Revista Iberoamericana para la Investigación y el Desarrollo Educativo
ISSN 2007 - 7467

https://doi.org/10.23913/ride.v15i30.2260

Scientific articles

Software de detección de estilos de aprendizaje basado en el modelo de Felder y Silverman

Learning style detection software based on the Felder and Silverman model

Software de detecção de estilo de aprendizagem baseado no modelo de Felder e Silverman

J. Francisco Figueroa-Perez
Universidad Autónoma de Sinaloa, México
juanfco.figueroa@uas.edu.mx
https://orcid.org/0000-0003-1878-4096

Manuel Rodríguez-Guerrero
Universidad Autónoma de Sinaloa, México
manuel.rodriguez@uas.edu.mx
https://orcid.org/0009-0005-5474-8959

Alan Ramírez-Noriega
Universidad Autónoma de Sinaloa, México
alandramireznoriega@uas.edu.mx
https://orcid.org/0000-0002-8634-9988

Yobani Martínez-Ramírez
Universidad Autónoma de Sinaloa, México
yobani@uas.edu.mx
https://orcid.org/0000-0002-4967-9187

Resumen

Los estilos de aprendizaje definen comportamientos característicos que identifican cómo una persona aprende y se adapta a su entorno. Estos proporcionan al docente elementos que pueden orientarlo para crear contenidos pedagógicos y didácticos apropiados y adaptados a las características de los estudiantes, con lo que pueden mejorar su desempeño, consolidando sus procesos de aprendizaje. Este artículo presenta un software de detección de estilos de aprendizaje basado en el modelo de Felder y Silverman para ayudar a identificarlos en un individuo o grupo. El documento describe las funcionalidades, arquitectura, detalles de implementación, y características generales del software. Se proporciona y discute un ejemplo de operación del sistema, así como los resultados de sus pruebas funcionales y no funcionales, los cuales fueron satisfactorios. Se concluyó que el sistema es una herramienta útil para los docentes, facilitándoles la identificación de los estilos de aprendizaje y la personalización de estrategias de enseñanza, lo que mejora el proceso educativo.

Palabras Clave: estilo de aprendizaje, software de detección de estilos de aprendizaje, modelo de Felder y Silverman.

Abstract

Learning styles define characteristic behaviors that identify how a person learns and adapts to their environment. These provide teachers with elements that can guide them in creating appropriate pedagogical and didactic content adapted to the characteristics of students, thereby improving their performance and consolidating their learning processes. This paper presents a learning style detection software based on the Felder and Silverman model to help identify learning styles in an individual or group. The document describes the functionalities, architecture, implementation details, and general characteristics of the software. An example of system operation is provided and discussed, as well as the results of its functional and non-functional tests, which were satisfactory. It was concluded that the system is a useful tool for teachers, facilitating the identification of learning styles and the customization of teaching strategies, which improves the educational process.

Keywords: learning style, learning style detection software, Felder and Silverman model.

Resumo

Estilos de aprendizagem definem comportamentos característicos que identificam como uma pessoa aprende e se adapta ao seu ambiente. Elas fornecem aos professores elementos que podem orientá-los na criação de conteúdos pedagógicos e didáticos adequados e adaptados às características dos alunos, melhorando assim seu desempenho e consolidando seus processos de aprendizagem. Este artigo apresenta um software de detecção de estilos de aprendizagem baseado no modelo de Felder e Silverman para ajudar a identificar estilos de aprendizagem em um indivíduo ou grupo. O documento descreve a funcionalidade, arquitetura, detalhes de implementação e recursos gerais do software. É fornecido e discutido um exemplo de operação do sistema, bem como os resultados de seus testes funcionais e não funcionais, que foram satisfatórios. Concluiu-se que o sistema é uma ferramenta útil para professores, facilitando a identificação de estilos de aprendizagem e a personalização de estratégias de ensino, o que melhora o processo educacional.

Palavras-chave: estilo de aprendizagem, software de detecção de estilo de aprendizagem, modelo de Felder e Silverman.

Reception Date: April 2024 **Acceptance Date:** January 2025

Introduction

Learning Styles (LS) are very important to promote quality teaching. Knowing the predominant LS in students at a given time is essential to adapt Teaching Strategies (TS) to the characteristics they present and thus contribute to raising their learning levels (Cárdenas Palomino et al., 2021) .

Getting students to learn is one of the main objectives of a teacher. However, this is something that is not always achieved. Although everyone is taught the same thing in the classroom, the result is not always as expected. One of the main causes of this problem is that the TSs used to help students learn are not always the most appropriate for their LSs. Therefore, it is not enough for teachers to master the technical aspects of the subject; they must also have tools to achieve the expected learning outcomes (Murcia et al., 2016).

This article presents a Learning Styles Detection Software (LSDS) based on the Felder and Silverman Learning Styles Model (FSLSM). The use of LS detection software has become an essential tool to carry out this task. Thus, in recent years, researchers and some software development companies have introduced this type of software for research or commercial purposes. A review of the background of the period between 2012 and 2022 that included scientific articles, conference papers, books, book chapters, and software tools available on the web yielded a total of 19 works closely related to the inclusion and exclusion criteria (Alghamdi et al., 2013; Bravo & Arias, 2020; Calderón, 2022; Camana , 2017; Carla Maria Alonso Jane, 2019; Céspedes Gómez & Reyes Rivero, 2016; Chablé et al., 2013; Creative Learning Systems , 2020; Cymeon Pty Ltd , 2022; González-Álvarez et al., 2012; Learnstyle , 2022; León & Carrillo, 2012; Núñez Cárdenas, 2013; Palomino-Hawasly et al., 2017; Puello et al., 2014; Rajper et al., 2016; Systems , 2020; World , 2021; Zatarain-Cabada et al., 2013) .

Among the works reviewed, interesting developments can be found at different stages of the period studied. Such is the case of those by Chablé et al. (2013) , Núñez Cárdenas (2013) and Zatarain-Cabada (2013) carried out at the beginning of the period studied. The first proposes an online system to evaluate and detect students' LSs that obtains the EAs using the Honey -Alonso questionnaire. The second focuses on applying data mining techniques to discover the combinations of LSs shown by students and uses the *Visual, Aural, Read / Write , Kinesthetic* (VARK) model and the third presents a system for the recognition of visual affect and learning style using Paul Ekman's seven basic emotions and the FSLSM. In more recent years, the topic has continued to be studied and several important works can also be found. Among them, the commercial software Learning Style Analysis Students (Creative Learning Systems, 2020) stands out, which is based on a proprietary six-layer pyramid model based on brain function and behavior to determine the combination of elements of a human's personal learning style. The commercial software LS Profiler (Cymeon Pty Ltd, 2022), is based on an evidence-based hybrid personality learning model and is suitable for eliciting LS in business, educational, community and clinical contexts. The commercial software RISE (Learnstyle, 2022), is capable of obtaining profiles of individual and group students allowing teachers to have a reference to plan effective instruction, delivery and participation of their class students. Being a commercial software, it does not provide details of the models used. Finally, the application to determine your learning style (Calderón, 2022) is a free desktop software that is based on the Honey -Alonso questionnaire to obtain individual learning styles.

As a result of this review, it was found that the vast majority of software developed so far has been desktop or web applications and that mobile applications available are few. This can be considered relatively normal since web and desktop applications are widely known and used for many years. However, although this type of software has gained ground, its development is still limited. On the other hand, in relation to obtaining LS, it was found that this is done mostly using the Kolb (1984) and Honey and Mumford (1982) models . Thus, software to detect LS faces demands such as:

1. Develop software with cross-platform support to cover a wider variety of modern computing devices, including mobile devices.

2. Incorporate models for obtaining LS that have shown their effectiveness in the literature associated with the subject, but have been little used by the software developed to date.

The literature on LS presents various models that propose various descriptions and classifications of LS. These include, among others, Kolb (Kolb, 1984), Honey and Mumford (Honey & Mumford, 1982) and Felder and Silverman (Felder & Silverman, 1988) .

The LSDS presented in this paper is based on the FSLSM (Felder & Silverman, 1988), which is an LS model designed for traditional learning and one of the preferred models in adaptive educational hypermedia and technology-enhanced learning (Chang et al., 2016; Graf et al., 2007) . Unlike other LS models, such as Honey and Mumford, which only focus on the perception and processing of information, the FSLSM focuses on perceiving, organizing, processing, and understanding information. This identification of the learning style can support a more comprehensive adaptation of the teaching style (Supangat & Mohd Zainuri , 2020) .

According to Supangat & Mohd Zainuri (2020), the FSLSM presents four dimensions of learning style:

- The first dimension of the FSLSM distinguishes between an active and reflective way of processing information. Active learners learn best by actively working with the learning material, applying it, and trying things out. Reflective learners prefer to think and reflect on the material.
- The second dimension of FSLSM covers sensory versus intuitive learning. Sensory learners prefer to feel learning and like to learn facts and concrete learning material. Intuitive learners prefer to learn abstract learning material, such as theories and their underlying meanings.
- The third dimension of the FSLSM, visual-verbal, differentiates between students who remember better and, therefore, prefer to learn from what they have seen, and students who benefit more from textual representations, regardless of whether they are written or spoken.

- The fourth dimension of FSLSM characterizes learners based on their understanding. Sequential learners learn in small, incremental steps and therefore have a linear learning progress. Global learners use a holistic thinking process and learn in large leaps when they tend to absorb learning material almost randomly without seeing connections. However, after they have learned enough material, they suddenly understand the bigger picture.

Individual learning style can be determined by analyzing individual inclination in these dimensions.

Table 1 Felder and Silverman LS model

Dimension	Learning style	Information
Prosecution	Active/Reflexive	How is information processed?
Perception	Sensory/ Intuitive	How is information perceived?
Entrance	Visual/ Verbal	Through what channel is information captured?
Comprehension	Sequential/Global	How is the understanding of the content facilitated?

Source: Felder and Silverman LS model based on Supagat & Mohd Zainuri (2020)

To obtain the LS with this model, the Index of Learning Styles (ILS) is used, which is a tool that allows evaluating learning preferences according to the 4 dimensions mentioned above. This is a questionnaire of 44 questions, where the students' personality preferences for each dimension are expressed with values between +11 and −11 (See Figures 1 and 2).

Figure 1ILS questionnaire

1. Entiendo mejor algo
a) Si lo practico
b) Si pienso en ello

2. Me considero:
a) realista
b) innovador

3. Cuando pienso algo acerca de lo que hice ayer, es más probable que lo haga con base en:
a) una imagen
b) palabras

4. Tengo tendencia a:
a) entender los detalles de un tema, pero no ver claramente su estructura completa,
b) entender la estructura completa, pero no ver claramente los deta

5. Cuando estoy aprendiendo algo nuevo me ayuda:
a) hablar de ello,
b) pensar en ello.

6. Si yo fuera profesor, preferiría dar un curso:
a) que trate sobre hechos y situaciones reales de la vida,
b) que trate con ideas y teorías.

7. Prefiero obtener información nueva de:
a) imágenes, diagramas, gráficas o mapas,
b) instrucciones escritas o información verbal.

8. Una vez que entiendo:
a) todas las partes, entiendo el total,
b) el total de algo, entiendo como encajan sus partes.

9. En un grupo de estudio que trabaja con un material difícil, es más probable que:
a) participe y contribuya con ideas,
b) no participe y sólo escuche

10. Es más fácil para mi:
a) aprender hechos,
b) aprender conceptos.

11. En un libro con muchas imágenes y gráficas es más probab que:
a) revise cuidadosamente las imágenes y las gráficas,
b) me concentre en el texto escrito.

12. Cuando resuelvo problemas de matemáticas:
a) generalmente trabajo sobre las soluciones con un paso a la vez,
b) frecuentemente sé cuáles son las soluciones, pero luego tengo dificultad para imaginarme los pasos para llegar a ellas.

13. En las clases a las que he asistido:
a) he llegado a saber cómo son muchos de los estudiantes,
b) raramente he llegado a saber cómo son muchos estudiantes.

14. Cuando leo temas que no son de ficción, prefiero:
a) algo que me enseñe nuevos hechos o me diga cómo hacer algo,
b) algo que me dé nuevas ideas en que pensar.

15. Me gusta como enseñan los maestros:
a) que utilizan muchos esquemas en el pizarrón,
b) que toman mucho tiempo para explicar.

16. Cuando estoy analizando un cuento o una novela:
a) pienso en los incidentes y trato de acomodarlos para configurar los temas,
b) me doy cuenta de cuáles son los temas cuando termino de leer y luego tengo que regresar y encontrar los incidentes que los demuestran.

17. Cuando comienzo a resolver un problema, es más probable que:
a) comience a trabajar en su solución inmediatamente,
b) primero trate de entender completamente el problema.

18. Prefiero la idea de:
a) certeza,
b) teoría

19. Recuerdo mejor:
a) lo que veo,
b) lo que oigo.

20. Es más importante para mí que un profesor:
a) exponga el material en pasos secuenciales claros,
b) me dé un panorama general y relacione el material con otros temas.

21. Prefiero estudiar:
a) en un grupo,
b) solo

22. Me considero:
a) cuidadoso en los detalles de mi trabajo,
b) creativo en la forma que hago mi trabajo

23. Cuando alguien me da direcciones de nuevos lugares, prefiero:
a) un mapa,
b) instrucciones escritas.

24. Aprendo:
a) a un paso constante; si estudio con ahínco, consigo lo que deseo;
b) en inicios y pausas; me llego a confundir y súbitamente lo entiendo.

25. Prefiero primero:
a) hacer algo y ver qué sucede,
b) pensar cómo voy a hacer algo.

26. Cuando leo por diversión, me gustan los escritores que:
a) dicen claramente lo que desean dar a entender,
b) dicen las cosas en forma creativa e interesante.

27. Cuando veo un esquema o bosquejo en clase, es más probable que recuerde:
a) la imagen,
b) lo que el profesor dice acerca de ella.

28. Cuando me enfrento a un cuerpo de información:
a) me concentro en los detalles y pierdo de vista el total de la misma,
b) trato de entender el todo antes de ir a los detalles.

29. Recuerdo más fácilmente:
a) algo que he hecho,
b) algo en lo que he pensado mucho.

30. Cuando tengo que hacer un trabajo, prefiero:
a) dominar una forma de hacerlo,
b) intentar nuevas formas de hacerlo.

31. Cuando alguien me enseña datos, prefiero:
a) gráficas,
b) resúmenes con texto.

32. Cuando escribo un trabajo, es más probable que:
a) lo haga (piense o escriba) desde el principio y avance,
b) lo haga (piense o escriba) en diferentes partes y luego las ordene.

33. Cuando tengo que trabajar en un proyecto de grupo, primero quiero:
a) realizar una "lluvia de ideas" donde cada uno contribuye con ideas,
b) realizar la "lluvia de ideas" en forma personal y luego juntarme con el grupo para compararlas.

34. Considero que es mejor elogio llamar a alguien:
a) realista,
b) imaginativo.

35. Cuando conozco gente en una fiesta, es más probable que recuerde:
a) cómo es su aspecto,
b) lo que dicen de sí mismos.

36. Cuando estoy aprendiendo un tema, prefiero:
a) mantenerme concentrado en ese tema aprendiendo lo más que se pueda de él,
b) hacer conexiones entre ese tema y temas relacionados.

37. Me considero:
a) abierto,
b) reservado.

38. Prefiero tomar cursos que den más importancia a:
a) material concreto (hechos, datos),
b) material abstracto (conceptos, teorías).

39. Para divertirme, prefiero:
a) ver televisión,
b) leer un libro

40. Algunos profesores inician sus clases haciendo un bosquejo de lo que enseñarán. Esos bosquejos son:
a) algo útiles para mí,
b) muy útiles para mí.

41. La idea de hacer una tarea en grupo con una sola calificación para todos.
a) me parece bien,
b) no me parece bien.

42. Cuando hago grandes cálculos:
a) tiendo a repetir todos mis pasos y revisar cuidadosamente mi trabajo,
b) me cansa hacer su revisión y tengo que esforzarme para hacerlo.

43. Tiendo a recordar lugares en los que he estado:
a) fácilmente y con bastante exactitud,
b) con dificultad y sin mucho detalle

44. Cuando resuelvo problemas en grupo, es más probable que yo:
a) piense en los pasos para la solución de los problemas,
b) piense en las posibles consecuencias o aplicaciones de la solución en un amplio rango de campos.

Source: ILS questionnaire based on Brito-Orta and Espinosa- Tanguma (2015).

Figure 2for the ILS questionnaire evaluation

Activo	11	9	7	5	3	1	1	3	5	7	9	11	Reflexivo
Sensorial	11	9	7	5	3	1	1	3	5	7	9	11	Intuitivo
Visual	11	9	7	5	3	1	1	3	5	7	9	11	Verbal
Secuencial	11	9	7	5	3	1	1	3	5	7	9	11	Global
Perfil de cada estilo ←						Neutro				Perfil de cada estilo →			

Source: Profiles and scores for the ILS questionnaire evaluation based on Prieto (2021).

In this way, and with the aim of providing teachers with a computational tool that allows them to better understand the profile of their students, this research proposes the development of an LSDS as a web application based on Angular with support for multiple computing devices that implements the FSLSM to obtain its LS. With this, teachers will be in a position to better understand the characteristics of their students, allowing them at any given time to adapt their teaching strategies and pedagogical materials to them.

Materials and methods

This research had an applied and quantitative approach, seeking to present a solution to a problem through the use of existing theories and tools, with a descriptive and experimental scope.

To evaluate the software, non-functional and functional testing were performed. Non-functional testing examines the performance of the application in terms of throughput, quality, reliability, scalability, and usability (Desikan & Ramesh, 2006). On the other hand, functional testing ensures that the core functions and features of the application are working properly by testing the core functionality of the software (Desikan & Ramesh, 2006).

To carry out the different tests, non-probabilistic convenience samples were selected from the total population of students in the Software Engineering program at the Mochis Engineering Faculty at the Autonomous University of Sinaloa, considering that the participants, Software Engineering students, have specific knowledge in computer systems testing, which makes them an ideal group for the study, although not representative of a broader population. (Casal & Mateu, 2003). To carry out the tests, a specific activity was designed in the system, which included the following steps:

1. Log in to the software.
2. Answer the FSLSM questionnaire.
3. Review the results provided by the system.

A moderate in-person test was then conducted using computers with Windows 10 and the Chrome 126 browser, in which each session lasted around 15 minutes.

Non-functional testing

To evaluate the usability of the developed software, two widely accepted tools in the literature were selected: the *System Usability Scale* (SUS) and the *Software Usability Measurement Inventory* (SUMI).

SUS is a fast, reliable and standardized method for measuring user satisfaction and perceived usability of a system (Lewis & Sauro, 2009) . It consists of a 10-item survey with five Likert-type response options.

According to SUS, a score above 70 is considered adequate, and usability improves as it approaches 100 points. (Bangor, 2009).

The statements are as follows:

1. «I would like to use this system frequently.»
2. «I found the system unnecessarily complex.»
3. «The system was easy to use.»
4. «I need the support of a technician or specialist to be able to use this system.»
5. «I found the functions of this system to be well integrated.»
6. "There are too many inconsistencies in this system."
7. "I imagine most people will learn to use this system very quickly."
8. «The system is very complicated to use.»
9. «I felt very safe using the system.»
10. «I need to learn a lot of things before I can use the system.»

SUMI is a consistent method for evaluating software quality from the user's point of view. It is used to detect usability flaws before releasing a product (Kirakowski & Corbett , 2006) . It consists of an 8-item survey with five response options.

The Likert scale used for SUMI classifies usability into five categories, where a higher score indicates a more positive perception of the software quality. The scale allows the overall feedback from all student opinions to be visualized in a single number. The SUMI statements are as follows:

1. «This software responds very slowly to data input. (Processing speed)»
2. «The instructions and help are useful (Help).»
3. «The software has ever stopped unexpectedly (Reliability).»
4. "The way the system presents information is clear and understandable (Clarity)."
5. «The organization of the menus seems quite logical (Menus).»
6. «The software allows the user to use the keyboard less (Accessibility).»
7. «Error prevention messages are not adequate (Error Messages).»
8. «The software has a very attractive presentation (Design).»

In both tools, SUS and SUMI, the responses for each statement use a Likert scale: Strongly disagree, disagree, neutral, agree, strongly agree.

The combination of these tools allowed a comprehensive evaluation of the software usability, the results of which are described in the corresponding section.

Functional testing

Functional testing verifies that the system meets the expected functionalities, which includes unit testing, which focuses on evaluating individual software components; integration testing, which verifies the interaction between different system modules; *Application testing, which verifies the interaction between the different components of the system; and Programming Interface* (API), which evaluate the functionality of the software's programming interfaces; and acceptance, which are formal evaluations carried out by end users or clients to confirm that the software meets specified requirements (Hambling et al., 2013) . Acceptance testing was used to perform this task on the software.

These tests made it possible to assess whether the software met users' expectations, providing key information on its operation before its final implementation.

The results obtained from these tests provided a comprehensive view of the system performance, both in functional and non-functional terms, which is detailed in the results section.

Software Development

This section describes the main elements of the developed software, including its functionalities, architecture, implementation details and features.

System Features

The LSDS was designed with key functionalities that allow the capture and analysis of learning styles using the FSLSM, ensuring its applicability for both individual students and groups. The main functionalities of the system are the following:

• Capture and storage of the FSLSM questionnaire for individual students or groups of students;

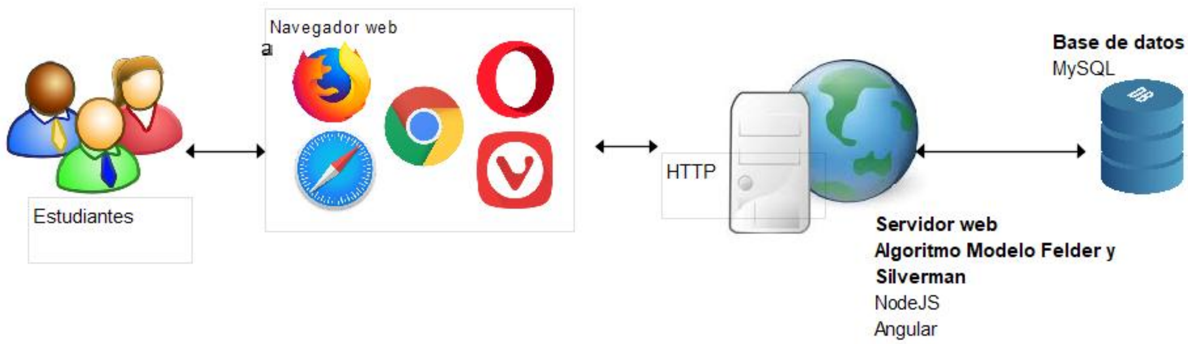
• Determination of LS for individual students or groups of students according to the FSLSM.

These functionalities form the basis of the LSDS, providing teachers with tools to identify learning styles and adapt educational strategies effectively.

Architecture

The LSDS is based on three-tier architecture, widely used in software development for its ability to organize system functions and optimize their performance (see Figure 3). According to Ingeno (2018), the data level (back- *end*) is where the information processed by the application is stored and managed, the logical level (business rules) is the core of the software where the collected information is processed using business logic, and the presentation level allows the user to interact with the application through the user interface.

Figure 3 Three-tier architecture of the LSDS.



Source: Own elaboration

This architecture ensures a clear separation of responsibilities between levels, facilitating maintenance, scalability and user interaction with the system.

Implementation

The implementation of LSDS integrates various technologies distributed across the three levels of its architecture, ensuring optimal performance and efficient user experience (see Figure 3), which are described below:

a) Data level: A MySQL database is used to store user information, individual questionnaires, and the LS of both individual students and groups, according to the FSLSM. MySQL is an *open-source* relational database management system (Christudas, 2019).

b) *NodeJS, Angular* and *TypeScript* are used. *NodeJS* is a cross-platform server environment that runs JavaScript code without the need for a web browser, facilitating server-side development. Angular is a framework used to develop web applications compatible with browsers and mobile devices. *TypeScript* is a programming language that extends *JavaScript* and is used by Angular to facilitate structured application development (Holmes & Harber, 2019).

c) Presentation level: HTML (*HyperText Markup Language*), CSS (*Cascading Style Sheet*) and *Javascript are used*. HTML is a markup language used to structure the content of a web page, such as text, images, and links. CSS is a language used to format the content of HTML web pages. JavaScript is a programming language used to create interactive web pages. It can update and change both HTML and CSS dynamically (Robbins, 2012).

This technological integration ensures a robust, flexible and scalable system, capable of adapting to the needs of users and facilitating the detection of learning styles.

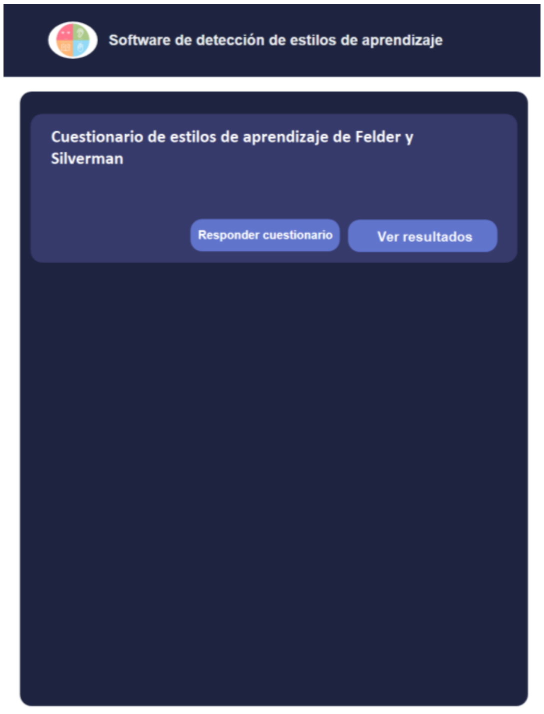
System Features

This section describes the main features of the LSDS, its user interface and the functionalities aimed at facilitating the detection of learning styles.

To showcase our proposal, we have developed the LSDS as a dynamic web application based on Angular, accessible from a web browser or a mobile device and using a *NodeJS server and a MySQL* relational database (see Figure 3).

Figure 4 shows the main screen that is displayed once the user logs into the system. Here the user can start answering the FSLSM questionnaire by selecting the “Answer questionnaire” option or, if he/she has already answered it previously, the “View results” button.

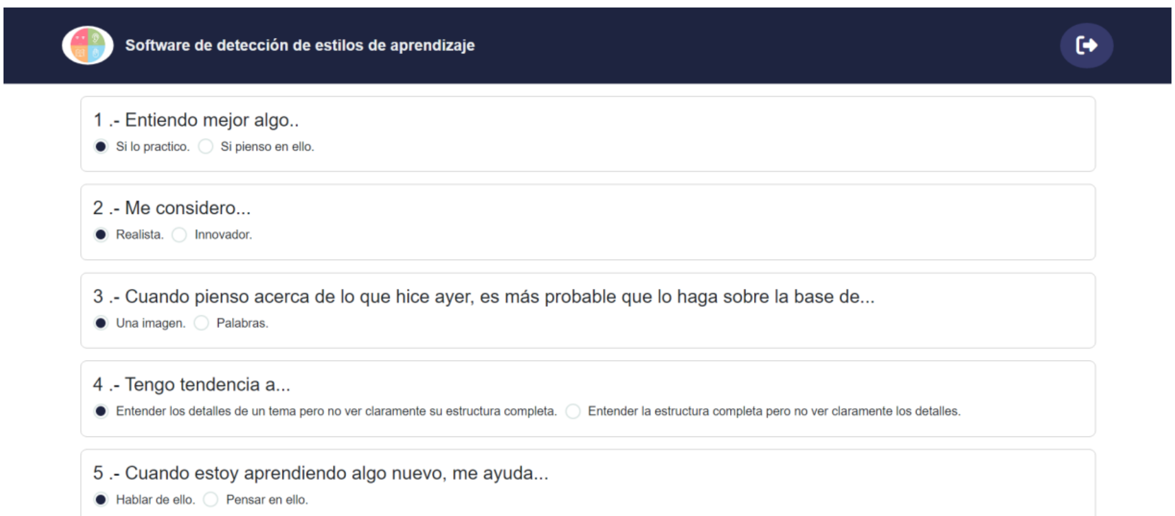
Figure 4 Main screen of the LS detection software **.**



Source: Own elaboration

If the user chooses to answer the FSLSM ILS questionnaire, the system displays the screen to capture its 44 questions. A fragment of this screen is shown below in Figure 5.

Figure 5FSLSM ILS questionnaire (fragment**)**



Source: Own elaboration

When the user answers the questionnaire, the system displays the results in graphical or tabular form. Figures 6 and 7 present the results provided by the LSDS that identify the user's LS in tabular and graphical format. In the case of the user taken as an

Revista Iberoamericana para la Investigación y el Desarrollo Educativo
ISSN 2007 - 7467

example, the trends in each dimension are "Active", "Sensory", "Visual" and "Global", respectively.

Figure 6. LSDS results in tabular form

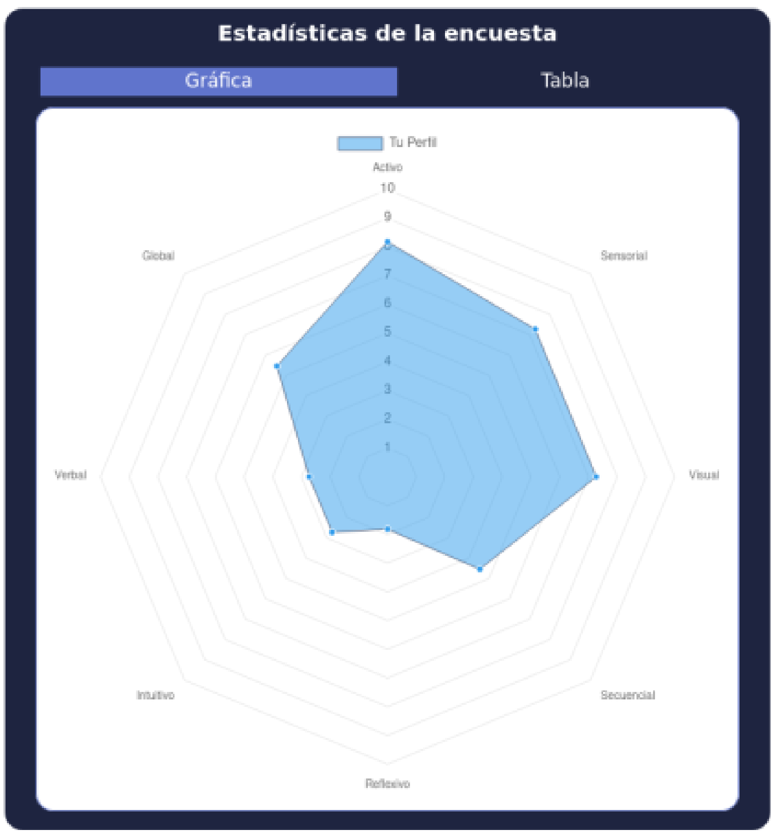
Estadísticas de la encuesta

Gráfica | Tabla

	11	9	7	5	3	1	1	3	5	7	9	11	
Activo			x										**Reflexivo**
Sensorial				x									**Intuitivo**
Visual				x									**Verbal**
Secuencial							x						**Global**

Source: Own elaboration

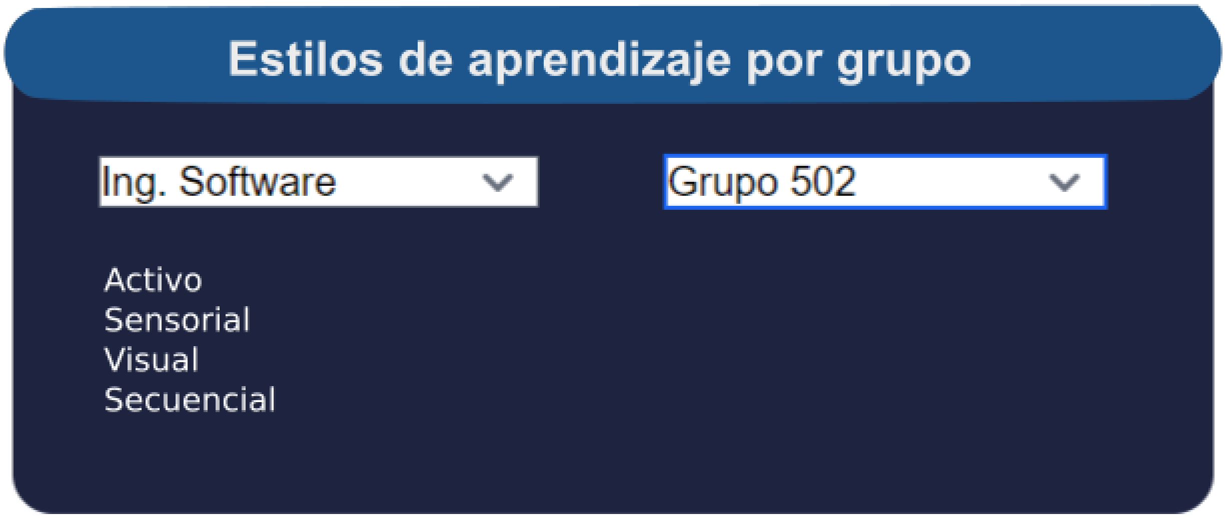
Figure 7LSDS results in graphical **form**



Source: Own elaboration

In addition to providing individual results, the software also allows determining learning styles for groups of students, based on the predominant inclinations in each dimension of the FSLSM. Figure 8 shows the results obtained for a particular group of students.

Figure 8 Learning styles by **group**



Source: Own elaboration

In summary, the features of the LSDS allow users, both individual and group, to obtain detailed and graphical information about learning styles, providing an effective tool for educational personalization.

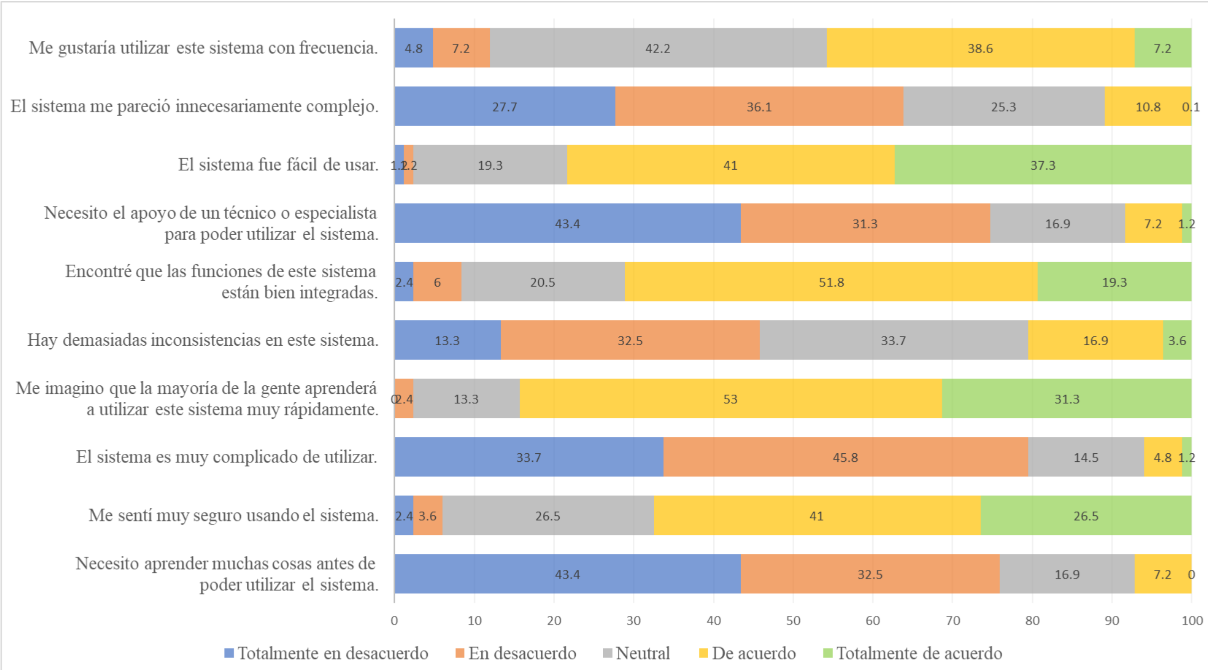
Results

This section presents the results obtained from the non-functional and functional tests performed on the LSDS, with the aim of evaluating its usability, precision and performance in different contexts.

Non-functional testing

For the SUS test there were 83 students and their results are shown in Figure 9. The statements appear in the lines and the students' opinions are represented by colored symbols. Thus, according to Lewis and Sauro (2009), the LSDS is considered "good" when it reaches 71.72 SUS points.

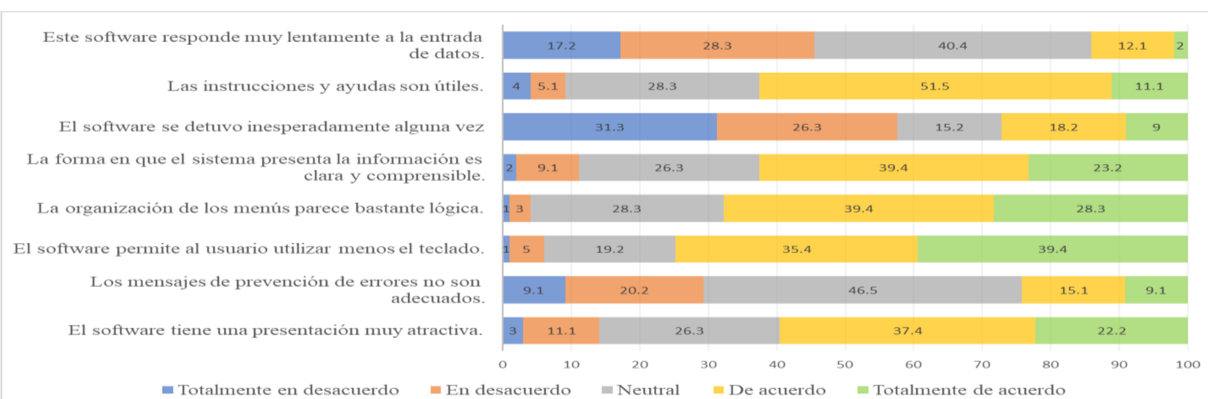
Figure 9assessment results



Source: Own elaboration

For the SUMI test there were 99 students and their results are shown in Figure 10. The same distribution as in SUS is followed. The statements appear in the rows, and a color scale represents the students' opinion. According to SUMI, the LSDS obtained 65.49 points, which corresponds to a "good" evaluation.

Figure 10evaluation results



Source: Own elaboration

Table 2 shows the individual results where the student and the score according to the associated learning style are considered. Table 3 shows the predominant trends in the number and percentage of students by learning style.

Once usability was evaluated through non-functional testing, functional testing was carried out to validate the software's capabilities in practical scenarios.

Functional testing

Regarding acceptance testing, once the results of the algorithm developed to implement the FSLSM were confirmed to be correct and in order to test the basic functionality of the LSDS, a group of 50 students was asked to carry out the entire process of testing activities listed above. As shown in Tables 2 and 3, each of the students in the group took the test, and the software determined their individual and group learning styles.

Table 2 Results per student of the Felder and Silverman test

Student	Asset	Thoughtful	Sensible	Intuitive	Visual	Verbal	Sequential	Global
1	5	0	1	0	9	0	9	0
2	0	3	9	0	11	0	11	0
3	5	0	0	7	7	0	0	7
4	9	0	1	0	5	0	9	0
5	0	7	11	0	11	0	7	0
6	3	0	7	0	1	0	1	0
7	1	0	0	5	1	0	1	0
8	5	0	3	0	3	0	0	5
9	0	5	11	0	3	0	9	0
10	3	0	3	0	11	0	11	0
11	7	0	5	0	0	7	3	0
12	11	0	0	11	5	0	11	0
13	0	9	3	0	7	0	0	3
14	9	0	9	0	3	0	1	0
15	5	0	7	0	9	0	7	0
16	5	0	0	1	1	0	3	0
17	0	11	7	0	3	0	0	5
18	3	0	3	0	0	7	3	0
19	9	0	0	7	3	0	5	0
20	11	0	7	0	5	0	3	0

21	0	5	5	0	0	5	0	9
22	1	0	1	0	3	0	3	0
23	3	0	0	9	9	0	9	0
24	0	7	9	0	5	0	11	0
25	11	0	7	0	5	0	0	11
26	3	0	0	9	5	0	3	0
27	0	3	1	0	0	5	7	0
28	11	0	1	0	7	0	11	0
29	3	0	9	0	11	0	0	3
30	0	1	0	11	0	1	7	0
31	9	0	7	0	7	0	3	0
32	9	0	3	0	1	0	0	5
33	0	5	11	0	0	11	1	0
34	1	0	0	1	9	0	5	0
35	3	0	5	0	1	0	0	7
36	0	11	11	0	7	0	1	0
37	7	0	3	0	9	0	11	0
38	7	0	7	0	11	0	1	0
39	5	0	0	3	0	9	0	9
40	1	0	5	0	5	0	11	0
41	1	0	11	0	5	0	1	0
42	5	0	11	0	1	0	9	0
43	3	0	3	0	7	0	0	9
44	3	0	0	3	7	0	11	0
45	1	0	7	0	5	0	9	0
46	5	0	1	0	0	3	0	3
47	5	0	5	0	11	0	3	0
48	9	0	9	0	9	0	0	7
49	1	0	5	0	11	0	0	5
50	1	0	0	7	1	0	0	7

Source: Own elaboration

Table 3 Group results of the Felder and Silverman **test**

Students	Asset	Thoughtful	Sensible	Intuitive	Visual	Verbal	Sequential	Global
50	39 (78%)	11(22%)	38(76%)	12(24%)	42(84%)	8(16%)	35(70%)	15(30%)

Source: Own elaboration

The results obtained confirm that the LSDS meets the established usability and functionality standards, proving to be a useful tool for identifying learning styles both at individual and group level.

Discussion

In recent years, various software have been developed for the detection of learning styles. Below, we review notable examples and how the LSDS presented in this research differs from them. The reviewed systems have had diverse approaches and have used various models and technologies. Such is the case of the one presented by Chablé et al. (2013), which is an online system that was evaluated in a pilot test, where students were able to answer the test on learning styles and the teacher was able to view the results both individually and as a group. Based on this test, the effectiveness of the system and its ease of use were determined. The software is based on the Honey-Alonso test to determine the LS. Research by Núñez Cárdenas (2013) found a trend of computer science students within the three higher education institutions analyzed with the Kinesthetic learning style as the dominant one, which will allow the development of teaching materials for the subjects with the highest failure rate, focused on this LS. The software is based on the VARK model to determine the LS. The work of Zatarain-Cabada (2013) managed to have the intelligent tutor system that he proposes identify the emotional states and the LS of the participating students. His future work includes providing learning materials that students can absorb regardless of their mood or LS. The LS Profiler software (2022) allows the development of individual learning plans for each staff member in an organization, assessing suitability for specific training courses, creating work teams and analyzing their strengths and weaknesses. The system uses the hybrid model of evidence-based personality learning to determine the LS.

The LSDS presented in this research is distinguished from previous software because it jointly addresses several of the current demands identified in the literature related to software to detect LS. One of these elements is the multiplatform support that it has and that is granted by being developed with a self-adaptive framework such as Angular, which allows it to be viewed from different devices such as computers, tablets and cell phones. Another important element is that it makes use of the Felder and Silverman model to identify LS, which has shown good results in the literature and has been little explored in the software developed to date.

The non-functional and functional tests considered for the evaluation of the LSDS allowed to know aspects related to the usability of the software and compliance with the requirements with the results issued.

As for non-functional testing, the results obtained in the SUS and SUMI evaluations were relatively positive and revealed several opportunities for improvement. Some areas for improvement, according to SUS, include those related to the survey items “I found the system unnecessarily complex”, “There are too many inconsistencies in this system” and “I need to learn many things before I can use the system”. This suggests the need to review which elements of the software can be adjusted to make it easier to use and to improve its help by including a step-by-step tutorial or interactive help.

According to SUMI, the software could improve items related to the survey items “Instructions and help are helpful,” “The software never stopped unexpectedly,” and, “Error prevention messages are not adequate.” The findings here are consistent with those found in SUS and the same improvements mentioned above can be applied.

Regarding the functional tests, the results obtained were positive in the sense that the software was able to determine the LS of each of the participating students and no problems were encountered when carrying out this task.

It is important to point out the current limitations of the software, which is only focused on determining the LS of the student who uses it and is not yet prepared to analyze groups of students or take advantage of the collective knowledge of their learning styles. However, it represents the beginning of work aimed at developing more robust software that covers this and other aspects that are indicated below as future work.

In summary, LSDS presents significant advances by integrating a little-explored model such as Felder and Silverman's and providing cross-platform support. However, there are still areas for improvement in terms of usability and group analysis that will be addressed in future work.

Conclusion

This article describes the development, features, operation, and an example of use of a new LS detection software. This system supports teachers and computationally implements Felder and Silverman's LS model.

The document presents the development decisions, such as the selected architecture and the details of its implementation, as well as the different types of tests that were applied to it to verify different aspects of its operation and that demonstrated the feasibility of using the software to detect the LS of a particular student. Findings that provide opportunities for system improvement are also described.

The results obtained demonstrate that the software is effective in identifying students' LS, allowing teachers to classify students and adapt TS to the detected characteristics.

Ultimately, LSDS represents an innovative tool for personalizing teaching, with clear opportunities to evolve towards a more robust system that facilitates working with groups of students and further optimizes the educational process.

Future lines of research

Although the LSDS has proven to be useful as a tool for identifying students' LS, there are still areas that can be explored to expand its functionality and impact in the educational field. Among them, the following future lines of research are proposed:

1. The integration of LSDS into a Teaching Strategy Recommendation Software based on Learning Styles that allows automatically determining the most appropriate TS according to the students' LS.
2. Explore different ways of classifying students according to their TS in order to recommend TS for the preparation of regular classes, special courses, extraordinary exams, etc.
3. Evaluate the impact of these systems on improving student academic outcomes.

These lines of research will not only improve the functionality of the LSDS, but also contribute to the development of more personalized and effective educational systems.

References

Alghamdi, M., Lamb, D. J., Al-Jumeily, D., & Hussain, A. J. (2013). *Assessing the impact of web-based technology on learning styles in education*. 348-353.

Bangor, A. (2009). Determining What Individual SUS Scores Mean: Adding an Adjective Rating Scale. *Journal of Usability Studies*, *4*(3).

Bravo, V. A. O., & Arias, M. A. N. (2020). Dominancia cerebral y estilos de aprendizaje: Un software para la adaptación de contenidos. *Revista de Estilos de Aprendizaje*, *13*(25), 113-124. https://doi.org/10.55777/REA.V13I25.1526

Brito-Orta, M. D., & Espinosa-Tanguma, R. (2015). Evaluación de la fiabilidad del cuestionario sobre estilos de aprendizaje de Felder y Soloman en estudiantes de medicina. Investigación en educación médica, 4(13), 28-35.

Calderón, N. T. (2022). *Aplicación para determinar su estilo de aprendizaje* (1.0) [Software]. Recuperado de https://www.educaycrea.com/2016/08/aplicacion-para-determinar-su-estilo-de-aprendizaje/

Camana, R. G. (2017). Herramienta para detección de estilos de aprendizaje en estudiantes de educación superior. *Revista Tecnológica-ESPOL*, *30*(3).

Cárdenas Palomino, F. R., Beltran, A., Cruz Cámaco, D. P. de la, Rojas Zuñiga, L. M., & others. (2021). Identificación de los Estilos de aprendizaje de los Estudiantes Universitarios: Revisión de Literatura. *Sinergias Educativas*, *1*(1).

Carla Maria Alonso Jane, E. G. S., Goar Orue Sánchez. (2019). Alternativas de desarrollo de software para caracterizar estilos de aprendizaje en los estudiantes -. *EduSol*, *19*(67), 17-26.

Casal, J., & Mateu, E. (2003). Tipos de muestreo. *Rev. Epidem. Med. Prev*, *1*(1), 3-7.

Christudas, B. (2019). MySQL. En B. Christudas (Ed.), *Practical Microservices Architectural Patterns: Event-Based Java Microservices with Spring Boot and Spring Cloud* (pp. 877-884). Apress. https://doi.org/10.1007/978-1-4842-4501-9_27

Céspedes Gómez, G., & Reyes Rivero, L. (2016). *Creación de un Prototipo Software que Permita Identificar el Estilo de Aprendizaje Predominante en los Estudiantes de Ingeniería de Software Bajo los Tipos Visual, Auditivo y Kinestésico (Vak)*.

Chablé, M. D. M. M., Reyna, M. I. S. M. V., & López, L. S. C. C. J. R. (2013). *Desarrollo de un sistema en línea para definir estilos de aprendizaje*. 88-88.

Chang, Y.-H., Chen, Y.-Y., Chen, N.-S., Lu, Y.-T., & Fang, R.-J. (2016). Yet Another Adaptive Learning Management System Based on Felder and Silverman's Learning

Styles and Mashup. *EURASIA Journal of Mathematics, Science & Technology Education*, *12*(5), 1273-1285. https://doi.org/10.12973/eurasia.2016.1512a

Creative Learning Systems. (2020). *Learning Style Analysis Students* (1.0) [Software]. Creative Learning Systems. Recuperado de https://www.superteacherstrategies.com/learning-style-analysis/learning-style-analysis-students/

Cymeon Pty Ltd. (2022). *Learning Styles Profiler* (1.0) [Software]. Cymeon Pty Ltd. Recuperado de http://www.cymeon.com/lss2.asp

Desikan, S., & Ramesh, G. (2006). *Software Testing: Principles and Practice*. Pearson Education India.

Felder, R. M., & Silverman, L. K. (1988). *Learning and teaching styles in engineering education*.

González-Álvarez, C., Medina-Betancourt, Y. ;, & Román, A. (2012). La estimulación de estilos de aprendizaje con el software "Rainbow". *Ciencias Holguín*, *XVIII*, 1-15.

Graf, S., Viola, S. R., Leo, T., & Kinshuk. (2007). In-Depth Analysis of the Felder-Silverman Learning Style Dimensions. *Journal of Research on Technology in Education*, *40*(1), 79-93. https://doi.org/10.1080/15391523.2007.10782498

Hambling, B., Goathem, P. V., & Goethem, P. van. (2013). *User Acceptance Testing: A Step-by-step Guide*. BCS.

Holmes, S., & Harber, Clive. (2019). *Getting MEAN with Mongo, Express, Angular, and Node*. Simon and Schuster.

Honey, P., & Mumford, A. (1982). *The Manual of Learning Styles, Homey, Maidenhead*. AITBS Publishers.

Ingeno, J. (2018). *Software Architect's Handbook: Become a successful software architect by implementing effective architecture concepts*. Packt Publishing Ltd.

Kirakowski, J., & Corbett, M. (2006). SUMI: The Software Usability Measurement Inventory. *British Journal of Educational Technology*, *24*, 210-212. https://doi.org/10.1111/j.1467-8535.1993.tb00076.x

Kolb, D. A. (1984). *Experiential learning: Experience as the source of learning and development*. FT press.

Learnstyle. (2022). *LEARNstyle* (1.0) [Software]. LEARNstyle Ltd. Recuperado de https://learnstyle.com/rise/

León, Y. del V. R., & Carrillo, J. A. O. (2012). *Diagnóstico del estilo de aprendizaje predominante basado en minería de datos y el modelo de Felder: Aplicaciones al*

Elearnig 3.0. Estilos de aprendizaje. Investigaciones y experiencias:[V Congreso Mundial de Estilos de Aprendizaje]. Santander, 27, 28 y 29 de junio de 2012.

Lewis, J. R., & Sauro, J. (2009). The Factor Structure of the System Usability Scale. En M. Kurosu (Ed.), *Human Centered Design* (pp. 94-103). Springer. https://doi.org/10.1007/978-3-642-02806-9_12

Murcia, R. F., Álvarez, L. C., & Corredor, C. M. (2016). El estilo de aprendizaje en educación virtual: Breve revisión de la literatura. *Virtu@ lmente*, *4*(1), 70-95.

Núñez Cárdenas, F. de J. (2013). Identificación de estilos de aprendizaje en alumnos universitarios de computación de la huasteca hidalguense mediante técnicas de minería de datos. *Producción Científica Profesorado*.

Palomino-Hawasly, M. Á., Culchac de la Vega, A., Rangel-Vellojin, J., Palomino-Hawasly, M. Á., Culchac de la Vega, A., & Rangel-Vellojin, J. (2017). LSDS: Sistema Diagnosticador de Estilos de Aprendizaje Orientado a los Ambientes de Formación Web. *Revista Tecnología en Marcha*, *30*(4), 80-92. https://doi.org/10.18845/TM.V30I4.3413

Prieto, G. (2021). Identificación de estilos de aprendizaje según el cuestionario ILS en una muestra de estudiantes de Psicología de la Facultad de Psicología de la Universidad de la República (Uruguay). REXE. Revista de Estudios y Experiencias en Educación, 20(44), 89-106.

Puello, P., Fernández, D., & Cabarcas, A. (2014). Herramienta para la Detección de Estilos de Aprendizaje en Estudiantes utilizando la Plataforma Moodle. *Formación universitaria*, *7*(4), 15-24. https://doi.org/10.4067/S0718-50062014000400003

Rajper, S., Shaikh, N. A., Shaikh, Z. A., & Mallah, G. A. (2016). Automatic detection of learning styles on learning management systems using data mining technique. *Indian Journal of Science and Technology*, *9*(15), 1-5.

Robbins, J. N. (2012). *Learning Web Design: A Beginner's Guide to HTML, CSS, JavaScript, and Web Graphics*. O'Reilly Media, Inc.

Sauro, J. (2018). *5 Ways to Interpret a SUS Score – MeasuringU*. https://measuringu.com/interpret-sus-score/

Supangat, S., & Mohd Zainuri, B. S. (2020). Development of E-learning System Using Felder and Silverman's Index of Learning Styles Model. *Development of E-Learning System Using Felder and Silverman's Index of Learning Styles Model*, *9*(5), Article 5.

Systems, C. L. (2020). *Software—Learning Styles* (1.0) [Software]. Systems, C. L. Recuperado de https://www.my-learning-styles.com/software/

World, N. M. (2021). *Test de estilos de aprendizaje* (1.0) [Software]. N. Magical World. Recuperado de https://apkcombo.com/es/test-de-estilos-de-aprendizaje/com.NewMagicalWorld.TESTDEAPRENDIZAJE/

Zatarain-Cabada, R., Barrón-Estrada, M. L., Camacho, J. L. O., & Reyes-García, C. A. (2013). *Integrating learning styles and affect with an intelligent tutoring system*. 247-253.

Contribution Role	Author(s)
Conceptualization	J. Francisco Figueroa- Perez
Methodology	J. Francisco Figueroa- Perez (main), Alan Ramirez-Noriega (supports)
Software	J. Francisco Figueroa- Perez
Validation	Alan Ramirez-Noriega (same), Yobani Martinez-Ramirez (same)
Formal Analysis	J. Francisco Figueroa- Perez (main), Manuel Rodriguez-Guerrero, Alan Ramirez-Noriega and Yobani Martinez-Ramirez (support)
Investigation	J. Francisco Figueroa- Perez (main), Manuel Rodriguez-Guerrero, Alan Ramirez-Noriega and Yobani Martinez-Ramirez (support)
Resources	J. Francisco Figueroa- Perez (main), Manuel Rodriguez-Guerrero, Alan Ramirez-Noriega and Yobani Martinez-Ramirez (support)
Data curation	J. Francisco Figueroa- Perez
Writing - Preparing the original draft	J. Francisco Figueroa- Perez
Writing - Review and editing	Manuel Rodríguez-Guerrero (same), Alan Ramírez-Noriega (same) and Yobani Martínez-Ramírez (same)
Display	J. Francisco Figueroa- Perez (main), Manuel Rodriguez-Guerrero, Alan Ramirez-Noriega and Yobani Martinez-Ramirez (support)
Supervision	J. Francisco Figueroa- Perez
Project Management	J. Francisco Figueroa- Perez
Acquisition of funds	J. Francisco Figueroa- Perez