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Relationship Between Learning Styles and Learning Objects:
A Systematic Literature Review

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ABSTRACT

The automation of learning object recommendation and learning styles detection processes has attracted the interest of many researchers. Some works consider learning styles to recommend learning objects. On the other hand, other works automatically detect learning styles, analyzing the behavior of students in intelligent tutorial systems in relation to the use of learning objects. Taking into account that advances in this field of research have been constantly presented in recent years, this paper analyzes the results of works discovered through a systematic literature review. The main objective was to discover and document the relationships between learning styles and learning objects considered by researchers in order to provide accurate content recommendations. The results show inconsistencies in the process, indicating that more and more in-depth research is still needed to allow a more accurate understanding of how to consider learning styles in the learning object recommendation process.

KEYWORDS

Adaptative Learning, E-Learning, Educational Research, Educational Technologies, Intelligent Tutorial System, Literature Review, Recommendation System

INTRODUCTION

Distance Education (DE) is highly investigated in literature with several proposed approaches, such as the adaptation of teaching. Perhaps, one of the most important goals in adapting the teaching-learning process is to provide coherent environments considering students' individual learning preferences and interests, as reported by Moraes *et al.* (2020) and Correa *et al.* (2020). Therefore, the adaptation of the teaching-learning process is a potential area to promote the improvement of Distance Education.

Learning Styles (LS) and Learning Objects (LO) are two important concepts related to the adaptability of teaching. According to Felder et al. (1988), Learning Styles are the student's individual learning preferences defined according to each individual's mode of perception, information

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processing, and problem solving. On the other hand, Learning Objects refers to the instructional actions indicated to the students, i.e., educational resources, such as videos, images, lectures, games, among others. Learning Objects have the potential to motivate students in the learning process and promote meaningful teaching (Nafea et al., 2019). Sensuse *et al.* (2020) point out that presenting different Learning Objects to students is one of the ways to identify the student's Learning Styles. The authors also comment on the complexity of taking into account the students' different characteristics and learning needs in the teaching-learning process. They highlight that the adaptation of teaching through Learning Styles and Learning Objects can considerably impact the student's teaching process and as a result, its performance.

Several researches addressing teaching personalization associate Learning Styles and Learning Objects, i.e., content is presented to the student through Learning Objects that meet the preferences dictated by the student's Learning Styles. In this context, Intelligent Tutoring Systems provide adaptive learning environments that operate from this perspective. Other factors are considered to facilitate the adaptation of teaching and learning, such as the student's context, knowledge and technology in use.

In this context, Learning Styles and their effects on the learning process are carefully examined by Coffield et al. (2004). Learning Styles and their corresponding instructional strategies have been intensively studied. Researchers in this field affirm that relating students' Learning Styles with appropriate instructional actions is relevant to the stimulation of the learning process. Studies attest that learning becomes more effective if the teaching methods are in accordance with students' Learning Styles (Haider et al. 2010; Graf et al. 2008; Liu et al. 2009; Alfonseca et al. 2006). Considering distance education and its challenges (Stella & Gnanam, 2004), providing personalized content based on Learning Styles in virtual learning environments helps to improve the effectiveness of the learning process, as attested by Liu et al. (2009).

Therefore, given the expressive growth in the quantity of works addressing Learning Styles and Learning Objects, this article seeks to understand how the research is evolving around these two themes. In literatura, the Learning Styles and Learning Objects are applied in different approaches (Junior *et al.* 2019; Joshi, 2020; Moraes *et al.* 2020; Pardamean *et al.* 2021). One of them is in detection of the student's Learning Styles and subsequent recommendation of Learning Objects, as noted in Wenger (2014); Peña et al. (2002); Nafea et al. (2019); Rasheed *and Wahid* (2021) . Another approach is the detection of the student's Learning Styles from the verification of the Learning Objects accessed during the pedagogical trajectory, as discussed by Franzoni et al. (2008) and Kolekar et al. (2017). According to Sáiz-Manzanares et al. (2021), considering Learning Styles does not guarantee, by itself, teaching effectiveness. In this sense, they point out that the combination with other factors is relevant for the success of the teaching-learning process.

Thus, this study focuses on understanding how the relationship between Learning Styles and Learning Objects emerge in aforementioned contexts. In order to achieve this goal, a Systematic Literature Review (SLR) has been developed to present a mapping of which educational resources are most related to certain student profiles. Afterwards, this work proposes a way to relativize the adequacy of different kinds of Learning Objects considering each Learning Style, associating weights to them. The computation of weights is defined from the frequency that the relationship is detected in articles identified along the Systematic Literature Review.

As a result, this work provides a detailed direction on how different types of Learning Objects are related to different Learning Styles. These relations are presented further in this paper, and it can be used by learning environments to automatically recommend Learning Objects that best fit to each student by choosing those with higher weight considering specific students' Learning Styles. Consequently, this classification of Learning Objects types considering how much they fit to each Learning Styles can support adaptivity in learning environments, which is a relevant contribution to this research field.

This work is organized as follows: section 2 discusses the works related; the research method adopted in this work, Systematic Literature Review, is presented in section 3; and the results and discussions are shown in section 4. Finally, section 5 presents the final considerations and indications for future work.

RELATED WORKS

Content recommendation according to student profile is a potential field for improving learning in Intelligent Tutoring Systems. Firstly, this section presents related works that use Systematic Literature Review to investigate Learning Objects and Learning Styles relations. Such studies differ from the proposal presented in this work in terms of scientific questions, databases used, and strategies adopted to accomplish the review. Subsequently, the works that address the recommendation of personalized content, that is, an indication of educational resources appropriate to students' Learning Styles, are presented. Some analysed works also aim to predict students' Learning Styles according to the educational resources accessed.

The application of custom recommendation in the educational context is receiving increasing attention due to its potential to increase the engagement of students in Virtual Learning Environments (VLE), maximizing the efficiency of instructional systems.

Valaski et al. (2011) analyze the models of Learning Styles used to adapt learning resources relying on works published between 2005 to 2011, and the research shows that the most used models (in order of precedence) were: Felder and Silverman, Kolb, Vark and Keefes. However, the data obtained throughout this research does not allow us to combine Learning Objects and Learning Styles. The authors present only the general characteristics of a restricted set of educational resources that fit each Learning Style. The authors do not explore the association between Learning Styles and Learning Objects in a quantitative way, which is the main differential of our work.

In a broader perspective than the work developed by Valaski et al. (2011), the Systematic Literature Review developed by Nascimento et al. (2017) identified: a) Learning Styles models used during the process of automatic and personalized content recommendation; b) verification of the adopted Learning Object metadata standards; c) Virtual Learning Environments; and, d) support mechanisms applied in the context of adaptive learning resource recommendation. Nascimento et al. (2017) considers works published from 2002 to 2016. The results indicated the predominance of the Felder and Silverman model, in accordance with the results reported by Valaski et al. (2011). Other Learning Styles models mentioned in the literature are Kolb, Vark & Honey-Alonso.

Correa et al. (2020) carried out a systematic review between 2010 and 2019 focusing on mobile and ubiquitous learning. The objective was to verify which factors are applied in this field in order to make the learning process more contextualized. They highlight Learning Styles together with personal and teaching information, as the second criteria most used in the context of mobile and ubiquitous learning. Thus, the analysis between 2010 and 2019 indicates that the concept of Learning Style is relevant in the literature.

The relationship between Learning Objects and Learning Styles is approached in different ways. Sensuse et al. (2020) carried out a systematic literature review to map the Learning Styles and the respective Learning Objects. The text relates LS and LO, focusing on impacts and different personalization strategies. However, the time window considers the period from 2013 to 2019, with only 15 works being analyzed.

Raj and Renumol (2018) state that personalization of a learning environment through the recommendation of Learning Objects according to Learning Styles should focus primarily on the mapping between Learning Styles and Learning Objects. Following this principle of mapping, other works present a similar approach.

Arias et al. (2009) provide content adaptation in accordance with Learning Styles and Learning Objects. In order to promote content adaptation, two tables are designed according to Felder and Silverman's Learning Style model and student analysis. The first table lists Learning Styles and resource types. The second is based on the association between Learning Style and Learning Object formats. These tables are important to guide the process of content adaptation.

Nafea et al. (2019) and Aissaoui and Oughdir (2020) also present a mapping between Learning Objects and Learning Styles for content personalization. The first work explores similarity measures to recommend Learning Objects according to the student's Learning Style. The second work proposes an ontology-based recommendation system to detect the student's Learning Style based on iteration with the system, and to recommend objects according to their Learning Style.

Differently from the correlated studies found in the literature, this work explores the relationship between Learning Objects and Learning Styles aiming to point out whether this relationship is univocal. It is considered that whenever some Learning Objects correlate to a specific Learning Style, the student's Learning Style detection may occur more assertively. In the case of a Learning Object correlating to various Learning Styles, the Learning Objects information for the Learning Style detection process seems to have minor relevance to identify the student's Learning Style, and therefore, the identification may not be accurate.

Other works support the theory of Learning Styles and Learning Objects in the personalization and adaptation of the environment. Abech et al. (2016) explore the use of mobile devices in the field of education. Thus, the authors, convinced that these devices are able to assist students in the teaching-learning process, reconciled the idea of the app with student-related factors, such as their Learning Style, environment and mobile devices. Peña et al. (2002) develop a multi-agent system with the goal to transform the Virtual Learning Environment into an Adaptive Hypermedia System considering Learning Styles.

Méndez et al. (2016) select educational resources stored in repositories according to the student's Learning Style based on the metadata of the Learning Objects, in an attempt to adapt the system to the needs and conditions of students. The title of the work mentions the issue of mapping, but the authors do not present an exhaustive study of mapping between Learning Objects and Learning Styles. Only 14 different types of Learning Objects are listed, based on three other references (Arias et al., 2009; Peña et al., 2002; Rodríguez et al. 2012). The authors aggregate the information in a single table of relationships between Learning Objects and Learning Style.

Rasheed and Wadid (2021) propose a model to detect the student's Learning Style. The proposed approach uses attributes such as student behavior in the online environment. The authors obtained optimistic and promising results, indicating that the prediction was adequate and can then indicate educational resources.

Heng et al. (2021) focus their study in personalized learning and propose the adaptation of teaching offering learning materials according to students' Learning Styles. The results indicated that the correct presentation of Learning Objects can maximize students' learning.

Pal et al. (2021) propose a framework to provide teaching adaptation. It considers a set of modules, including the student's Learning Style. This module, together with student context, education, background knowledge, cognitive ability, location, and others, are the factors analyzed to provide personalized teaching. With these factors, it was possible to adapt educational resources according to the students' realities and needs.

The related works demonstrate that the literature focuses on surveys that deal with Learning Styles and Learning Objects for teaching personalization. This observation highlights the greater importance and the validity of this systematic literature review. By developing this study, this work intends to extend the related work focusing on mapping Learning Styles and Learning Objects to customize learning environments, investigating the relationship between Learning Objects and Learning Styles listed in different works, and scattered over several databases.

METHODOLOGY

The Systematic Literature Review (SLR) process proposed by Kitchenham (2004) contemplates three steps and was the chosen method adopted to develop this work. The first step is planning, where research questions are identified and the review protocol is drafted. In the second phase there is the selection of studies, which is guided by the protocol elaborated in the first step. Finally, the third stage analyzes the results and points out where they were reported.

In the planning stage, it is necessary to define a review protocol that specifies the methods that will be used to conduct SLR (Kitchenham, 2004). The elements that make up this protocol are: objective and justification for the research, research questions, strategy used to perform the search for primary studies, and selection and exclusion criteria for papers. The first element to be elaborated is the objective for the execution of the SLR, so this article investigates the relationship between Learning Styles and Learning Objects, during the process of automatic and personalized content recommendation. Thus, the following research questions were outlined:

[RQ] Is it possible to perceive any pedagogical and educational relation between Learning Styles and Learning Objects ?

Some specific questions (SQ), considered to help answering the main question, were:

SQ [1] Are Learning Objects recommendable according to students' Learning Styles considering pedagogical and educational theories available in the literature?
SQ [2] What types of Learning Objects, considering their specific pedagogical and educational characteristics, are best suited to particular Learning Styles?
SQ[3] From the perspective of personalized learning, what are the limitations and difficulties related to this process, considering pedagogical and educational concepts related to Learning Objects and Learning Styles?

To perform this research, the ACM Digital Library, IEEE Xplore Digital Library, Science Direct, Scopus, and Google Scholar databases were used. The period of time considered was between 2002 and 2020. The terms selected for constructing the search string were: (Recommendation OR Personalization OR Indication OR Detection OR Mapping) AND (Learning Objects OR Educational Resources OR Educational Objects) AND (Learning Styles OR Student Profile OR Learning Preferences OR Cognitive Styles). The terms were searched in Portuguese, English and Spanish. The string was calibrated during the research to provide the effective return of studies addressing the subject under study.

After defining the search strategy, it is necessary to analyze the process of discarding unrelated works. In this work, this process consisted of three stages. The first, elimination, was based on the joint reading of the title, abstract and conclusion, since the title usually does not provide sufficient details for the evaluation of the material. Considering that the elimination phase of the work involves the subjectivity of the researcher, the strategy to guide this process was the definition of exclusion and quality criteria. One measure to verify whether or not the work reached the research objective was the definition of 6 quality and exclusion criteria presented in Table 1 and Table 2.

Figure 1 shows the number of works exploring Learning Styles and Learning Objects relationships through the past years. It can be seen a great interest of the academic community about this theme over the recent previous years. It is worth mentioning that the graph demonstrates the number of works that address LO and LS, together, in different paradigms and approaches.

The number of publications follows an increasing order until the period from 2012 to 2016. The drop in the number of publications associated with the subject under study may be justified due to critics raised on the theory of Learning Styles. Some researches, Kirschner (2017), Rohrer and

Table 1. Quality Criteria

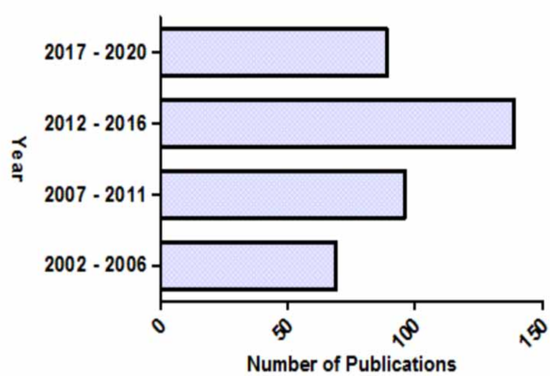
Is the direct association made between Learning Styles and Learning Objects?
Does it contain useful information that can be used to help answer research questions?
Does it propose to designate resources according to the student's Learning Styles?
Is there any perceived limitation regarding the recommendation of Learning Objects?
Are students' Learning Styles identified from the Learning Objects accessed?
Is the approach proposed in the paper clear and is the path that led to the results obtained transparent?

Table 2. Exclusion Criteria

Specific approach on methods and techniques for detecting Learning Styles.
Languages other than English, Portuguese and Spanish.
Does it propose to assign resources according to the student's Learning Styles?
Duplicate studies from the same or different bases.
Specific research niche.
The process to identify the student's Learning Styles was not automatically performed or the work used questionnaires to identify the Learning Styles without using computational techniques.

Pashler (2012), Dekker et al. (2012), Costa et al. (2020) indicate the ineffectiveness of considering LS in the teaching-learning process, with the following arguments being pointed out: generalization of ineffective learning modes, dichotomies that do not include all the characteristics of a student, lack of studies that prove the accuracy of the applicability of the approach, among others.

Figure 1. Relation of recovered results to the corresponding years.



After completing the first step of the review, the next step is Conducting. Thus, the works kept in the first phase (title and abstract) were eliminated by diagonal reading and, subsequently, by the complete reading. Figure 2 points the number of discarded works in each phase of the elimination process. Figure 2 was created from the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) recommendation to better describe the steps adopted in this systematic literature review. According to Page et al. (2021), the PRISMA recommendation aims to guide the scientific community in reporting the steps performed during the systematic review preparation. PRISMA is considerably used by the scientific community, given its various benefits, such as allowing clear and concise revisions.

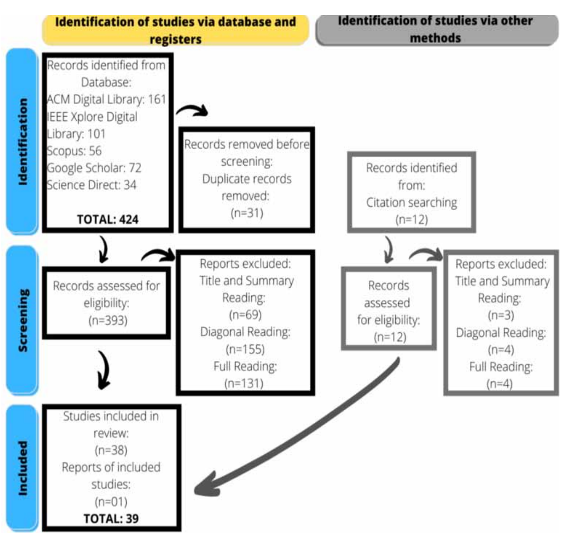
A total of 424 works were retrieved as described as follows: 161 from the ACM Digital Library, 101 from IEEE Xplore, 34 from Science Direct, 72 from Google Scholar, and 56 from Scopus. After removing duplicates, 393 works remained.

A precaution to be taken to avoid errors in the implementation of the SLR is to take by definition that a work should be kept for analysis in the next step in case of doubt whether or not it should be removed in the current step analysis. In this sense, 69 works were excluded in the first phase (Title and Summary). The elimination became more expressive in the second phase (Diagonal Reading), where 155 papers were excluded and, finally, 131 papers were discarded with Full Reading. The full elimination process left 39 works to be investigated.

In addition, each reference from all the 393 works were also checked. If any citation met the theme explored in this work, then that work was also retrieved for analysis. In this sense, this process returned 12 publications. The same exclusion criteria explained above were adopted. Thus, title and abstract excluded 03 works while diagonal reading excluded 04 works. The complete reading excluded 04 more records, leaving only one publication to consolidate the results.

The works kept in phase 3 (full reading) were reviewed in order to answer the research questions. Due to the fact that the retrieved publications were in three languages, it was necessary to analyze the nature of each different kind of Learning Object, since different words were used with the same meanings and objectives. The exercise object, for example, was used in the self-assessment, discursive and multiple choice modalities. When different terms were used to characterize the same nature of activity, they were merged and categorized in the same class. Otherwise, if the Learning Objects had different goals, different categories were created. Subsequently, these objects were associated with the students' profiles. Later, these objects were related to specific Learning Styles. This relationship was based on information retrieved from articles that indicated which educational resources were indicated for each student's profile.

Figure 2. The exclusion process performed.



RESULTS

The 39 works recovered in the Systematic Literature Review are based on the Felder and Silverman Learning Style model (FSLSM). The predominance of this model is justified by Valaski et al. (2011), Graf et al. (2009) and Dorça et al. (2016). Among its advantages are the availability and wide range of information dealing with the dimensions of the model and its relationships with the learning resources adapted, also, by the use of the dimensions concept which makes it clearer with more complete information. Thus, given the importance of the FSLSM, the works that used this model were chosen to be analyzed.

The Felder and Silverman model organizes information according to learning dimensions. Information processing refers to the way students act on content, encompassing the dichotomy of Active and Reflective styles. Active students prefer to learn actively, i.e., they tend to learn by acting on the content. In turn, students with reflective profiles choose to process theoretical contents, which favor the exercise of thought to reflect the information transmitted (Felder et al., 1988).

The Model Input dimension integrates Visual and Verbal Learning Style, and is related to how the student prefers to receive information, either by representative visual instruments (Visual Style) or by presenting content via text or audio format (Verbal Style). The Perception dimension is related to how the student perceives content, and includes the Sensitive and Intuitive styles. The Intuitive style configures students who prefer content that induces abstraction, reflection and imagination. On the other hand, the Sensitive style characterizes students who prefer to associate the processed information with the real world through practical tests (Dorça et al., 2016), (Heng et al., 2021).

Finally, the Information Organization dimension indicates how the student prefers to receive the evolution and sequencing of the information presented. Sequential style characterizes the student who opts for step-by-step learning, global profile students prioritize navigation autonomously (Felder et al., 1988).

A significant number of publications addressing this topic were found. In general, this work discusses the content adaptation according to the student's Learning Style and the detection of the Learning Style according to the Learning Objects accessed.

The present work uses a descriptive statistical analysis of the collected data to answer the research questions. The analyses performed in this work aim to measure the characteristics of the elements of the population composed by the 39 evaluated works. Thus, each work retrieved was analyzed qualitatively and quantitatively (depending on the essence of the research question).

Our statistical analysis started by listing all the kinds of Learning Objects cited in all the 39 retrieved works. All kinds of Learning Objects were cataloged and due to the fact that the retrieved works were in three languages, it was necessary to analyze the nature of each Learning Object, since, in general, different words were used with different meanings and objectives. When different terms were used to characterize the same nature of activity, they were merged and categorized into the same class. In turn, if LO had different objectives, different categories were created. In this sense, 44 LO were identified, according to Table 3.

Figure 3 shows the frequency of Learning Objects in relation to each specific Learning Style. These frequencies were calculated by counting the number of LO associated to each LS.

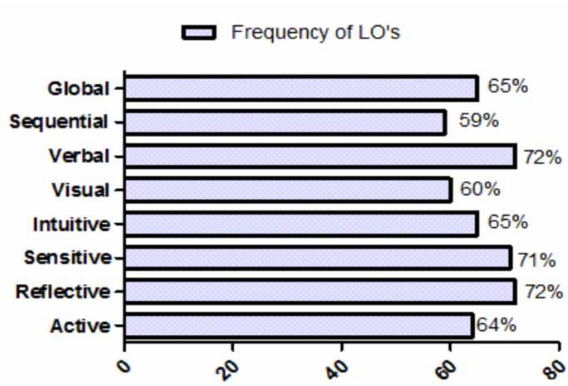
The initial results drawn from Table 3 and Figure 3 allowed us to answer our first specific research question: **SQ [1] Are Learning Objects recommendable according to students' Learning Styles considering existing pedagogical and educational theories available in the literature?**

The results presented in Figure 3 show that all Learning Styles are related to several Learning Objects. Therefore, pedagogical and educational theories are taken into account, as the intention is to provide learning resources that correspond to the needs of each student's profile. The association between the two elements is not performed randomly, but on the contrary: educational resources are indicated according to the student's learning preference. In addition, the graph shown in Figure 3 shows that there are no significant differences between the number of objects retrieved for each style, and no style stands out in the number of associated Learning Objects.

Table 3. Learning Objects retrieved

Animations	Questions and Answers
Real Life Application	Multiple Choice Exercises
Audio (sound)	Discursive exercises
Assessments (exams, tests)	Step by step exercises
Brainstorming	Explanations
Case Study	Facts and Practical Materials
Chat	Forums
E-mail	Glossaries
Problem statements (problem statements)	Graphics (sketches)
Definitions	Images (figures)
Demonstrations / Experiments	Games
Diagrams	Lesson
Group Discussion	Lists (topics)
Examples	Overview Map
Practical exercise	Concept maps
Self Assessment Exercises	Maps
Read and solve	Web pages (wikis)
Lectures	Quizzes
References (Assignments, Sequences)	Summaries
Simulations	Slides and Presentations (slide index)
Educational Software	Tables
Narrative Texts (readings, narratives, texts)	Vídeos (movies)

Figure 3. Ratio of Learning Objects meeting specific Learning Styles.



From the retrieved works, there is a significant number of researches discussing the adaptation of contents according to the student's profile. Different approaches and methods, in addition to the research focus specified in this paper, are discussed, such as the focus on inclusive learning and the recommendation of Learning Objects according to the technology used by the student. Thus, it is noticeable that the theme in question is a research area of great interest in the academic community. The authors agree that adaptability of teaching is essential to ensure effective and personalized learning, as well as to enhance the student's chances to complete the course (Zaina, 2010; Franciscato et al., 2008).

Next, the subsequent question was **SQ [2] What types of Learning Objects, considering their specific pedagogical and educational characteristics, are best suited to particular Learning Styles?** Knowing that it was possible to map the Learning Object to the respective Learning Style, and that the association between the two items is made in order to offer contents to students effectively taking into account their Learning Styles, the mapping was built generating the relative graphics with each dimension profile.

The mapping between Learning Objects and Learning Styles was carried out from a quantitative analysis, by counting the number of LO corresponding to each LS. Descriptive statistical analysis was again used to process the retrieved data. In this sense, Figure 4 shows the number of Learning Objects retrieved for each Learning Style in the Felder and Silverman model. One can verify that all student profiles are assisted by educational resources.

An interesting fact is that results demonstrated that a kind of LO can be associated with different learning styles in the same dimension. For example, the same kind of educational resource can be associated with the active and also reflective style, in different recovered works. Thus, it is not possible to talk about a unique relationship in each dimension, since most LO meet two or more student profiles with contrary learning predilections. Figure 4 shows the number of LO retrieved for each LS, as well as the intersection values that represent the number of educational resources that meet both styles in the same dimension. The value of intersections are considerable in all four dichotomous dimensions, that is: Active x Reflective, Sensitive x Intuitive, Visual x Verbal, Sequential x Global. Thus, it can be concluded, according to the retrieved works, that the same Learning Object can be suitable for different Learning Styles. In this context, it is impracticable to determine a search for the educational resource considering a specific preference.

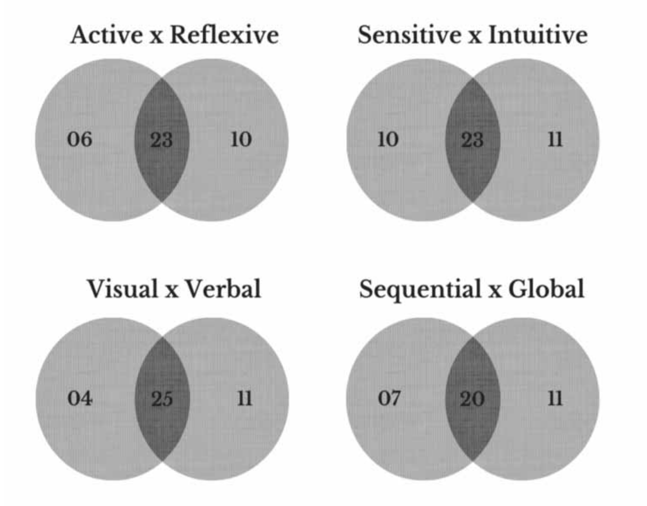
In the Processing dimension, which includes the Active and Reflective styles, 23 educational resources meet both profiles. This indicates that of the total Learning Objects recovered for Active Style (29 learning objects), 79% of them are also associated with Reflective Style. This index is also significant in the Reflective Style, where 69% of LO are also related to the antagonistic style of its dimension. In the Input dichotomy, 89% of Visual Style digital resources are associated with Verbal Style, the latter having 69% of common LO. The intersection of Visual Style is alarming, as only 11% of educational resources are specific to this profile. Therefore, predicting a student's Learning Style based on the accessed Learning Object would be an ineffective method as it would present several inconsistencies.

The Sensitive and Intuitive Styles of the Perception dimension also had considerable intersections, 72% of the Learning Objects indicated to the sensitive students are similar to the opposite dimension. The intersection of the Intuitive Style reaches 80%, meaning that more than half of the educational resources indicated for its profile are also being associated with the Sensitive Style. However, in Sequential and Global styles, the same fact was observed, and in Sequential Style the intersection reached was 74% and 64% in Global Style.

According to the intersections of each Learning Style, it is possible to see that in all cases, more than half of Learning Objects are indicated to different profiles of the same dimension. Figure 4 shows how considerable the intersection is when considering the relation between Learning Styles and Learning Objects.

Based on the concept of Learning Styles, it is understandable that it configures students' individual learning characteristics. When associating Learning Styles with Learning Objects types,

Figure 4. Number of intersections of LO in relation to the dimensions of FSLSM.



it is expected that the indicated educational resource conforms to the learning characteristics dictated by a specific Learning Style. If these resources are not unique to each profile, it can be stated that this association presents inconsistencies in the Learning Object recommendation process. Thus, the following question is put: to what extent is the Learning Object a classifier of the student profile to assist in the prediction of Learning Style? Or to the contrary, to what extent is the Learning Style a student profile classifier for Learning Object recommendation?

The fact that the same educational resource meets Learning Style of the same dimension questions the effectiveness of prediction, since from the 44 Learning Objects retrieved in this review, only 22% of this total are unique to certain LS. Thus, ensuring the prediction of LS, based on its own, monitoring access to learning resources may not guarantee effective identification of LS. It is known that adapting an Intelligent Tutoring System goes beyond the recommendations and presentations of LO. There are other factors used to understand student behavior and provide more effective personalization of the environment, as found in the work of Yannibeli, Godoy and Amandi (2006). However, the importance of the LS and LO in this process is undeniable. Thus, this work presents results that raise important questions.

The last specific research question **SQ[3] From the perspective of personalized learning, what are the limitations and difficulties related to this process considering pedagogical and educational concepts related to Learning Objects and Learning Styles?**, brings out the following considerations.

- **Basic knowledge of the student:** The basic knowledge of the student, internalized in his/her school career in basic education, influences the progress of the student in a technical and/or higher level course. Therefore, the domain of basic concepts drastically influences the understanding capacity of more complex contents. This would trigger a misinterpretation of the effectiveness of education, since the failure of the student will not be caused due to the system's personalized recommendation, but due to the absence of the necessary basic knowledge.
- **Possibility of inconsistencies during the Learning Style detection:** In general, the LS prediction is performed only once and no further investigations are done. This limitation becomes a great problem due to potential changes of students' learning preferences throughout their school careers.

- **The importance of capturing students' context:** Individual students' information and learning sessions conditions are important, so that the presented educational resources are supported by the technology available to them.
- **Evaluation of the quality and effectiveness of Learning Objects:** Taking under consideration the popularity and effectiveness of the recommended educational resources for a given student allows us to evaluate the potential of the LO for a particular LS.
- **Shortage of in-depth studies that establish the relationship between a Learning Style and the Learning Object:** with the searches performed from the application of the literature review method, it was possible to recover a total of 353 works that had the theme of the LO and the LS. However, in only 39 of them, considered in this review, it was possible to remove information about the direct relationship of a LO and an LS. The literature includes research that describes the architecture of content personalization but does not delve into the relationship between the student's profile and the recommended learning resource.

The listed difficulties corroborate with Kirschner (2017), Li et al.(2016) and Costa et al.(2020). After the publication of these works, there was a disbelief in the use of learning Styles and a reduction in the number of publications in the area, as shown in Figure 1. For Kirschner (2017), the classification of a student in a specific and distinct style can be exclusionary. Thus, differences between people in any dimension of style are gradual and not nominal. Moreover, Li et al. (2016) admits that Learning Styles are being used in a disorganized way and for this reason has become a myth in literature. Costa et al. (2020) indicate that there is no relationship between Learning Styles and student behavior in learning environments.

The results obtained with the systematic review of the literature demonstrate a great deal of research involving the use of Learning Style and Learning Objects in personalization of virtual learning environments, but there is an absence and need for further study of the relationship between these two concepts for more effective results.

In addition, the Felder and Silverman Learning Styles Model ensures that the student's Learning Style is not nominal but gradual within the dichotomies of each dimension of the model, as suggested by Kirschner (2017). To enhance the personalization process, this work proposes that, just as Learning Styles are gradual, Learning Objects are also gradually related to Learning Styles.

Finally, with the achieved results, it is possible to answer the main research question: **[RQ] Is it possible to perceive any pedagogical and educational relation between Learning Styles and Learning Objects ?**

After answering the specific research questions, it can be concluded that there is a pedagogical and educational relation between Learning Objects and Learning Styles. SQ[1] collaborates by demonstrating that there is a set of Learning Objects associated with each Learning Styles. All Learning Styles had a significant number of associated types of Learning Objects. However, the SQ[2] demonstrated that there is no consensus among the works retrieved, regarding the construction of these relationships. In short, results demonstrated that the LO can be associated with two styles of the same dimension.

Thus, it can be concluded that this relationship should not be seen in a binary way, but in a gradual way, in which an object can favor, to some degree, different Learning Styles. This idea is in line with the proposal of the Felder and Silverman Model that ensures that the student's Learning Styles is not nominal, but gradual within the dichotomies of each dimension of the model.

These adjustments in the process can improve the adaptability of the environment and, linked to other factors such as the student's context, location, hardware, cognitive ability, students' prior knowledge, can mitigate some of the limitations of the learning personalization process based on the relationship between LO and LS, mentioned in the response to SQ[3].

Thus, the second stage of this work focuses on finding a way to weigh the relevance of each educational resource. The proposed calculation is based on the number of occurrences that a given

Learning Object has been linked to a Learning Style. From this perspective, Equation 1 was defined to weigh the relevance of a Learning Object for each Learning Style.

$$w_{ei} = \frac{x_{ei}}{\sum_{n=1}^{8} x_{en}} \tag{1}$$

Where:

w_{ei} the weight of the Learning Object *e* associated with the Learning Style *i*.

x_{ei} it is the frequency of the educational resource *e* in a specific Learning Style *i*.

x_{en} it is the sum of the frequency of the Learning Object *e* in all dimensions (8 dimensions) of the Learning Style.

The relationship between the weights found can be seen in Table 4. In practice, weights can be relative in the context of detecting Learning Style or in recommending content. The calculation to obtain the weights was performed based on the ratio between the number of occurrences of a specific learning object recovered in a specific LS and the sum of the frequency of this same object considering all LS. The frequency data come from the mapping carried out between each style and educational resource. This mapping is derived from the information collected from the articles retrieved in this review.

In this context, Table 4 gives a direction on how different types of Learning Objects are related to different Learning Style. For example, considering audio Learning Objects, they fit Sensitive and Verbal Learning Styles with weights of 0.20 and 0.80 respectively. Therefore, it can be affirmed that audio Learning Objects are well fitted to Verbal Learning Style, and less fitted to Sensitive Learning Style, and non fitted to the other Learning Style. The same analysis is considered for the other Learning Objects types. Considering that Table 4 covers a huge diversity of different Learning Objects types, it can be used by learning environments to automatically recommend Learning Objects that best fit to each student by choosing those with higher weight considering specific students' Learning Style. Consequently, this classification of Learning Objects types, considering how fit they are to each Learning Style, can support adaptivity in learning environments, which is an interesting contribution to this research field.

In other words, the weights can be used as the degree of importance of a Learning Object for a particular Learning Styles. For example, although the animation object is present in the Active and Reflective dimensions, weights are called, 4% and 22%, respectively. This indicates that Animation is a type of Learning Object best suited for students with a Reflective profile. In cases where weight has equal value for two dichotomies, this approach is not as efficient.

This work intends to advance with regard to the incorporation of weights related to Learning Objects in the context of detecting students' Learning Styles. These weights are derived from the results of the SRL, therefore, they are based on a scientific study of the literature based on the methodology proposed by Kitchenham (2004).

Table 4. Weight for the learning objects in relation to the learning styles.

Learning Object Type	Active	Reflective	Sensitive	Intuitive	Visual	Verbal	Sequential	Global
Audio	0.00	0.00	0.20	0.00	0.00	0,80	0,00	0.00
Animations	0.04	0.22.	0.04	0.17	0.30	0.04	0.17	0.00
Real Life Application	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Assessments (exams, tests)	0.35	0.15	0.10.	0.05	0.05	0.08	0.10	0.05
Brainstorming	0.25	0.00	0.00	0.00	0.25	0.25	0.00	0.25
Case Study	0.00	0.40	0.20	0.20	0.00	0.20	0.00	0.20
Chat	0.22	0.11	0.22	0.22	0.11	0.11	0.00	0.00
E-mail	0.22	0.00	0.11	0.11	0.11	0.33	0.00	0.11
Problem statements	0.38	0.05.	0.19	0.05	0.05	0.19	0.05	0.05
Definitions	0.00	0.00	0.00	0.50	0.00	0.50	0.00	0.00
Demonstrations/Experiments	0.26	0.13	0.19	0.00	0.26	0.06	0.06	0.03
Diagrams	0.05	0.19	0.15	0.16	0.27	0.08	0.08	0.11
Group Discussion	0.25	0.00	0.00	0.00	0.00	0.75	0.00	0.00
Examples	0.12	0.20	0.10	0.15	0.12	0.10	0.10	0.12
Practical exercise	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Exercise	0.30	0.09	0.06	0.09	0.09	0.11	0.15	0.13
Self Assessment Exercises	0.25	0.11	0.07	0.11	0.11	0.16	0.09	0.09
Questions and Answers	0.25	0.00	0.50	0.00	0.00	0.00	0.25	0.00
Multiple Choice Exercises	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Discursive exercises	0.13	0.13	0.13	0.13	0.13	0.13	0.08	0.13
Step by step exercises	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
Explanations	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.00
Expressions	0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00
Practical facts and materials	0.00	0.25	0.50	0.00	0.00	0.25	0.00	0.00
Forums	0.21	0.00	0.14	0.14	0.07	0.29	0.00	0.14
Glossaries	0.00	0.20	0.00	0.27	0.00	0.20	0.13	0.20
Graphics (sketches)	0.05	0.20	0.20	0.09	0.25	0.02	0.08	0.12
Images (figures)	0.05	0.05	0.18	0.13	0.44	0.05	0.03	0.08
Games	0.00	0.17	0.17	0.17	0.17	0.00	0.17	0.17
Lesson	0.00	0.40	0.00	0.20	0.00	0.20	0.00	0.20
Read and solve	0.00	0.00	0.50	0.00	0.00	0.50	0.00	0.00
Lists (topics)	0.00	0.31	0.00	0.15	0.15	0.08	0.00	0.23
Overview Map	0.13	0.13	0.00	0.13	0.13	0.38	0.00	0.13
Concept maps	0.14	0.14	0.14	0.14	0.00	0.14	0.29	0.00
Maps	0.17	0.08	0.08	0.00	0.42	0.08	0.00	0.17
Web pages (wikis)	0.10	0.20	0.10	0.00	0.10	0.20	0.15	0.15
Speeches	0.00	0.15	0.15	0.08	0.08	0.31	0.15	0.08
Questionnaires	0.25	0.13	0.18	0.14	0.00	0.25	0.13	0.00
References	0.07	0.11	0.07	0.11	0.15	0.07	0.19	0.22
Abstracts	0.00	0.17	0.00	0.17	0.00	0.17	0.17	0.33
Simulations	0.28	0.11	0.24	0.09	0.19	0.00	0.09	0.00

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Table 4. Continued

Learning Object Type	Active	Reflective	Sensitive	Intuitive	Visual	Verbal	Sequential	Global
Slides and Presentations	0.05	0.22	0.20	0.10	0.15	0.07	0.15	0.07
Educational Software	0.00	0.17	0.17	0.17	0.17	0.00	0.17	0.17
Tables	0.08	0.32	0.20	0.00	0.16	0.16	0.00	0.08
Narrative Texts	0.02	0.33	0.11	0.12	0.02	0.30	0.09	0.02
Videos (movies)	0.11	0.11	0.14	0.09	0.34	0.09	0.06	0.06

CONCLUSION

The purpose of this research was to understand the relationship between the Learning Objects and Learning Styles, having as object of study a set of publications retrieved through the Systematic Literature Review. Thus, when constructing the mapping between Learning Objects and Learning Styles. It was found that there is no Learning Object specific to each Learning Styles. It was also possible to verify the intersection of educational resources present in the same dimension. The obtained values, that is, intersections with values above 60%, made clear the impossibility of using the Learning Styles models for content personalization. The use of this method would bring several inconsistencies in the preference, causing an erroneous personalization.

An interesting contribution of this work is given by Table 4, which provides relations between Learning Objects types and Learning Styles in a quantitative way considering weights that show how much a given Learning Objects type is fitted to a specific Learning Styles. Therefore, it can be used by learning environments to automatically recommend Learning Objects that best fit to each student by choosing those with higher weight considering specific students' Learning Styles. Consequently, this classification of Learning Objects types considering how fit they are to each Learning Style can support adaptivity in learning environments.

Therefore, this work led the way to a new study that was the calculation of weights. Thus, the result achieved offers the academic community a reflection, until then unrealized, of the relevance of educational resources for each student profile. Weights are a new approach in the literature and are a way to promote improvements in the prediction of LS and LO recommendation. These weights can be combined with other factors for personalization of teaching, such as: student context, location, hardware, cognitive ability, students' prior knowledge. More recent approaches include eye movement as a way to predict the student's Learning Style and thus provide greater assertiveness in adapting the content.

Excessive research on the subject over a short period of time has shown that it is necessary to reassess the true essence of providing quality teaching and also consider the effectiveness of Learning Styles in representing students' learning characteristics, as well as rethink and reassess the relationship between Learning Objects and Learning Styles.

As a proposal for future work, the application of weights in an adaptive learning system is a promising search field. Also the study on the insertion of new predictive factors, such as student personality traits, considering that the effectiveness of using only LS is questionable, is another study for exploration.

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