure 2. *In step S2, volunteers filled a form to indicate the criteria they would consider appropriate to classify Introductory Physics questions by learning styles in the FSM*

Figure 3 shows an example of a question, adapted and translated to English[5], used in step S3.

An object is restricted to moving in a circular orbit around the origin, with a fixed radius of 5m (see figure). This object is subject to a circular force, whose module obeys the expression $|F| = 2t^3$, where t is the time in seconds. Consider that at $t = 0$, the particle has no linear momentum. What is the magnitude of the angular momentum (L) of this object when $t = 2s$?

a. L=40kg.m^2/s
b. L=50kg.m^2/s
c. L=20kg.m^2/s
d. 0, since the force torque is zero.

Classify the question according to FSM learning styles dimensions:

Visual	☐
Verbal	☐

Sensory	☐
Intuitive	☐

Sequential	☐
Global	☐

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[5] The actual set of questions was presented to participants in the Portuguese language.

Figure 3. A sample question to be classified by volunteers in the LSCM step S3. The volunteers were oriented only to classify the questions by learning styles (i.e. checking the proper learning styles on the right), therefore it was not expected or required to answer the questions – i.e. check choices a) to d)

Pre-class Questions Classification

A total of 181 pre-class questions adopted in the Introductory Physics course were classified by one of the researchers concerning their learning styles. The details of how this classification was performed are available in the **Results** section.

ILS Questionnaire – Students' Learning Styles Identification

In this step, all participant students (N=123) received an email with 2 links: a) a link to the ILS Questionnaire website (Felder & Soloman, 2000) and; b) a link to a Google Forms spreadsheet, managed by the researchers of this work, in which the students were oriented to input the feedback received after completing the ILS Questionnaire. Figure 4 shows a sample of the first 4 questions of the ILS Questionnaire (Felder & Soloman, 2000):

Figure 4. Sample of the first 4 questions of the ILS Questionnaire (Felder & Soloman, 2000)[6]

After completing the ILS Questionnaire, the system shows a feedback page indicating how the student is classified in each learning style dimension. For example, Figure 5 shows the feedback page for a student that would be classified as Active, Sensing, Verbal and Global. Then, he/she would input in the received data in the Google Forms spreadsheet, indicating, for each dimension, his/her learning style.

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[6] Retrieved from https://www.webtools.ncsu.edu/learningstyles/ Accessed: April 2nd, 2019.
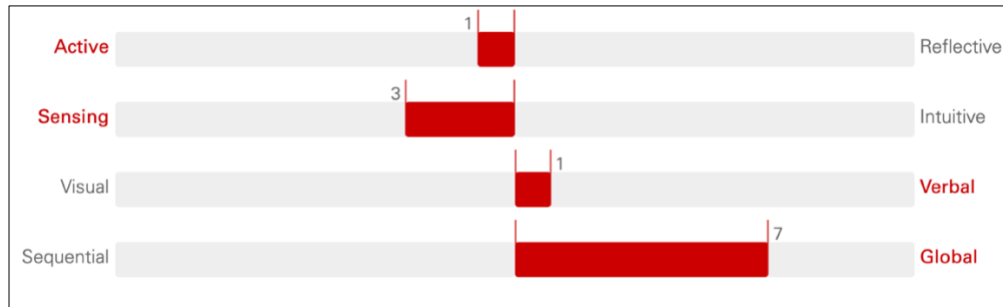
Figure 5. *Example of the feedback received after completing the ILS (Felder & Soloman, 2000)[7]*

LSQuiz – Students' Learning Styles Identification

In previous work (Caceffo & Azevedo, 2014; Caceffo, 2015) we designed a Ubiquitous Classroom Response System (LSQuiz), implemented as a Moodle plugin (Moodle System, 2018). Moodle, a free and open-source learning management system, is adopted by many universities and courses around the world, including the Introductory Physics course in which this research was conducted.

LSQuiz allows the instructor to submit quizzes to students, receiving back their answers and providing feedback. It also supports Ubiquitous Computing and collaboration between students, considering context factors like location and affinity among them (Weiser, 1999). Details of LSQuiz can be found in previous works (Caceffo & Azevedo, 2014; Caceffo, 2015).

For this research, we added a feature on the LSQuiz supporting the classification of questions by the FSM learning styles. Figure 6 shows an example of this feature, adapted and translated to English[8]:

Figure 6. *LSQuiz feature related to the classification of questions by Learning Style in the Moodle System*

Also, with this feature, the LSQuiz can predict students' learning styles by analyzing the entire record of students' answers. The prediction is based on the work of Latham, Crockett,

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[7] Retrieved from https://www.webtools.ncsu.edu/learningstyles/ Accessed: April 2nd, 2019.

[8] The actual implementation of the LSQuiz was in the Portuguese language.

Mclean & Edmonds (2009) and Latham, Crockett, Mclean & Edmonds (2012), which describes the prediction of learning styles in conversational intelligent tutors based on the proportion of right answers in each style.

The students' learning styles, in each dimension, are calculated by LSQuiz as represented in Equation 1:

$$LS = \frac{CA}{TA} - \frac{CB}{TB} \qquad \text{(Equation 1)}$$

In Equation 1, LS is the learning style dimension, and CA and CB indicate the total number of right questions answered in each of the two opposite styles for that dimension, respectively. Similarly, TA and TB represent the total number of questions answered in those two possibilities. Therefore, the strength of each students' learning style ranges from –1 to 1, being neutral (i.e., having no preference) at zero.

As an example, consider a questionnaire with 9 questions, 5 being classified as Visual (TA = 5) and 4 classified as Verbal (TB=4). If a student correctly answered 4 Visual questions (CA=4) and 2 Verbal questions (CB=2), then the prediction of that student's learning style on the Visual-Verbal dimension will be 4/5 – 2/4 = 0.3, *i.e.,* he or she would be slightly more Visual than Verbal.

We first classified 181 multiple-choice questions on Moodle with the LSQuiz according to the LSCM criteria defined in the previous section. Then, we ran the LSQuiz to process the answers of 63 students enrolled in the course. The LSQuiz automatic prediction identified, for each student, his/her learning style in each dimension.

Figure 7 shows an example of a student that, accordingly to the LSQuiz prediction, was classified as Sensitive, Verbal and Sequential. The figure design was purposely crafted to be similar to the ILS feedback screen (see Figure 3).
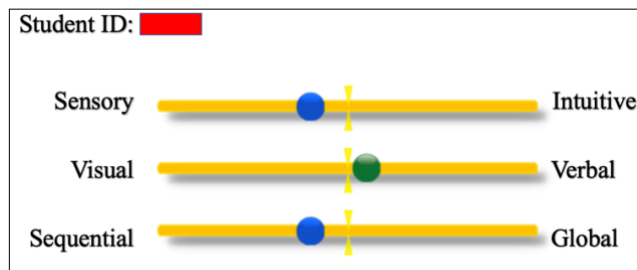

***Figure 7.** Example of a student's learning styles prediction performed by the LSQuiz*

It is important to note, however, that although the LSQuiz is able to display in a user-friendly interface the predicted learning styles for a given student, the volunteers of this experiment did not visualize the feedback screen. This occurred because the questions and data processing occurred

a posteriori, *i.e.*, a few weeks after the students had answered in the Moodle system all the pre-class questions.

Data Analysis

Overall, it was analyzed the proportion of students classified in each learning style through the ILS and by LSQuiz. Also, we performed an individual analysis, checking, for each volunteer, whether he/she was classified in the same style by both methods.

ILS Internal Consistency – Independent Study

In the previous subsections, it was explained that the volunteers were oriented to answer the original ILS questionnaire (Felder & Soloman, 2000) and then use a Google Form spreadsheet, managed by this work researchers, to input their learning styles data.

Although this is a valid method to allow the comparison of the students' learning styles obtained through the ILS and LSQuiz, it does not support the analysis of the ILS internal consistency, *i.e.*, if the students consistently answered the questions according to their styles. In order to proceed with such analysis, it would be required to know, individually, how each ILS question was answered.

Moreover, the number of participants in the previous study (N=63) is much lower than the number adopted in the ILS internal consistency studies available in the literature, which ranges from 242 to 572, as described in Table 1.

Therefore, it was decided to carry out a new and independent experiment (*i.e.* with another and larger group of students) to identify the internal consistency of ILS. Thus, all 1050 students of the subsequent semester of the Introductory Physics course were invited to participate and answer an online questionnaire similar to the ILS but managed by the researchers – so that it would be possible to keep tracking of each one of the answers. Overall, 123 students accepted the invitation.

We initially assessed the ILS internal consistency by calculating the standard Cronbach's alpha from each one of the 44 answers of the ILS questionnaire. We also followed previous studies in the literature (Michalos, 2014; Warrens, 2015; Heo, Namhee & Myles, 2015; Bamber & Manifold, 1978) to assess the ILS internal consistency through the Split-Half reliability test, which splits the questionnaire into 2 parts, checking the correlation among the answers.

RESULTS

Learning Styles Classification Method

As expected, we found the FSM guidelines do not provide enough information for classification of the questions, which leaves classification subjective to classifier's interpretation. Tables 2, 3 and 4 report the frequency of all criteria guidelines employed individually by all the 14 volunteers during the LSCM experiment for the Sensory-Intuitive, Visual-Verbal, and Sequential-Global dimensions, respectively. We opted to not use the Active-Reflective dimension since this dimension should be related both to the students' behavior and to the environment in which the questions are answered, and we could not access this information from an online questionnaire. Therefore, the Active-Reflective was not considered in the final mapping.

In some cases, different volunteers used distinct criteria to classify questions at the opposite ends of the same dimension. One example is the use of algebraic and numerical values in the Sensory-Intuitive learning style dimension (Table 2). Seven subjects interpreted that Sensory questions are those ones that use numerical values in its solving process, while two subjects associated the use of numbers to intuitive questions. After the discussion phase of the LSCM, volunteers agreed that it makes more sense to associate algebraic calculations (i.e., letters instead of numbers) to the Intuitive style and numerical calculations to the Sensory style.

Table 2. *Criteria chosen by the volunteers (N=14) on how to classify questions in the Sensory-Intuitive dimension, after reading Felder & Silverman (1988). Criteria indicated with [S] were selected to classify questions*

Dimension	Criteria	Total
Sensory	[S] Question has practical content.	11
	[S] The question-solving process requires numerical values.	7
	The question with a concise statement.	2
	Question statement with a large amount of data and information.	2
	Questions with a visual representation.	1
	The question that asks for exact results.	1
Intuitive	[S] Question has an abstract and theoretical content.	9
	[S] The question-solving process requires algebraic calculations.	6
	Question statement with a large amount of data and information.	3
	The question-solving process requires numerical values.	2
	Question statement with few and concise data.	2
	The question requires details (description of which content/knowledge is required)	2
	The question with a global scenario.	1

Specifically, concerning the Visual-Verbal dimension (Table 3), three volunteers believed that questions which lead students to draw graphs, pictures or images should be classified as Visual. Although this analysis is initially valid, it creates an additional issue because it depends on the classifier's personal interpretation of the question. Thus, unless specifically said in the question statement, it is not possible for the classifier to know if the students will use charts or diagrams to answer the question.

Table 3. *Criteria chosen by the volunteers (N=14) on how to classify questions in the Visual-Verbal dimension, after reading Felder & Silverman (1988). Criteria indicated with [S] were selected to classify questions*

Dimension	Criteria	Total
Visual	[S] Question statement with visual elements (graphs, drawings or images).	13
	The question-solving process leads students to draw graphs or images.	3
	More relevant information is through visual elements.	1
	Question without visual elements but with a visual scenario description.	1
Verbal	[S] Question with discursive (text) statements, not containing visual elements.	11
	Questions with formulas and equations.	3
	Questions with theorems.	1
	Questions with a detailed description.	1
	More relevant information is through textual elements.	1

Finally, Table 4 shows how the volunteers classified the questions in the Sequential-Global dimension. Most of the participants stated that a sequential question should present linear thinking, with increasing difficulty (12 participants), also covering a specific part of the proposed content (8 participants). On its turn, a global question should cover a wide range of interrelated concepts (11 participants). In the discussion step participants also pointed out that, in order to do a proper classification of a question in this dimension, it would be required to consider not only that question but also the questions before and after it, thus analyzing the context and the difficulty progression of the questions.

Table 4. *Criteria chosen by the volunteers (N=14) on how to classify questions in the Sequential-Global dimension, after reading Felder & Silverman (1988). Criteria indicated with [S] were selected to classify questions*

Dimension	Criteria	Total
Sequential	[S] Question statement presents linear thinking with increasing difficulty.	12
	[S] Question covers a small, specific part of the proposed content.	8
	The question with sequential content.	3
	The question with a long description.	1
	The question with many dependent items.	1
Global	[S] Question covers a wide range and interrelating concepts.	11
	Question requires a holistic interpretation.	4
	Direct questions.	1
	The question with one unique/independent item.	1
	The question with a short description.	1
	The question that presents a formula (but it is not evident how to use it).	1
	The question with the template: "Complete the following phrase or statement:"	1

Analysis of the individual classification shows that, even when the same criterion is heavily chosen by most subjects, the classification can still diverge. For example, 35 of the 53 questions available in the Visual-Verbal style diverged, despite the fact that more than 75% of the subjects used the same criteria for visual and verbal styles. In this specific example, the final mapping defined that questions that explicitly require the student to use a visual element in the solving process should be classified as Visual in order to minimize the classification subjectivity. In the absence of visual elements, the question should be classified as Verbal.

Overall, the set of criteria chosen to classify questions were taken after analysis of the data gathered in the discussion step of the LSCM, and it is indicated by [S] in the tables. Considering the smaller set of criteria obtained after the discussion step of the LSCM, most of the questions in the questionnaire presented to the students were Intuitive (75.1%), Verbal (90.1%) and Sequential (73.5%). It is worthwhile noting that the questions were taken from standard databases of classical Introductory Physics textbooks, and therefore can be assumed to be representative of the types of Physics questions that most undergraduate students face during learning at this level.

Students' Learning Styles Identification

From the students' responses to the 181 online questions, we could predict each student's learning style with the LSQuiz software. Also, each student answered the ILS questionnaire (Felder & Solomon, 2000). Table 5 summarizes the fraction of students classified by style for each independent dimension in the FSM using the LSQuiz and, for comparison, the ILS approach.

Table 5. The fraction of students as classified by ILS and LSQuiz. Question (N=181) and student (N=63 for Sensory-Intuitive and Sequential-Global and N=61 for Visual-Verbal dimension) classification were performed independently from each other

Learning Style	Students (LSQuiz) (%)	Students (ILS) (%)
Sensory	60.6	49.2
Intuitive	39.4	50.8
Visual	58.7	58.7
Verbal	41.3	41.3
Sequential	81.0	54.0
Global	19.0	46.0

Across all students, the LSQuiz classifies the whole group with sensory (60.6%), visual (58.7%) and sequential (81%) styles. The ILS is less specific, with roughly similar values between sensory (49.2%) and intuitive (50.8%) styles, and sequential (54.0%) and global (46.0%) styles. It is worth noting that the results in Table 5 represent an average across all students. Therefore, students that were classified as one style by one method were not necessarily classified by the

same style with the other classification method. Individual correlation between both methods – ILS and LSQuiz – were analyzed in the following subsection.

One fundamental difference between the LSQuiz and the standard ILS is that the former has the possibility of a student being classified as neutral in one dimension (it happens when Equation 1 is zero). Because the traditional ILS has no neutral values for the learning styles (i.e., students always are categorized into one of the two styles in each dimension), students classified as neutral in any dimension were removed from the analysis. This removed two students in our model for the Visual-Verbal dimension. Therefore, we considered N = 63 for Sensory-Intuitive and Sequential-Global styles and N=61 for Visual-Verbal dimension in our analysis.

Data Analysis – Comparison of Individual Prediction of Learning Styles

In order to quantify the ILS predictive power of students' performance, Table 6 compares the number of students classified by learning style for each dimension, when the two methods are used independently. The last row shows that the agreement between the methods (i.e., the number of students that were classified in the same style by both methods) barely exceeds random chance. For the Sensory-Intuitive dimension, only 50.8% of students were classified in the same style by the two methods (95% confidence interval: 37.9% - 63.6%). The highest agreement between the ILS and the LSQuiz is for the Visual-Verbal dimension, with 58.7% (95% confidence interval: 45.6% - 71.0%). For the Sequential-Global dimension, the agreement was 54.0% (95% confidence interval: 40.9% - 66.6%). In all cases, the ILS could not predict the students' actual performance (as measured by the LSQuiz) better than 50%, considering the confidence intervals. When the performance in LSQuiz was neutral (i.e., the value of zero in Equation 1), any prediction from the ILS was not considered as an agreement.

Table 6. *The total number of students classified by learning styles through ILS and LSQuiz (N=63). The agreements row (ILS & LSQuiz) shows how many students were categorized in the same way by both methods (e.g. if a student was classified as Visual by ILS and by LSQuiz, he/she was counted in the agreements row)*

Classification by	Sensory	Intuitive	Visual	Verbal	Sequential	Global
ILS	31	32	37	26	34	29
LSquiz	37	24	37	26	51	12
ILS & LSQuiz	19	13	24	13	28	6

On its turn, Table 7 shows the Pearson correlation between the ILS and LSQuiz data for each one of the three learning styles dimensions addressed in this study.

Table 7. *Pearson correlation between the ILS and LSQuiz data for each one of the three learning styles dimensions addressed in this study. The average column shows the overall correlation, considering all dimensions*

	Sensory Intuitive	**Visual Verbal**	**Sequential Global**	**Average**
Coefficient	0.354	0.507	0.760	0.540
p-value	0.353	0.506	0.760	0.539

As explained by Mukaka (2012), the rule of thumb for interpreting the size of a correlation coefficient is: .00 to .30, negligible correlation; .30 to .50, low correlation; .50 to .70, moderate correlation; .70 to .90, high correlation and; .90 to 1.00, very high correlation. Usually, .70 is the minimum acceptable correlation suggested in the literature. On this way, it is possible to state the ILS and LSQuiz data has, for the Sensory-Intuitive dimension, a low correlation; for the Visual-Verbal, a moderate correlation (although in the borderline to the low correlation) and; the Sequential-Global, a high correlation – the only dimension with a coefficient above 0.7.

ILS Internal Consistency

As described in the methodology section, the ILS data from 123 students were used to calculate the Cronbach's alpha and the Split-half reliability test. The analysis was performed with the statistical software R. We obtained internal consistencies that varied from 0.51 to 0.78 (considering 95% confidence intervals) for most of the learning styles dimensions (Table 8). These values are within the ones previously reported in the literature. For the Sequential-Global dimension, our Cronbach's alpha is considerably lower. Interestingly, however, our results were similar when we considered two different methods to measure internal consistency, which strengthens cross-validation between methods.

Table 8*. ILS Internal Consistency for participant students of the Introductory Physics course (N = 123)*

	Active – Reflexive	Sensory – Intuitive	Visual – Verbal	Sequential – Global
Cronbach's Alpha	0.62	0.70	0.62	0.30
Cronbach's Alpha *95% confidence interval*	*0.52 – 0.71*	*0.62 – 0.78*	*0.51 – 0.70*	*0.04 – 0.48*
Split-half reliability index	0.62	0.69	0.61	0.30

DISCUSSION AND CONCLUSIONS

The Felder & Silverman learning styles model (FSM) has been widely employed to better comprehend and improve learning in the fields of Science, Technology, Engineering, and Math (STEM). The FSM assumes that students have learning preferences regarding how the information is obtained, processed, perceived and understood. In order to classify students in these four dimensions, the index of learning styles (ILS) – an online questionnaire composed of 44 questions – has been proposed (Felder & Soloman, 2000). Although FSM is very attractive, it lacks experimental validation, and questions about how learning styles information can be used to further improve learning are still subject to debate.

Our study hypothesized that the FSM could be predictive of students' performance in an Introductory Physics course. If valid, it would allow the design of novel educational approaches, such as Ubiquitous Computing systems focused on the personalization of learning. In this context, Physics is a discipline with great potential because, in addition to a broad demand of learning, several active learning approaches have been successfully developed already, such as the Peer Instruction (PI). Therefore, in this work, we developed an online software able to predict students' learning styles based on students' performance in general Physics questions (LSQuiz). The LSQuiz is a plugin designed specifically for the Moodle platform and was tested in an Introductory Physics course designed with PI.

The first difficulty that arises with the FSM is the classification of learning preferences. The original guidelines of criteria established for each style and dimension are subjective. In order to overcome misinterpretation, we developed a Learning Styles Classification Method (LSCM). Our approach is based on the subject's interpretation followed by a group discussion to establish common criteria for classification, thus providing more objective guidelines and criteria to categorize questions through Learning Styles. We consider the number of volunteers that participated in the LSCM development (N = 14) was sufficient to reach a minimum consensus about the criteria to how to classify questions. Based on this approach, we classified all 181 Physics questions that students answered online during the course. We then assessed the students' learning styles through the LSQuiz, ILS, and compared the results.

The original purpose of the FSM was to provide instructors with a priori knowledge of students' learning styles, which could be used later by the instructor to support and even adapt his/her teaching according to the class styles.

Overall, as presented in Table 7, we found a moderate correlation between the ILS and the students' performance (as measured by the independent classification with the LSQuiz), with a Pearson's correlation coefficient of 0.54 – below the .70 usually accepted in literature. These data are corroborated by the individual analysis presented in Table 6, which shows that the ILS could not predict a student's actual performance, as measured by the LSQuiz, better than random.

However, when independently analyzing the learning styles dimensions, it is possible to identify that the correlation is greater in some dimensions (especially Visual-Verbal, with a 0.50 coefficient, and the Sequential-Global, which has a 0.76 coefficient) and smaller in the Sensory-Intuitive, which has a 0.35 correlation. Indeed, when the Sensory-Intuitive dimension is not considered, the Pearson's correlation coefficient is 0.633, a still moderate correlation, but closer to the 0.70 thresholds.

It is important to state, however, that the results related to the Sequential-Global dimension are not supported by the internal consistency of the ILS identified in the literature (ranging from 0.41 and 0.56, as shown in Table 1) and in this study (0.30, as shown in Table 8). Therefore, although we found a high correlation between the ILS and LSQuiz in the Sequential-Global dimension, the ILS low consistency in this dimension makes the results unreliable.

When considering the Visual-Verbal dimension, the literature presents an ILS Cronbach's alpha internal consistency ranging from a 0.56 to 0.74 (see Table 1), which is consistent to the 0.62 value found in this study (see Table 8). This consistency, although below the 0.7 minimum value suggested by Nunally (1978) and Lance *et al.* (2006), is above the Tuckman's (1999) threshold of 0.50 for attitude tests. Therefore, the Pearson correlation between the ILS and LSQuiz found for the Visual-Verbal dimension could be considered reliable, indicating a moderate correlation between the students' learning styles and their performance in questions classified in this dimension.

Finally, our results suggest that, although in general the correlation between the ILS and the students' performance is not better than random chance, the adoption of customized learning practices – including, but not limited to questionnaires – in the Visual-Verbal dimension have potential and could be the focus of further studies.

Particularly, in this study, we classified previous existing/adopted questions as visual or verbal. As these questions were previously created without prior guidance or standardization, it is possible that their classification was often close to the borderline (i.e., the question could present characteristics of both learning styles), which may have negatively impacted the results.

In future work, it would be possible – through the LCSM designed in this study – to **create** a specific questionnaire, with questions designed from scratch to meet the LCSM requirements and guidelines for the Visual and Verbal learning styles, possibly leading to a higher correlation between the ILS and the students' performance.

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REFERENCES

Araujo, I. & Mazur, E. (2013). Instrução pelos colegas e ensino sob medida: uma proposta para o engajamento dos alunos no processo de ensino aprendizagem de física. *Caderno Brasileiro de Ensino de Física, 30(2): 362-384, agosto de 2013*.

Bamber, D. & Manifold, V. (1978). Evaluation of a method for studying forgetting: Is data from split-half recognition tests contaminated by test interference? *Bulletin of the Psychonomic Society. 11(2):126-128. ISSN= 0090-5054. DOI= 10.3758/BF03336786.*

Bawaneh, A., Zain, A. and Saleh, S. (2011). The Effect of Herrmann Whole Brain Teaching Method on Students' Understanding of Simple Electric Circuits. *In European Journal of Physics Education, 2(2):1-23, ISSN 1309-7202.   Available at: http://www.eu-journal.org/index.php/EJPE/article/view/133. Date accessed: 04 Apr. 2019.*

Bonwell, C.C. & Eison, J.A. (1991) Active Learning: Creating Excitement in the Classroom. *ASHEERIC Higher Education Report No. 1, George Washington University, Washington, DC, 1991.*

Caceffo, R. & Rocha, H. (2011). Ubiquitous Classroom Response System: An Innovative Approach to Support the Active Learning Model. *In Ubiquitous Learning: An International Journal*, v. 3, p. 43-55, 2011.

Caceffo, R., Rocha, H. & Azevedo, R. (2011). Ferramenta de apoio para o aprendizado ativo usando dispositivos com caneta eletrônica. *Em Revista Brasileira de Informação na Educação*, v. 19, p. 25-41, 2011.

Caceffo, R. & Rocha, H. (2012). Design and Model of a Ubiquitous Classroom Response System Through Context Factors. *In Ubiquitous Learning an International Journal*, v. 4, p. 61-77, 2012.

Caceffo, R. & Azevedo, R. (2014). LSQuiz: A Collaborative Classroom Response System to Support Active Learning through Ubiquitous Computing. *In 11th International Conference on Cognition and Exploratory Learning in Digital Age (CELDA 2014),* Porto, Portugal, October 2014. pp 63-71. ISBN: 978-989-8533-23-4

Caceffo, R. (2015). Arquitetura para Suporte a Aplicações Ubíquas que Viabilizam a Criação de um Ambiente de Aprendizado Ativo em Sala de Aula. Tese de Doutorado. Instituto de Computação da Unicamp - Unicamp. Campinas, SP - Brasil. Fevereiro de 2015.

Caceffo, R., Gama, G. & Azevedo, R. (2018). Exploring Active Learning Approaches to Computer Science Classes. *In Proceedings of the 49th ACM Technical Symposium on Computer Science Education (SIGCSE '18).* ACM, New York, NY, USA, 922-927. DOI: https://doi.org/10.1145/3159450.3159585

Chickering, A. & Gamsom, Z. Seven Principles for Good Practice (1987). *AAHE (American Association for Health Education) Bulletin 39:3-7. Ed 282491.6, 1987.*

Dunn, R., Dunn, K., & Freeley, M. E. 1984. Practical applications of the research: Responding to students' learning styles – step one. *Illinois School Research and Development*, 21(1), 1 – 12.

Felder, R. M. & Silverman, K. (1988). Learning and teaching styles in engineering education. *Journal of Engineering Education, 78(7):674–681*

Felder, R, M. & Soloman, B. (2000). Index of Learning Styles. Retrieved February 10, 2019, from *http://www.engr.ncsu.edu/learningstyles/ilsweb*

Felder, R, M. & Soloman, B. (2015). Learning Styles and Strategies. Retrieved February 10, 2019,   from *https://www.amionline.org/Files/Documents/Learning%20Styles%20Explanation%20-%20Felder-Solomon.pdf*

Felder, R. M. & Spurlin, J. (2005) Applications, Reliability and Validity of the Index of Learning Styles. *International Journal Engineering and Education, vol 21, No 1, pp, 103-112, 2005 0949-149x/9*

Geake, J. (2008). Neuromythologies in education. *Educ. Res. 50, 123–133. doi: 10.1080/00131880802082518*

Hall, E. & Moseley, D. (2005). Is there a role for learning styles in personalized education and training. *International Journal of Lifelong Education, 24(3) 243-255.*

Heo, M., Namhee, K., Myles, F. (2015). Statistical power as a function of Cronbach alpha of instrument questionnaire items. *BMC Medical Research Methodology. 15(1):86. ISSN= 1471-2288. DOI = 10.1186/s12874-015-0070-6.*

Herrmann, N. (2000). *The theory behind the HBDI and whole brain technology.* [Online]. [Accessed April 2019]. Available at: http://www.docin.com/p-90989057.html

Kolb, D. A. (1981). Learning styles and disciplinary differences. *The modern American college, 232-255.*

Lance, C., Butts, M., & Michels, L. (2006). The Sources of Four Commonly Reported Cutoff Criteria What Did They Really Say? *Organizational Research Methods Volume 9 Number 2 April 2006 pp202-220 Sage Publications*

Larkin, T. (2000). Learning Styles in Introductory Physics: Enhancing Student Motivation, Interest, & Learning. International Conference on Engineering and Computer Education, São Paulo, Brazil, August 2000

Larkin, T. & Budny, D. (2003). Learning styles in the physics classroom: A research-informed approach. ASEE Annual Conference Proceedings.

Larkin, T. & Budny, D. (2004). "Learning Styles: Applications in the Physics and Engineering Classrooms." (2004). Retrieved from: https://www.semanticscholar.org/paper Accessed: April 2019

Latham, A., Crockett, D., McLean, D. & Edmonds, B. (2009). Using Learning Styles to enhance computerized learning systems. *Proc. 2009 Annual Research Student Conference. Manchester, UK: Manchester Metropolitan University.*

Latham, A., Crockett, K., Mclean, D. & Edmonds, B. (2012) A conversational intelligent tutoring system to automatically predict learning styles. Computers & Education – An International Journal 59(1):95–109. Elsevier.

Livesay, G., Dee, K., Neuman, E., Hites, L. (2002). Engineering Student Learning Styles: A Statistical Analysis Using Felder's Index of Learning Styles. *Annual Conference of the ASEE, Montreal, Quebec, June 2002*

Litzinger, T., Lee, S., Wise, J., Felder, R. (2005). A study of the reliability and validity of the Felder-Soloman Index of Learning Styles. *Proceedings of the 2005 American Society for Engineering Education Annual Conference & Exposition. American Society for Engineering Education*

Michalos, A. C. (2014) Cronbach's (Alpha) Coefficient. *Encyclopedia of Quality of Life and Well-Being Research. pp1357. Springer Netherlands, Dordrecht. ISBN = 978-94-007-0753-5. DOI=0.1007/978-94-007-0753-5_100818*

Moodle System. (2018) Retrieved February 19, 2019, from https://docs.moodle.org/36/en/About_Moodle

Nunnally, J. C. (1978). *Psychometric theory (2nd ed.)*. New York: McGraw-Hill

Mukaka M. M. (2012). Statistics corner: A guide to the appropriate use of the correlation coefficient in medical research. *Malawi medical journal: the journal of Medical Association of Malawi*, *24*(3), 69–71.

Önder, F., & Silay, İ. (2015). The importance of learning styles to form more successful cooperative groups in a physics course. European Journal of Physics Education, 6(4), 1. Retrieved from https://doi.org/10.20308/ejpe.48367

Tuckman, B.W. (1999). *Conducting Educational Research, 5th ed.* Wadsworth Group.

Warrens, M. J. (2015). On Cronbach's Alpha as the Mean of All Split-Half Reliabilities. *Quantitative Psychology Research: The 78th Annual Meeting of the Psychometric Society. Springer International Publishing, Cham. pp293-300. ISBN= 978-3-319-07503-7. DOI = 10.1007/978-3-319-07503-7_18*

Watkins, J. & Mazur, E. (2013). Retaining Students in Science, Technology, Engineering, and Mathematics (STEM) Majors. *Journal of College Science Teaching, Vol. 42, No. 5, 2013.*

Weiser, M. (1993). Some computer science issues in ubiquitous computing. Communications. ACM 36, 7 (July 1993), 75-84. DOI=http://dx.doi.org/10.1145/159544.159617

Zajacova, B. (2013). Learning Styles in Physics Education: Introduction of Our Research Tools and Design, In Procedia - Social and Behavioral Sciences, Vol 106, 2013, pp1786-1795, ISSN 1877-0428, https://doi.org/10.1016/j.sbspro.2013.12.201.

Zingaro, D. & Porter, L. (2014). Peer Instruction in computing: The value of instructor intervention. *Journal of Computers & Education. Volume 71, February 2014, Pages 87-96, Elsevier Science Ltd. Oxford, UK.*

Zwanenberg, V., Wilkinson, L. & Anderson, A. (2000). Felder and Silverman's Index of Learning Styles and Honey and Mumford's Learning Styles Questionnaire: How do they compare and how do they predict? *Educational Psychology, 20 (3), 365–381.*

Zywno, M.S. (2003). A Contribution of Validation of Score Meaning for Felder-Soloman's Index of Learning Styles. *Proceedings of the 2003 Annual ASEE Conference. Washington, DC: ASEE*