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A Mixed Methods Framework for Usability Profiling in Learning Environments: Integrating Adapted Heuristics and Machine Learning

Un framework de métodos mixtos para el perfilado de usabilidad en entornos de aprendizaje: integrando heurísticas adaptadas y aprendizaje automático

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Abstract

Traditional usability evaluations of Learning Management Systems are often based on aggregate metrics that mask the heterogeneous experiences of diverse user populations, thus yielding limited actionable insights for personalized improvements. To address this significant gap, this research proposed a systematic six-phase methodological framework that integrates user-centered design principles, contextually adapted educational heuristics, and advanced machine learning techniques to deconstruct usability data and generate distinct data-driven user profiles. The methodology consisted of an empirical single-case study using a mixed-method approach to evaluate the implementation of a virtual Moodle environment for adult education in Comfacauca in Colombia. Data were collected from a heterogeneous sample of 50 students using the System Usability Scale questionnaire and the qualitative think-aloud protocol. These datasets were analyzed by combining descriptive statistics with Principal Component Analysis and K-means clustering. Although the platform achieved a strong aggregate SUS score of 73.9, analytical results enabled the successful identification of four distinct user profiles with unique technical needs, behavioral patterns, and cognitive challenges, which would have remained hidden with conventional single-score methods. For example, the framework revealed that perceptions of usability were more strongly correlated with the students' academic cycle than with their chronological age, directly challenging common demographic stereotypes. Finally, it is concluded that this comprehensive framework provides a reproducible methodological protocol for educational institutions to gain deeper, user-centered insights. This approach enables the transition from generic adjustments to the development of highly specific and differentiated support strategies, demonstrating the profound value of combining traditional usability methods with unsupervised clustering algorithms to transform general user feedback into actionable pedagogical intelligence.

Keywords

Learning environment, machine learning, usability evaluation, user-centered design, user profiles.

Resumen

Las evaluaciones de usabilidad tradicionales de los Sistemas de Gestión del Aprendizaje suelen basarse en métricas globales que enmascaran las experiencias heterogéneas de las diversas poblaciones de usuarios, proporcionando información útil limitada para realizar mejoras personalizadas. Para abordar esta brecha, esta investigación propuso un marco metodológico de seis fases que integró principios de diseño centrado en el usuario, heurísticas educativas adaptadas contextualmente y técnicas de aprendizaje automático para deconstruir datos de usabilidad y generar perfiles de usuario basados en datos. La metodología consistió en un estudio empírico de caso único que utilizó un enfoque de métodos mixtos para evaluar la implementación de un entorno virtual Moodle de educación de adultos en Comfacauca, Colombia. Los datos se recopilaron en una muestra heterogénea de 50 estudiantes utilizando la Escala de Usabilidad del Sistema y el protocolo cualitativo de pensamiento en voz alta. Estos conjuntos de datos se analizaron combinando estadística descriptiva con el Análisis de Componentes Principales y algoritmos de agrupamiento K-means. Aunque la plataforma obtuvo una buena puntuación global SUS de 73.9, los resultados lograron la identificación exitosa de cuatro perfiles de usuario distintos con necesidades técnicas, patrones de comportamiento y retos cognitivos, lo que habría permanecido invisible utilizando métodos convencionales de puntuación única. En esta línea, el marco reveló que la percepción de usabilidad estuvo más fuertemente correlacionada con el ciclo académico de los estudiantes que con su edad cronológica, desafiando estereotipos demográficos comunes. Finalmente, se concluye que este marco proporciona un protocolo metodológico reproducible para que las instituciones educativas obtengan conocimientos más profundos y centrados en el usuario. Este enfoque facilita el desarrollo de estrategias de apoyo específicas y diferenciadas, demostrando el valor de combinar métodos tradicionales de usabilidad con algoritmos de agrupamiento para transformar los comentarios generales en inteligencia pedagógica procesable.

Palabras clave

Entorno de aprendizaje, aprendizaje automático, evaluación de usabilidad, diseño centrado en el usuario, perfiles de usuario.

1. INTRODUCTION

Education facilitated by Information and Communication Technology (ICT) has become a fundamental pillar of lifelong personal and career development for both youths and adults, providing them with the means to complete their primary and secondary schooling [1]. In 2021, the worldwide ICT-mediated education market was valued at $315 billion and is expected to grow at an annual rate of 9.1% [2]. Furthermore, the COVID-19 crisis acted as a major accelerator for this sector; with school closures impacting over 90% of learners globally, it propelled the widespread implementation of digital learning platforms and triggered unprecedented growth in online education [3].

In this sense, Learning Management Systems (LMS) have established themselves as important tools in distance learning modalities [4]. Their function transcends mere storage of educational content, requiring the incorporation of qualitative and technical attributes [5]. Among these, an intuitive user interface and a variety of content formats stand out. At the software level, scalability, reliability, and availability are essential. In addition, an effective LMS should facilitate collaborative learning and seamlessly integrate with other technological tools [6], [7].

In this context, the systematic evaluation of LMS platforms is a fundamental process, as it allows for optimizing the user experience, maximizing return on investment through efficient resource use, facilitating technology adoption, reducing the user learning curve, and identifying areas for continuous improvement [8]. To this end, various methodologies employ multiple techniques, ranging from collecting direct user feedback [9] and analyzing usage reports [10] to applying multi-criteria decision methods such as DEMATEL [11].

Despite these methodological advances, a critical analysis of the current state of the art reveals a significant scientific gap regarding how usability data is processed and interpreted. Conventional evaluation frameworks frequently rely on standardized instruments that yield aggregate, monolithic metrics [12], [13]. While multi-criteria decision-making models, such as DEMATEL, or comparative heuristic frameworks [14] provide a broader evaluation matrix, they still tend to synthesize findings into a unified, generalist perspective. This monolithic approach masks the inherent heterogeneity of diverse user populations, rendering the resulting insights insufficient for granular, actionable improvements [15].

Furthermore, while machine learning has seen widespread adoption in educational environments, its application has predominantly focused on Learning Analytics, such as predicting student dropout or academic performance [16], rather than usability evaluation. Studies that do incorporate mixed-methods approaches for usability often run qualitative and quantitative streams in parallel rather than fully integrating them [17]. Crucially, there is a distinct lack of systematic frameworks that use unsupervised machine learning (e.g., clustering) to decompose standardized usability scores into multidimensional user profiles. Without this computational segmentation, educational institutions are forced to apply "one-size-fits-all" interface adjustments that may benefit one demographic while hindering another.

In response to these limitations, research proposals have emerged introducing various frameworks and specific techniques [18]. However, these efforts remain largely isolated and have not converged into a unified standard that ensures evaluation comparability and reproducibility. Therefore, there is a lack of comprehensive methodological frameworks that evaluate usability and incorporate user profile segmentation to enable personalized improvements, in line with the scientific literature's consensus on the need for personalization and adaptability in LMS environments.

To address this gap, this article proposes and validates a novel mixed-methods methodological framework that fundamentally rethinks how usability data is treated. The novelty of our approach lies in its methodological departure from traditional usability studies. Rather than treating an aggregated System Usability Scale (SUS) score as the final evaluative endpoint, our framework treats it as an input to advanced dimensionality reduction and K-means clustering. By systematically integrating contextualized educational heuristics, qualitative think-aloud protocols, and unsupervised machine learning, this approach deconstructs quantitative usability data to segment students into meaningful, actionable profiles.

To demonstrate its real-world utility, an implementation study was conducted at the Comfacauca Virtual Business Education Center (CEVEC), a Moodle-based platform for youth and adult education in Colombia. This context represents an ideal test case due to the diversity of its student population, which spans a wide range of ages and levels of digital competence. Building upon preliminary concepts presented at the XI Ibero-American Conference on Human-Computer Interaction [19], this extended research provides robust empirical evidence to validate a reproducible model. This model empowers institutions to transition from generalized usability feedback to targeted, personalized interface and pedagogical support strategies.

Consequently, the main objective of this research was to develop and validate a comprehensive mixed-methods framework designed to overcome the limitations of aggregate usability metrics by integrating adapted heuristics and machine learning techniques to systematically identify distinct, actionable user profiles in virtual learning environments.

Finally, this article is organized as follows. Section 2 details the mixed-methods framework, including the user-centered design framework, the adaptation of Nielsen's heuristics, and the machine-learning techniques employed for data analysis. Section 3 presents the framework validation using the System Usability Scale (SUS) survey, the think-aloud protocol, and principal component analysis, which identified distinct user profiles. Section 4 discusses the implications of these results, contextualizing them within existing literature. The study's limitations are addressed in Section 5, and Section 6 concludes the paper with a summary of the main contributions and suggestions for future research.

2. MATERIALS AND METHODS

This paper proposes a systematic, six-phase methodological framework to address the limitations of traditional, aggregate usability metrics in educational settings. Grounded in User-Centered Design (UCD) principles [17], the framework serves as a reproducible protocol for any institution seeking to measure and deconstruct the usability of its LMS. Its primary contribution

is integrating qualitative diagnostics, quantitative benchmarks, and machine learning techniques to segment users into distinct, actionable profiles.

Methodologically, the framework integrates a tripartite evaluation approach. First, SUS questionnaires [20] were utilized to quantitatively assess user perceptions. This was complemented by think-aloud protocols [21], which captured real-time cognitive dynamics and user interactions during task execution. Ultimately, an educational adaptation of Nielsen's heuristic principles [22], was implemented to uncover structural design flaws from a user-centric perspective. The operationalization of these methods follows the sequential phases depicted in Figure 1.

2.1 Proposed methodological framework

The proposed framework (Figure 1) is structured in six sequential phases, with each phase generating specific inputs for the next. This structure consolidates the approach into a comprehensive, systematic, and reproducible methodology for evaluating usability in learning management environments. Unlike traditional approaches, which tend to offer aggregated, simplified analyses, this model incorporates qualitative and quantitative diagnostic techniques to overcome their limitations and provide a deeper, more contextualized understanding of user behavior.

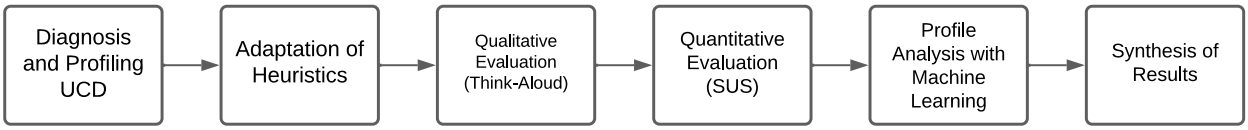


Figure 1. The six-phase mixed-methods framework for usability profiling. Source: own elaboration.

The rationale is to create an analysis funnel that moves from a broad user understanding to specific, actionable insights. The sequence is deliberate: it begins with foundational qualitative work (Phases 1 and 2: UCD Profiling and Heuristic Adaptation) to ensure the entire evaluation is tailored to the specific educational context. This is followed by a dual-pronged data-collection approach: rich, in-depth narratives (Phase 3: Think-Aloud) and scalable quantitative metrics (Phase 4: SUS). The framework's primary innovation lies in what follows. Instead of treating the aggregate SUS score as the final result, it uses this data as an input for advanced analysis (Phase 5: Machine Learning), deconstructing the single metric to reveal distinct user profiles that would otherwise remain invisible. The final synthesis phase (Phase 6) then enriches these data-driven profiles with the qualitative context gathered earlier. This integrated methodology is robust because it addresses the limitations of individual methods, creating a reproducible process that translates complex user behavior into targeted improvement strategies. The six phases that make up the framework are described in detail below.

Phase 1: Contextual inquiry and user profiling (UCD): the foundational phase of the framework focuses on understanding the target user population. Grounded in UCD, this stage employs ethnographic techniques to define the users' context, needs, and preexisting mental models. The key output of this phase should be the development of user personas or empathy maps [23]. These artifacts guide the evaluation process, ensuring subsequent phases are tailored to the specific user group. This initial diagnosis ensures that the subsequent evaluation is tailored to the specific characteristics of the user group, rather than applying generic assumptions. This phase produces synthesis artifacts, such as user archetypes or empathy maps, which serve as guides and constant reference points throughout the process, ensuring that the adaptation of heuristics (Phase 2) and the interpretation of results (Phase 6) align with users' actual characteristics.

Phase 2: Adaptation of heuristics: recognizing that general usability heuristics may not fully capture the nuances of educational environments, this phase involves contextualizing established principles, such as those by [24]. The objective is to develop a set of adapted heuristics that incorporate pedagogical considerations, such as relevance of content, support

for interactivity, and educational equity [25]. This tailored heuristic set becomes the specific lens through which the platform's design and functionality are qualitatively assessed. This phase produces a set of adapted and contextualized usability heuristics that serve as the primary analytical lens for qualitative evaluation (Phase 3), enabling the identification of usability problems specifically relevant to a learning context.

Phase 3: Qualitative evaluation (think-aloud): this phase focuses on gathering rich, in-depth data about the user experience. It employs observational methods, such as the think-aloud protocol [26], in which representative users verbalize their thoughts, actions, and frustrations while performing predefined tasks on the platform. The goal is to capture direct, unfiltered cognitive processes to understand the "why" behind user behaviors, identify specific pain points in the user journey, and collect qualitative evidence of usability issues. The primary outcome of this phase is a detailed record of qualitative data, including transcripts, observation notes, and a prioritized list of identified usability issues, which will provide the necessary context for interpreting the quantitative results of Phase 4 and enriching the characterization of profiles in Phase 6.

Phase 4: Quantitative evaluation (SUS): following the qualitative deep dive, this phase aims to quantify user perceptions on a scale. It uses standardized, reliable, and validated instruments such as the System Usability Scale [27]. The primary objective is to obtain a robust quantitative benchmark of the platform's perceived usability. While insufficient, this aggregated score is the critical input dataset for the machine learning analysis in the next phase. Finally, the main result of this phase is a quantitative dataset containing each participant's perceived usability scores. This dataset is the primary input for Phase 5, where it will be analyzed using machine learning techniques to identify latent patterns.

Phase 5: Profile analysis with machine learning: This is the core innovative component of the framework. Instead of treating the quantitative data as a final, monolithic result, this phase deconstructs it using advanced analytical techniques. First, dimensionality reduction methods such as PCA are applied to identify the underlying latent variables that explain the greatest variance in user responses. Subsequently, clustering algorithms such as K-means segment users into distinct, statistically significant groups based on their positions in the reduced-dimensional space. The output of this phase is clearly defined, segmented user profiles (clusters) based on quantitative perception patterns, transforming a single usability score into a map of diverse profiles that will be the subject of analysis and interpretation in Phase 6.

Phase 6: Synthesis of results: the final phase integrates findings from all previous stages to build a holistic, actionable understanding of the user’s experience. It involves characterizing the identified user profiles (Phase 5) by cross-referencing their quantitative patterns with the qualitative insights from the think-aloud sessions (Phase 3) and the initial user diagnosis (Phase 1). The framework's final result is a comprehensive diagnostic report. This report is not limited to a list of usability issues but also presents a detailed characterization of each user profile and a set of strategic, customized improvement recommendations for each segment.

2.2 Framework validation: a study in an adult learning environment

To demonstrate the proposed framework's applicability and validate its effectiveness, all six phases were implemented within the Centro Educativo Virtual Empresarial Comfacauca (CEVEC), a Moodle-based platform for youth and adult education in Colombia. This context provided an ideal testbed due to its diverse student population. The following sections detail the specific procedures and instruments used during each phase.

2.2.1 Context and participants

It was applied to the CEVEC learning environment to validate the proposed framework. The study population for this validation consisted of 50 students enrolled at CEVEC, with a mean age of 28 years and an age range of 16 to 60 years. This broad age distribution enabled the assessment of the intervention's effects across a heterogeneous age spectrum, consistent with prior research [28]. CEVEC's educational structure is organized into academic cycles that group students by educational attainment rather than age, thereby facilitating the inclusion of diverse age cohorts within each cycle. Participants were drawn from all instructional cycles offered at the institution, Cycle III (equivalent to 6th and 7th grades), Cycle IVA (8th grade), Cycle IVB (9th grade), Cycle V (10th grade), and Cycle VI (11th grade). The sampling strategy was initially randomized, as all students enrolled in the aforementioned cycles were invited to participate. However, the final sample was obtained through non-probabilistic convenience sampling based on voluntary participation [29].

The empirical phase was conducted between May 28 and June 10, 2024, encompassing a series of targeted activities designed to evaluate student engagement with the Learning Management System (LMS). Individual students actively participating in the study served as the primary units of analysis. To maximize comprehension and contextual relevance, the data collection instrument was linguistically adapted; notably, the standard term “system” was replaced with “platform” to align with the participants' everyday vernacular. The resulting questionnaire was administered digitally to a cross-sectional sample of students spanning multiple academic years.

2.2.2 Implementation of the framework's phases

Each stage was systematically implemented within the CEVEC context to validate the proposed six-phase framework empirically. The following describes the specific procedures and instruments used to instantiate each phase of the methodology.

The framework applied the UCD method, focusing on understanding the school's students, who represent the research unit of analysis. The data elicitation process was informed by Lean methodologies to obtain as much data as possible [30]. To this end, an empathy map was constructed with the student's profile [31]. In line with the framework's first phase, a diagnostic study was conducted to understand the target user population. Employing UCD principles, an empathy map was constructed to synthesize the needs, motivations, and pain points of the CEVEC students (Figure 2). This artifact served as the foundational guide for the subsequent evaluation phases.



Figure 2. Phase 1 output: example empathy map for contextual user profiling.
Source: own elaboration.

2.2.3 Adaptation of Nielsen's heuristics for an educational context

In alignment with the Phase 2 protocol, a specialized set of usability heuristics was developed. By contextualizing established usability principles [24] for educational environments, this study established a targeted analytical lens (Table 1). Crucially, whereas Nielsen's foundational metrics prioritize domain-agnostic usability, these adapted heuristics systematically integrate core pedagogical frameworks, addressing the specific dynamics of learning, instruction, and educational accessibility [32].

Table 1. Adapted heuristic framework for evaluating usability in educational environments. Source: [19].

Heuristics	Metric
Adaptability to the educational environment	• The site provides a user-friendly interface suitable for the educational environment. • The navigation and design elements are tailored to the specific needs of students and teachers.
Relevance of educational content	• Site content is aligned with educational and curricular objectives. • Diversified and updated content covering various topics and educational levels is provided. • The site offers educational resources in different formats to suit various learning styles.
Interactivity and participation	• Active interaction between students and teachers is encouraged through forums, chats, or collaborative activities. • Students can actively participate in learning through hands-on activities, exercises, and interactive assessments. • Immediate and personalized feedback is provided to facilitate learning and continuous improvement.
Accessibility and educational equity	• The website is accessible to users with different abilities and special needs. • Personalization and customization options are provided to ensure an inclusive educational experience for all students. • Educational equity is promoted by providing all users with free or affordable educational resources.
Security and data protection	• The site implements robust security measures to protect users' privacy and personal data. • Clear and transparent policies are established regarding collecting, storing, and using user information. • Guidance and resources are provided to educate users about safe online practices and protecting personal information.
Personalization of learning	• The site offers customization options that allow students to tailor the content and pace of learning to their individual needs. • Content and educational resource recommendations are provided based on each student's progress and preferences.
Collaboration and educational community	• Collaboration between students, teachers, and parents is encouraged through dedicated tools and spaces for discussions, group projects, and joint activities. • The site facilitates the creation and participation in online learning communities where users can share resources, ideas, and educational experiences.
Aesthetics and minimalist design	• The information is relevant. • The content is well-classified. • The content is well-organized. • Content is well distributed throughout the site
Evaluation and progress monitoring	• Varied and meaningful assessment tools allow teachers to measure student progress and performance effectively. • Students can track their progress and receive continuous feedback on their performance and areas for improvement.
Resources and support for autonomous learning	• The site provides a wide range of educational resources, tutorials, and guides that enable students to learn autonomously and self-directedly. • Tools and strategies are offered to develop study, organization, and time management skills that support independent learning.
Integration of educational technology	• Innovative technological tools and platforms enrich the learning experience and promote creativity and active student participation. • The site provides guidance and resources to train teachers and students to use educational technology effectively in the classroom and beyond.
Speed and media	• The site content can be accessed only in text format. • The media (images, video, sound) take too long to load the site. • The size of the files is indicated when downloading files from the site. • The technical quality of videos, images, and sound is acceptable. • The media reinforces the content of the message.

The primary advancement of this framework lies in transcending conventional usability metrics to encompass pedagogical dimensions, including learner interactivity and active participation. To operationalize this, novel heuristic categories were introduced: Relevance of Educational Content, Accessibility and Educational Equity, and Personalization of Learning. Ultimately, the application of these context-specific heuristics establishes a robust methodological foundation, enabling a precise diagnosis of both the structural strengths and functional vulnerabilities of the LMS.

2.2.4 Description of the think-aloud protocol

The qualitative evaluation phase employed the think-aloud protocol to gather in-depth data. Representative tasks included platform registration, course navigation, and quiz completion. The study aimed to validate the proposed framework in a real-world context, such as the CEVEC platform, using the "think-aloud" protocol [26] to identify problems with navigation, comprehension, and use of the LMS. Students were randomly selected, with special emphasis on adults who are representative of the target audience, to obtain a variety of perspectives. Testing was conducted in a controlled, distraction-free environment with access to the platform and pre-prepared test questionnaires.

The tasks evaluated included platform registration, course navigation, and quiz completion, typical activities within educational contexts. The study protocol comprised an introduction, think-aloud instructions, platform overview, task execution, follow-up questions, data recording, and conclusions.

Sessions were conducted individually and lasted approximately 45 minutes per participant. The protocol consisted of three standardized tasks representing the core user journey, (T1) Account creation and profile configuration (max 10 mins); (T2) Locating a specific course syllabus and downloading a reading material (max 15 mins); and (T3) Completing a simulated multiple-choice quiz and reviewing the feedback (max 15 mins). A facilitator was present to observe and record screen interactions.

The data collected during the evaluation sessions were analyzed to identify recurring patterns and specific problems, which were classified by severity and priority for correction. Finally, a report of results was prepared that included the results obtained, specific recommendations, and suggested actions to improve the CEVEC platform's usability.

2.2.5 Implementation of analytical phases and data analysis

A specific data analysis pipeline was established to execute Phases 5 and 6 of the framework. The quantitative data collected in Phase 4 were processed using Microsoft Excel, PAST [23], and the R programming language [33] was implemented for multivariate analysis and the application of advanced machine learning techniques [34]. Advanced analytical techniques were applied to deconstruct the aggregate SUS scores. The analytical pipeline integrated packages such as FactoMineR and factoextra [35] to perform PCA for dimensionality reduction, followed by K-means clustering to segment users into distinct profiles. Active variables for the PCA included survey responses (Q1-Q10), while demographic data were used as supplementary variables.

The analytical pipeline for the framework was structured in several activities. The first consisted of cleaning and validating the data, including detecting and treating outliers, to ensure the quality of the information. Next, descriptive statistics were calculated to characterize the student groups. Subsequently, dimensionality reduction was performed using PCA, and the K-means algorithm was applied to identify natural clusters within the student population. Finally, graphical representations were generated to facilitate visual interpretation of the results and support the final analysis.

The final synthesis was achieved by cross-referencing the quantitative profiles identified in Phase 5 with the qualitative insights from the think-aloud sessions (Phase 3) and the initial user diagnosis (Phase 1).

It is important to clarify that the analyzed dataset comprised exactly 50 participant records (observations). The data matrix generated 750 data points in total, resulting from the evaluation of 50 participants across 15 variables. The questionnaire responses (Q1-Q10) were treated as active variables in the PCA. In addition, gender and academic cycle were incorporated as supplementary qualitative variables, and age and social class were incorporated as supplementary quantitative variables. These variables were projected into the principal component space without influencing its construction, thereby allowing us to observe their distribution and relationships with the identified profiles.

3. RESULTS AND DISCUSSION

This section presents empirical results from validating the proposed methodological framework, which was applied in the context of the CEVEC learning environment. The findings demonstrate the framework's capacity to generate progressively deeper insights, moving from a high-level quantitative benchmark to granular, actionable user profiles. It begins by presenting the aggregate usability score from the quantitative evaluation (Phase 4), followed by the contextual qualitative findings from the think-aloud protocol (Phase 3). The section culminates by showcasing the user segmentation derived from the machine learning analysis (Phase 5), collectively validating the framework's approach to usability profiling.

3.1 System usability scale survey findings

Executing Phase 4 of the framework, the Quantitative Evaluation (Figure 3), provides a baseline usability benchmark. In the validation study, the System Usability Scale yielded a composite score of 73.9 for the platform, with a mean of 15.24 for positively worded (odd-numbered) items and 14.32 for negatively worded (even-numbered) items. According to the available literature, a score of 68 or higher indicates acceptable usability, while a score below 68 suggests significant usability deficiencies [20]. Therefore, it can be inferred that the CEVEC LMS exceeds the average threshold, evidencing above-average usability.

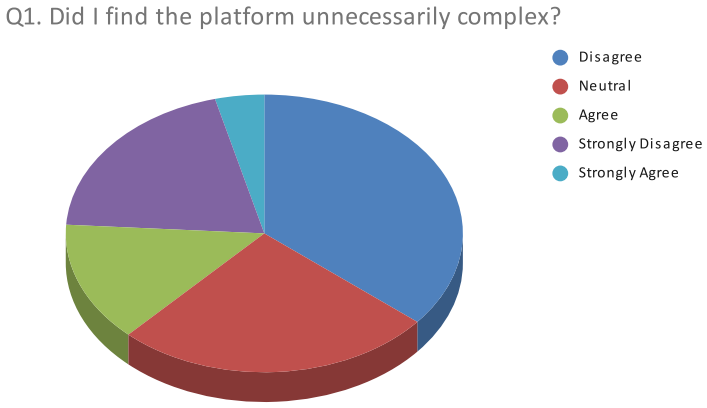


Figure 3. Phase 4 Benchmark: Survey example of Aggregate SUS Score. Source: own elaboration.

In addition, the survey results reinforce this conclusion, 85% of users expressed an intention to use the platform regularly, suggesting high acceptance. Likewise, 90% rated the interface

intuitive and accessible, implying a reduced learning curve. 88% of respondents considered that using the platform does not require technical assistance or advanced knowledge, reinforcing its ease of use.

Regarding functional consistency, 87% of participants highlighted the need to integrate the system's functionalities to facilitate navigation and improve the user experience. In addition, 89% estimated that users could achieve a basic level of operational competence in less than 30 minutes, demonstrating rapid appropriation of the tool.

However, opportunities for improvement were also identified. 75% of users recommended incorporating confirmation and feedback messages, especially at the end of critical tasks, to improve the system's clarity. On the other hand, 80% suggested adding additional functionalities, such as the option to "save and continue later" and a progress bar in the questionnaires, to optimize navigation and progress tracking.

These results indicate a general positive trend toward frequent platform use, with most students showing a favorable predisposition toward it. Most responses suggest that the platform is not complex, reflecting a positive perception of simplicity and ease of navigation. In addition, the survey reveals that technical support is not considered necessary to use the platform, suggesting an adequate learning curve and an intuitive interface.

Some students perceive the platform's functionality as cohesive, suggesting a well-designed information architecture and smooth user experience. The consistency across the different functions and the ease of learning reinforce the idea that the platform is intuitive and accessible to a broad audience, given the age range of users.

Along these lines, the platform was perceived as safe and reliable, providing consistency and clarity in its use and the learning environment. Students tend to value usability aspects, such as ease of use, simplicity, consistency, and the integration of functions. In addition, the perception is that neither an extensive learning curve nor constant technical support is required to sustain the platform's positive assessment.

3.2 Findings from the think-aloud protocol

The insights from Phase 3 (Qualitative Evaluation) are presented next. The think-aloud protocol (Figure 4) was employed to uncover the 'why' behind the quantitative scores. The literature establishes that the SUS questionnaire is a reliable tool for evaluating the usability of web platforms [36]. However, it is essential to complement this evaluation with qualitative methods to observe how tasks are carried out on the website under study [25]. For this purpose, the think-aloud protocol was used, yielding qualitative results and insights into the LMS platform's use. This study used the CEVEC units of study and applied them to students, including activities such as greetings and introductions, think-aloud instructions, and the execution of tasks on the platform by all participants in the protocol. Fifty students participated in the think-aloud protocol, ranging in age from 16 to 60 years, and had experience with technology ranging from 1 to more than 10 years.

The Qualitative Evaluation (Phase 3) is designed to uncover the 'why' behind user behavior. The think-aloud protocol in the validation context confirmed the platform's general intuitiveness but, more critically, identified specific pain points, such as the need for confirmation messages and insights into progress bars that are unattainable through quantitative scores alone.

Consequently, the results indicated that mandatory fields were clearly labeled, facilitating understanding of the task. However, the lack of a successful registration confirmation message was noted, which could detract from the user experience. Participants found the course navigation straightforward, and the modules clearly labeled. However, messages indicating the following steps and confirmation at the end of each course section were identified as needed, which could provide more explicit guidance and reduce uncertainty during navigation.



Figure 4. Experimental setup for the think-aloud protocol sessions. Source: own elaboration.

Completing the questionnaire was intuitive, and the instructions were clear. However, the lack of a confirmation message at the end of the questionnaire was highlighted. In addition, an option to save and continue later was suggested, along with a progress bar to indicate completed and remaining questions, which improved the user experience by providing greater control and visibility into progress.

Participants described the tasks as simple, intuitive, quick, and straightforward. The evaluated tasks did not present navigation problems, but the need for status messages at the end of each task was identified. It was also recommended that an option to save and continue later, a feature considered but not implemented in the prototype, and a progress bar should be included when completing the questionnaire to indicate completed and remaining questions.

3.3 Identification of relevant patterns using machine learning techniques

The core innovation of the framework is demonstrated in the results from Phase 5, which deconstructs aggregate quantitative data to uncover latent user subgroups. PCA was applied to identify underlying patterns in the data, a statistical technique that reduces the dimensionality of the dataset by transforming a set of correlated variables into a new set of uncorrelated variables called principal components. The dataset analyzed consists of 50 observations (individuals) and 10 quantitative variables. The graphical analysis of the PCA results revealed outliers. In particular, two individuals (students 17 and 22) accounted for 33.9% of the cumulative contribution to the construction of the first plane, indicating a disproportionate influence on the data structure. Due to their outlier status, these individuals were excluded from the analysis, and a second PCA was performed on the remaining data.

The inertia explained by the first dimensions of the PCA (Figure 5) reveals the data set's internal structure and allows the optimal number of dimensions to be estimated. In this case, the first two principal components together explain 51.9% of the total inertia, indicating that more than half of the data's total variability can be represented in a two-dimensional space. This value exceeds the reference threshold of 36.32%, corresponding to the 0.95 quantiles of the inertia distribution under a random model, suggesting that the observed structure is statistically significant. Consequently, the first two dimensions contain most of the relevant information in the dataset, so the interpretation and description of the results will be limited to these two principal dimensions.

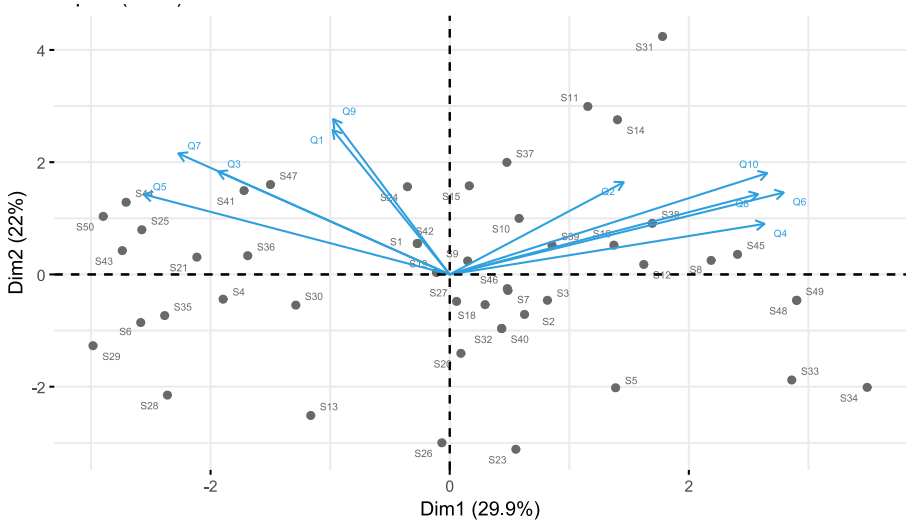


Figure 5. Principal Component Analysis biplot of individual student perceptions.
Source: own elaboration.

Figure 5 illustrates the projection of individuals onto the first two principal components. Dimension 1 (horizontal axis) differentiates individuals such as S45, S34, S48, S49, S33, S5, and S23 characterized by strongly positive coordinates from individuals such as S43, S29, S25, S50, S28, S6, S35, S13, and S44 characterized by strongly negative coordinates. The former group is associated with high scores on variable Q4 and low scores on Q3, Q7, Q5, and Q9. Conversely, the latter group exhibits high scores on Q3, Q7, and Q5 and low scores on Q10, Q6, Q4, and Q8. Furthermore, Dimension 2 (vertical axis) contrasts individuals such as S14, S31, and S11 (positive coordinates) with those such as S45, S34, S48, S49, S33, S5, and S23 (negative coordinates). The positively scored group shows elevated values on Q10, Q9, Q8, Q6, and Q2, whereas the negatively scored group shows high values on Q4 and low values on Q3, Q7, Q5, Q9, and Q1.

On the other hand, Dimension 1 of the plane, corresponding to the graph's horizontal axis, represents the most decisive component in student segmentation, linked to perceptions of usability and general trust in the Moodle platform. The positive pole (on the right side of the graph) corresponds to variables reflecting a negative experience. Students at this extreme (e.g., S45, S34, S48, S49, S33, S5) form a group that perceives the platform as complex, unintuitive, and requires external assistance for practical use. In contrast, the negative pole (left side of the graph) is associated with variables indicating a positive, autonomous user experience. Students at this extreme (such as S43, S29, S25, and S50) report that Moodle's interaction is characterized by its ease of use and functional consistency in its management. Consequently, Dimension 1 allows users to be classified according to their perception of the platform's ease of use and the confidence it inspires in them.

The second dimension (vertical axis) reveals a subtler differentiation related to the specific nature of the difficulty's students perceive. The variables with the greatest weight in this dimension are Q10, Q8, Q6, and Q2, although a positive contribution from Q9 is also observed. At the upper pole of the graph (positive coordinates), students such as S14, S31, and S11 are grouped, and they present a profile of advanced but critical users. Despite expressing confidence in using the platform (Q9), these individuals identify and highlight structural complexity, functional inconsistency, and a steep learning curve. They are not intimidated by the tool but are aware of its limitations.

In contrast, the lower pole (negative coordinates) is characterized by a low perception of platform complexity or inconsistency. Students in this group do not identify significant structural flaws and depend on external support (as reflected in Q4). This profile corresponds to users who, although they do not face specific technical difficulties (low scores on Q2, Q6, Q8),

experience a general feeling of insecurity or need assistance to operate the platform independently.

To enrich interpretation, supplementary demographic variables (age, academic cycle, and gender) were projected onto the plane (Figure 6). These variables contribute to the construction of the axes, but their positions in the graph reveal their correlations with the principal dimensions. Concerning the "Academic cycle" variable, it can be seen that students belonging to the initial cycles (I, II, III) are positioned on the right side of the graph, strongly associated with the positive pole of Dimension 1, indicating that students in these cycles tend to perceive the platform as more difficult, cumbersome, and requiring technical support. In contrast, the higher cycles (V, VI) are located on the left and lower part, associated with a more positive perception of usability and greater autonomy.

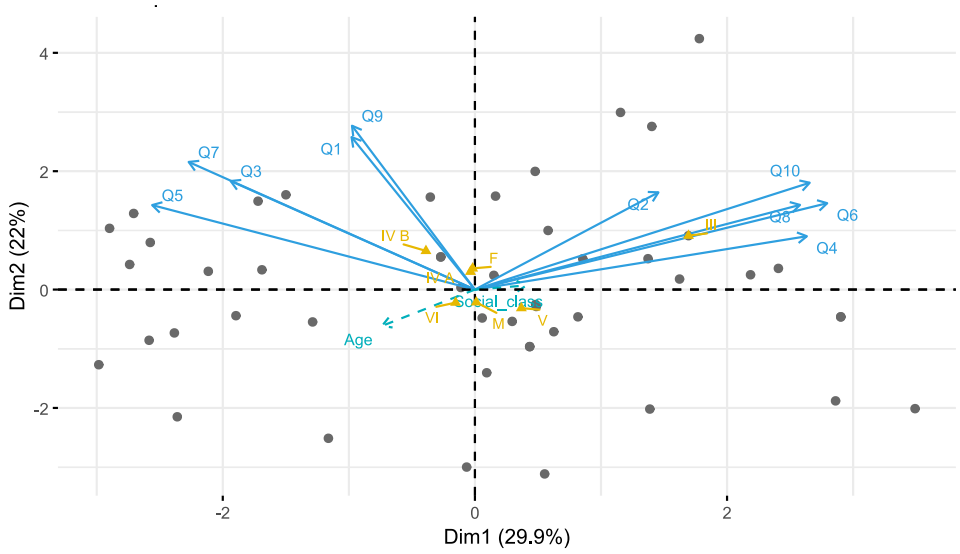


Figure 6. PCA Biplot of student perceptions with projected supplementary variables. Source: own elaboration.

The age vector points towards the lower-left quadrant, indicating that older students tend to have a more positive perception of the platform, find it easier to use, feel more autonomous, and are less overwhelmed by its complexity. This result is significant because it challenges the common stereotype that older age is associated with greater technological difficulties. Finally, the positions of the Male and Female genders are very close to the graph's origin, indicating that this variable is not strongly discriminating in this analysis. Therefore, there is no clear correlation between gender and a specific type of perception of the Moodle platform, suggesting that the experiences of men and women are, as a whole, heterogeneous and do not follow a pattern defined by this variable.

3.4 Identification of student profiles regarding perception

The culminating output of the framework's analytical phase (Phase 5) is segmenting users into distinct, data-driven profiles. Applying K-means clustering to the principal components (Figure 7) in the validation practically demonstrates this capability. However, to avoid arbitrary segmentation, the optimal number of clusters (k) was determined mathematically before executing the K-means algorithm. It utilized a combination of the Elbow Method and Average Silhouette Width analysis. The WCSS plot exhibited a distinct 'elbow' or inflection point at k=4, indicating that adding a fifth cluster provided marginal diminishing returns in variance explanation. This was corroborated by the Silhouette analysis, which showed that k=4 yielded the highest average silhouette score, indicating strong internal cohesion and adequate

external separation among the user segments. This process enabled a deeper identification of student profiles, which could then translate into precise strategic implications for the CECAV context. The four profiles identified below are examples of the actionable personas this framework can generate, which differ in nature but not in utility in other educational settings.

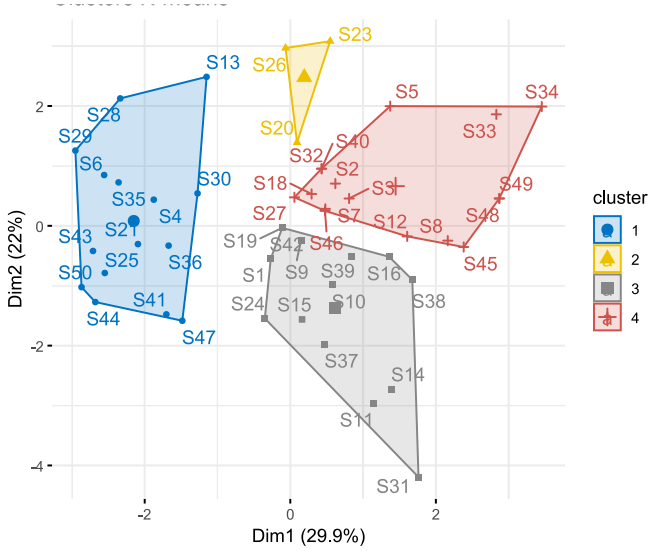


Figure 7. Phase 5 Final Output: Data-Driven User Profile Segmentation via K-Means Clustering. Source: own elaboration.

In this regard, satisfied and autonomous students perceive the platform as easy, coherent, and practical. This profile tends to be found among older students and those in higher academic cycles, representing a group that successfully adapts to the virtual environment. A second group uses the platform confidently but is very aware of its complexity and learning curve, which can become a valuable source of constructive feedback, but does not represent a dominant demographic profile.

The third cluster consists of students who require general technical support rather than criticizing specific functions. This quadrant shows a higher concentration of students in lower academic cycles (I, II, III). This group would benefit from proactive support, visual guides, and reinforcement of their digital confidence. Finally, the fourth group is the one that suffers the most from the platform, so their experience would improve significantly with optimizations in the user interface design to reduce cognitive load.

Identifying these distinct profiles illustrates the framework's power to reveal heterogeneity in user experience, confirming that a one-size-fits-all approach to support is insufficient. This outcome is not unique to the CECAV platform but is a key deliverable of the framework itself, a methodology for moving beyond generic feedback to develop differentiated support strategies tailored to specific user needs. While in this case, the profiles pointed toward a mix of usability improvements and pedagogical support, in another context, they might reveal needs related to accessibility, content relevance, or collaborative features. Ultimately, this process translates raw data into a clear mandate for targeted intervention.

3.5 Discussion

The primary contribution of this research lies in its development and validation of a systematic mixed-methods framework designed to overcome the limitations of traditional usability evaluations in educational settings [37]. Conventional approaches, often culminating in a single aggregate score like the SUS, provide a valuable but incomplete picture, masking the diverse and often contradictory experiences within a heterogeneous user base, as noted in [38].

The proposed framework addresses this gap by creating a structured process that moves beyond a monolithic metric. By integrating user-centered design, contextualized heuristics, and, most critically, machine learning, it deconstructs quantitative data to reveal distinct, actionable user profiles [16]. The significance of this methodological approach lies in its ability to provide educational institutions with a reproducible means not only to measure usability but also to fundamentally understand the nuanced realities of their users, thereby enabling the development of targeted, evidence-based support strategies rather than a one-size-fits-all solution.

The framework's application within the Comfacauca CEVEC LMS validated its empirical effectiveness. The platform achieved a SUS score of 73.9, substantially surpassing the universally accepted usability threshold of 68 established [39]. This robust usability metric is particularly notable given the heterogeneous nature of the student demographic, a cohort often characterized by varying levels of digital literacy and potential barriers to technology adoption [40]. Furthermore, these findings align with [36], who reported comparable usability success for Moodle-based environments, suggesting that CEVEC's underlying Moodle architecture significantly drives its strong usability benchmark.

Positive feedback obtained through quantitative (SUS questionnaires) and qualitative (think-aloud protocol) methods reinforces this claim, as users find the platform intuitive and easy to navigate, and require minimal technical assistance. Ease of use is crucial in adult education contexts [41], where learners prioritize efficient access to educational content and practical learning experience, minimizing distractions from the platform itself [42]. The perception of a short learning curve and adequate LMS functionality indicates a successful UCD for CEVEC. These results demonstrate the effectiveness of the ADDIE instructional design model employed during the development of CEVEC, which emphasizes structured, user-centered planning [43], [44].

Notably, the study's methodological approach, based on UCD principles and employing mixed methods, is a strength. The initial diagnostic phase, which focused on understanding the specific needs and challenges of CEVEC students, was important in contextualizing the usability evaluation. In addition, adapting the Nielsen heuristic to incorporate pedagogical considerations, accessibility, and specific student needs represents a contribution to the domain, going beyond generic usability principles and offering a more specific framework for evaluating educational platforms such as LMSs.

The think-aloud protocol revealed specific areas for improvement, despite the overall positive usability [45]. The identified need for confirmation messages (e.g., successful registration, section completion), features such as "save and continue later," and progress indicators are helpful ideas for future platform iterations. These adjustments can improve the user experience, especially in mitigating uncertainty and fostering a sense of control during learning activities.

A significant contribution of this research is applying machine learning to deconstruct the aggregate SUS score and identify distinct user profiles. The identification of four distinct user profiles, a direct output of Phase 5, the analysis revealed that a single approach to user assistance may be inadequate, demonstrating that usability may not be a universal attribute of the system but rather an emergent property of the interaction between the platform and the specific characteristics of the users [46]. It is important to note that older students and those in higher academic cycles reported a more positive and autonomous experience, perceiving the platform as less complex. This contradicts the stereotype that older users have difficulties with technology, as indicated by another research [47]. Other results suggest that factors such as motivation, previous life experience, or a more methodical approach to learning may enable adults to navigate the LMS more effectively than their younger, less academically advanced peers.

Despite these promising outcomes, a balanced analysis of the framework must explicitly address its methodological and practical limitations. Primarily, the approach depends on sample size; robust execution of dimensionality reduction and machine learning algorithms requires

sufficient data volume (N=50 in this study). Consequently, the clustering's stability can be highly sensitive to small sample sizes or slight data variations, meaning that the boundaries of the identified user profiles might shift or lack reproducibility when applied to more constrained datasets. Therefore, this research should be viewed as an initial proof-of-concept rather than a globally validated tool. Additionally, the complexity of implementation poses a notable practical barrier, as executing this comprehensive six-phase methodology requires an interdisciplinary team with specialized expertise spanning qualitative user research, instructional design, and advanced multivariate statistics. Finally, there are inherent limitations regarding generalizability beyond the context studied. Because the framework was empirically validated within a specific Moodle-based adult education platform, the findings cannot be extrapolated universally.

Ultimately, while mindful of these limitations, the results obtained can be used to effectively administer CEVEC and similar educational platforms, demonstrating that the diverse user profiles identified require targeted, differentiated support strategies rather than generic solutions for the entire student body. Building upon this foundation, future research should focus on applying and testing this framework across a broader range of environments, including traditional universities, K-12 settings, and corporate training platforms, using larger sample sizes to assess its generalizability and stability. Furthermore, longitudinal studies could track how user profiles evolve over time and with increased platform familiarity. A particularly compelling avenue for future work is directly integrating this profiling methodology into adaptive learning systems, creating a mechanism to deliver dynamic, personalized user support and interface adjustments in real time, fully realizing the potential of data-driven, user-centered educational technology.

4. CONCLUSIONS

This research addressed the critical limitation of traditional usability evaluations in learning environments, which often rely on monolithic, aggregate metrics that mask the heterogeneous experiences of diverse user populations. It introduced and provided an initial evaluation of a novel, six-phase mixed-methods framework that systematically integrates user-centered design, contextually adapted heuristics, and advanced machine learning to deconstruct usability data and generate distinct, data-driven user profiles. The framework's core innovation is transforming a single quantitative score into a rich, segmented understanding of user perceptions and behaviors.

The application of this framework within the CEVEC adult learning environment demonstrated its potential practical utility and analytical power. While yielding a high aggregate SUS score of 73.9, indicating above-average usability, the framework's machine learning phase identified four statistically significant user clusters, each with unique needs, challenges, and perceptions. This analysis revealed nuanced insights that would have remained invisible through conventional methods, such as the finding that perceptions of usability were more strongly correlated with a student's academic cycle than with age, challenging common stereotypes about adoption of technology among older learners. This suggests that the framework provides not just a measure of whether a system is usable, but for whom and in what specific ways.

The principal implication of this work is the provision of a robust and reproducible methodological protocol that empowers educational institutions to move beyond generic feedback and develop targeted, evidence-based support strategies tailored to specific student segments. By identifying groups ranging from "Satisfied and Autonomous" to those requiring significant interface optimization, institutions can allocate resources more effectively, design more inclusive learning experiences, and proactively address user friction before it impacts learning outcomes. Ultimately, this research establishes the potential value of combining traditional usability methods with machine learning to translate broad usability feedback into actionable intelligence.

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CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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IA STATEMENT

During manuscript preparation, the authors used Microsoft Copilot to refine grammatical structure and enhance textual clarity. After this computational assistance, the authors conducted a comprehensive manual review and revision of the manuscript to ensure accuracy and coherence. They accept full responsibility for the integrity and authenticity of the final content. All analyses and interpretations presented herein are original contributions derived from the authors' independent expertise and scholarly judgment.