Universidad de Valladolid

Máster universitario

# Ingeniería Informática

Trabajo Fin de Máster

# Exploring Human-Centered Learning Analytics & Artificial Intelligence Tools for Educational Purposes

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**Universidad de Valladolid**

**June 27, 2025**

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# Universidad de Valladolid

## Máster universitario en Ingeniería Informática

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**Expone**:

Que el alumno D. JESUS BREZMES GIL-ALBARELLOS, ha realizado el Trabajo final de Máster en Ingeniería Informática titulado "Exploring Human-Centered Learning Analytics & Artificial Intelligence Tools for Educational Purposes".

Y que dicho trabajo ha sido realizado por el alumno bajo la dirección del que suscribe, en virtud de lo cual se autoriza su presentación y defensa.

En Valladolid, June 27, 2025

## Agradecimientos

En primer lugar, quiero expresar mi más profundo agradecimiento a mis padres, por su apoyo constante y su confianza en mí durante todo este proceso. Gracias por ser mi ejemplo de paciencia y dedicación. Sin su respaldo y su motivación diaria, este logro no habría sido posible.

También quiero agradecer sinceramente a mis supervisores por su orientación, por su disponibilidad y por su experiencia. Gracias por acompañarme en cada etapa del proyecto.

## Resumen

Este trabajo fin de master se basa en la revisión bibliográfica sistemática realizada por mis supervisores, que se centró en estudios empíricos sobre el diseño, desarrollo e implementación de herramientas de análisis del aprendizaje centrado en el ser humano y de inteligencia artificial en la educación. A partir de los artículos incluidos en dicha revisión, se identificó un subconjunto de herramientas relevantes mediante un proceso de selección inicial. A continuación, se analizaron estas herramientas para comprender mejor sus características y ofrecer a las partes interesadas una visión general estructurada de los sistemas disponibles que se ajustan a los principios centrados en el ser humano de la analítica del aprendizaje.

La metodología adoptada para este trabajo se inspiró en DESMET, permitiendo una evaluación sistemática y estructurada de las características de las herramientas. El proceso implicó la lectura iterativa de la literatura asociada, la exploración práctica de las herramientas y la comunicación directa con los autores o desarrolladores para validar la información extraída. Inicialmente se utilizó un enfoque mixto combinando codificación deductiva (top-down) e inductiva (bottom-up) para definir categorías amplias que abarcaran tanto los aspectos cualitativos como cuantitativos de las herramientas. Estas categorías fueron refinadas progresivamente a través de múltiples iteraciones, para mejorar la coherencia interna y la claridad temática.

Se llevaron a cabo dos rondas de contacto para validar los datos recopilados con los propios autores, varios aportaron valiosos comentarios que se incorporaron al análisis final. El resultado es una visión general categorizada y basada en características de las herramientas HCLA y HCAI, que ofrece ideas prácticas para los investigadores y profesionales que buscan adoptar o explorar más a fondo los enfoques centrados en el ser humano en la tecnología educativa.



## Palabras Clave

Análisis del aprendizaje centrado en el ser humano, Inteligencia Artificial centrada en el ser humano, Análisis del aprendizaje, Diseño centrado en el ser humano, DESMET, Análisis sistemático, Análisis de características

## Abstract

This dissertation builds upon a systematic literature review conducted by my supervisors, which focused on empirical studies involving the design, development, and implementation of human-centered learning analytics and artificial intelligence tools in education. From the articles included in that review, a subset of relevant tools was identified through an initial screening process. These tools were then analyzed to better understand their features and provide stakeholders with a structured overview of available systems that align with human-centered principles in Learning Analytics.

The methodology adopted for this work was inspired by DESMET, enabling a systematic and structured evaluation of tool characteristics. The process involved iterative reading of associated literature, hands-on exploration of the tools, and direct communication with the authors or developers to validate the extracted information. A combination of deductive (top-down) and inductive (bottom-up) coding was initially used to define broad categories covering both qualitative and quantitative aspects of the tools. These categories were progressively refined through multiple iterations to enhance internal coherence and thematic clarity.

Two rounds of outreach were conducted to validate the collected data, with several authors providing valuable feedback that was incorporated into the final analysis. The outcome is a categorized, feature-based overview of HCLA and HCAI tools, offering practical insights for researchers and practitioners seeking to adopt or further explore human-centered approaches in educational technology.

## Keywords

Human-Centered Learning Analytics, Human-Centered Artificial Intelligence, Learning Analytics, Human-Centered Design, DESMET, Systematic Analysis, Feature Analysis

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# 1: Introduction

This chapter outlines the motivation and problem statement that frame this research. It presents the main goal and specific objectives pursued in this dissertation. Additionally, the chapter provides a brief overview of the methodology followed, highlighting the use of the DESMET framework, an iterative research process combining both quantitative and qualitative analyses, and the involvement of supervisors and authors in the validation stages. Finally, the structure of the document is described, guiding the reader through the organization of the subsequent chapters.

## 1.1 Motivation and Problem Statement

The use of technology in education has increasingly become a valuable asset for both students and teachers, offering numerous benefits driven by the rise of new technologies and the ongoing digitization process. Technology is usually promoted in classrooms from pre-school to university through different tools and platforms. As Ao Yu (2024) [69] points out, the use of devices, media, games, or online learning management systems can be elements that favour the motivation of students and teachers, the improvement of the learning experience, as well as simplifying their work.

The increasing adoption of Learning Management Systems (LMS) like Moodle and Canvas at all levels of education, including elementary, secondary, and tertiary, mirrors the expansion of the use of digital platforms in supporting teaching and learning. These systems provide a broad array of functionalities ranging from content management and monitoring student progress to enabling communication and collaboration [23].

The widespread adoption of LMSs has played a key role in the development of LA, as these platforms enable continuous tracking and analysis of learner interactions in digital learning environments. The availability and volume of educational data, which is handled today, has opened up new possibilities to analyze learning processes and to analyze the decision making of the various stakeholders (e.g., educators, students, administrators). In this context, the fields of Learning Analytics (LA) and Artificial Intelligence in Education (AIED) have emerged. *LA is the collection, analysis, interpretation and communication* *of data about learners and their learning that provides theoretically relevant and actionable insights to enhance learning and teaching* [59]. LA can support the development of lifelong learning skills by promoting self-reflection and student awareness. Through timely and personalized feedback, it enhances individual learning experiences while also fostering collaboration, creativity, and critical thinking. Additionally, data-driven insights empower educators to improve teaching quality and implement effective innovations [59].

In recent years, this virtual environment has been further redefined by the emergence of generative Artificial Intelligence (AI) technologies like ChatGPT [44] and GitHub Copilot [25] that are now poised to play a significant role in learning spaces. These technologies do not only enable learners and teachers to produce content and code but also introduce new possibilities for adaptive learning and intelligent feedback. In this regard, the use of Learning Analytics (LA) and AI tools becomes increasingly relevant to understand, support, and augment learning processes.

From the student's perspective, the impact of tools based on LA and AI can help transform the learning experience, helping to make learning more personalised and interactive. This can help increase motivation and improve active engagement. The use of progress visualisations, gamified challenges and intelligent recommendations encourage more active participation. From a teacher's perspective, these technologies aim to simplify and support pedagogical work [58]. For example, some of the tasks where such tools are introduced include:

- **Reducing the orchestration burden:** Automated analysis and dashboards allow teachers to monitor individual and group progress without investing large amounts of time.
- **Detecting at-risk students:** Alert systems can flag patterns that indicate demotivation, underachievement, or disengagement.
- **Facilitating feedback:** AI-based models can generate personalised reports or recommendations to increase the amount of feedback provided by teachers [41].

Before we dive into the topic, it is worth mentioning that for several years now, many people in the academic and technological world have been working on creating tools to help improve how we learn and teach. Many solutions focus on these technological advances, but, in most cases, these proposals do not adhere to the needs of end users, are not usable, or are simply not adopted in reality.

One potential way to address this issue is by involving teachers and students early in the design and development process of Learning Analytics and AI tools. This participatory approach is commonly referred to as Human-Centered Design (HCD). A human-centered approach means that the purpose, functions, and interactions of a system are shaped by the people who will use it, not just by designers or researchers. It involves understanding key stakeholders, their relationships, and the context in which the system will operate [51].

A human-centric approach is important in the domains of LA and AIED due to concerns over data privacy and agency. By taking into account human variables including usage motivations and methods, a shift towards Human-Centered Design not only tackles these issues but also facilitates a more seamless adoption [51]. Although this subject is developing fast, there are obstacles as well as opportunities for scalable, data-intensive systems [4]. Making sure that these resources are made with, not just for, the people who are at the center of education, teachers and students, is crucial [4].

## 1.2 Main Goal and Objectives

While previous literature reviews in the field of LA and AIED have provided valuable insights into research trends, theoretical frameworks, and pedagogical implications, they often focus primarily on analyzing the studies themselves, examining methodologies, outcomes, and research gaps. However, they tend to pay less attention to the tools being designed, especially in terms of their concrete features, modes of interaction, and alignment with human-centered principles.

In contrast, our work offers a systematic review and feature-level analysis of the tools described in the literature. Instead of stopping at just analyzing the studies, we decided to dig a bit deeper. We looked into how the tools are actually built, their design, the technology behind them, how they work, who they're made for, and the kinds of interactions they allow. By focusing on these characteristics, modes of interaction and alignment with human-centered principles, we can come to identify which design elements are most successful in practice. Sharing this knowledge with the wider community can help guide the development of future HCLA and HCAI tools, making their design processes more efficient and their outcomes more effective and usable.

This review's main objective, therefore, is to make a profound analysis of tools related to the Human Centered Learning Analytics (HCLA) or Human Centered Artificial Intelligence (HCAI) concept. The identification of the available tools will be done in such a manner that common categorizations among the several existing tools can be made, allowing for the proposition of a classification system that supports organization and analysis in the context of these two fast-emerging areas.

This approach not only provides a broad overview of the current state of the art in HCLA and HCAI tools, but also provided a solid basis for identifying trends, research gaps and opportunities for future tool development. The creation of a classification system further contributes to improving the organization of knowledge in the field, facilitating its understanding and application in practical scenarios.

To this end, an attempt was made to answer a series of questions that guided the research process:

- **What are the common characteristics of the tools identified?** Identify the common characteristics of the developed tools, such as the types of solutions proposed, the intended objectives, the target users, and the design approaches adopted.
- **Which stakeholders, when and how were involved the the tool life-cycle?** The different facets of stakeholders in terms of end-users, developers, researchers, and decision-makers were assessed regarding how they had been involved during the various phases of the tool life cycle, including design, development, implementation, evaluation, and continuous improvement, in order to understand how their perspective is integrated into the development of human-centered tools.
- **Is there any evidence about the adoption of the tools?** This question aims to assess the developmental state of the selected tools, whether they are fully implemented and validated in real-world contexts, or still in experimental stages, and to consider whether these findings may offer broader insights into the maturity of the Learning Analytics field.

## 1.3 Contribution

In order to answer the previous questions, a systematic feature analysis of HCLA and HCAI tools has been carried out following the DESMET methodology [33]. The tools evaluated in this study were selected through a filtering process applied to the articles included in the Systematic Literature Review (SLR) on Human Centered LA and AIED conducted by Topali et al. (2024) [62]. An initial screening was carried out by the supervisors to identify tools relevant to the focus of this dissertation A. Those have been classified following both deductive (top-down) and inductive coding (bottom-up). These categories cover both qualitative and quantitative aspects. Throughout the first iterations, these categories are refined to ensure that the study is coherent (bottom-up approach).

## 1.4 Document Structure

This thesis is organized into several chapters that follow a logical progression, reflecting the development of the research.

- **Chapter 2 - Related Work:** This chapter provides the foundation for research by exploring existing knowledge and work in relevant areas.
- **Chapter 3 - Methodology:** In this chapter, I introduce DESMET and how I applied it in this thesis. I describe the artifact I worked with, why I chose it, and the tools I analyzed. Then, I walk through the research procedure, my approach to content analysis, how the work evolved through iterations, and how I validated the findings.

- **Chapter 4 - Results:** This chapter presents the main results from the analysis of the different tools.
- **Chapter 5 - Discussion:** This chapter reflects on the results according to the posed questions. Then, I compare them with the previous studies, share recommendations for practice or research, and acknowledge the limitations of my work.
- **Chapter 6 - Conclusions & Future Work:** This section summarizes the main insights of this dissertation and suggests future directions that could build on this work.
- **Appendices:** These annexes present complementary information that supports the main content of this work. They include the list of articles analyzed (A), the detailed coding of the tools used (B), and descriptions of the instruments employed for data collection (C & D).

# 2: Related Work

This chapter reviews the existing literature related to LA and AIED. The chapter also examines examples of tools developed under the HCLA and HCAI frameworks, illustrating their various applications and benefits. These examples are drawn directly from the tools discussed in this dissertation. Finally, it presents some conclusions from systematic reviews of the literature assessing the current state of HCLA and HCAI systems.

## 2.1 Learning Analytics and Artificial Intelligence in Education

According to the Society for Learning Analytics Research, Learning Analytics is defined as "the collection, analysis, interpretation and communication of data about learners and their learning that provides theoretically relevant and actionable insights to enhance learning and teaching" [59]. Practical applications include, for example, dashboards that allow teachers to monitor their students' progress in real time. Another example is adaptive systems that personalize learning according to individual student performance, recommending specific activities or adjusting the pace of content. To do this, LA uses different types of indicators, which can be both analogue and digital. Analogue indicators include class attendance or active participation (such as raising hands), while digital indicators include metrics such as time spent connected to the platform, clicks on study materials or grades obtained in online quizzes.

Learning analytics is a multidisciplinary field that involves the collaboration of experts in education, statistics and technology, among others, to derive insights from learning data. It is characterized by a continuous cycle: collecting data about learners and their context, processing and analyzing it using a variety of techniques, and using the results to improve learning and teaching before restarting the process [26].

The field has evolved into both an academic discipline and a commercial marketplace since its inception in 2011. LA also addresses challenges such as expanding data collection to capture the complexity of learning and navigating issues related to privacy and data ownership [57]. It integrates concepts and techniques from machine learning, artificial intelligence, information retrieval, statistics, and visualization. It is one of those fields where everything seems to be evolving rapidly, and everyone is trying to keep up. Moreover, LA acts as a convergence point for several related areas in Technology-Enhanced Learning (TEL), such as academic analytics, action analytics, and educational data mining [10].

LA tools are developed to automate educational processes, monitor student behavior, and personalize learning experiences at scale and with minimal effort. However, the primary challenge in developing and implementing such tools is not only technical but also human in nature [51]. The key goals of any project should be to ensure that the final product meets the needs of users, promotes good adoption, and provides a positive user experience.

A potential solution to achieve these goals is to involve them throughout the lifespan of the tool, from the very beginning of the product design, followed by the development and evaluation. These strategies are often referred to as human-centered approaches.

One of the main concepts of this dissertation is the application of Human-Centered approaches in the field of Learning Analytics, known as Human-Centered Learning Analytics (HCLA). This approach seeks to combine the potential of LA with the specific needs of educational stakeholders, developing efficient and user-friendly solutions that fundamentally improve teaching and learning practices [51]. Co-design and participatory design approaches, which include educators and students as key partners in the LA design process, serve as its cornerstones [37]. This is essential to match the tools with the learning environment, making them more useful and enjoyable to use [51].

The evolution of technologies has enabled the development of intelligent systems. These systems make autonomous decisions, such as predictions or recommendations, based on existing data. Researchers in the field are using LA to feed these systems and to apply AI in the educational field. As with LA, in the field of AIED, HCAI processes are also being applied to the development of tools to increase their usefulness and adoption.

The idea of HCAI has come to the forefront as a framework that prioritizes human values and needs in the development of AI. UNESCO's report on AIED emphasizes the importance of a human-centered approach to AI. Through initiatives such as the Beijing Consensus and its policy guidance documents, UNESCO supports governments in responsibly integrating AI into education, while equipping teachers and students with the skills to navigate both the opportunities and risks it presents [64]. This approach stands in stark contrast to AI models that focus solely on performance or autonomy, as it highlights systems designed to enhance human decision-making instead of replacing it. For instance, Shneiderman (2020) [56] suggests that the future of responsible AI hinges on creating systems that are reliable, safe, trustworthy, and ultimately accountable to human oversight. He presents an HCAI framework that strikes a balance between automation and human control. Instead of seeing AI as independent agents, it encourages developers to view it as socio-technical systems, where human users play a crucial role.

Tahaei, Constantinides et al. (2023) [61] examine the current status and future projections of Human-Centered Responsible Artificial Intelligence (HCR-AI). The authors identify that, despite the variety of terms used by different scientific communities (such as 'ethical AI', 'responsible AI' or 'human-centered AI'), they all share the common goal of ensuring that AI systems respect human rights, promote social welfare and reduce potential harm. In other words, they all agree that AI needs to be on the side of people, not the other way around. Among the current challenges, the authors highlight the need to establish sound regulatory frameworks.

## 2.2 Systematic Literature Reviews on HCLA and HCAI

Recently, two systematic literature reviews on HCLA and HCAI have been published. The first one, by Topali et al. (2024) [62], reviews 47 papers, focusing on empirical studies. The main findings are that the community engages stakeholders in design and, to a lesser extent, evaluation, mainly to identify needs and design scorecards for teachers and learners. However, little research adopts existing human-centered design guidelines, indicating an opportunity to improve effectiveness by incorporating recognized standards and principles. Furthermore, the importance of pedagogical contextualization and assessment in real-world settings is highlighted. Finally, further research into the application of these approaches in the educational technology industry is recommended in order to realize their full potential.

The other systematic literature review, authored by Alfredo et al. (2024) [4], covers 108 papers, focusing on how the different educational stakeholders are included in the design process, the balance between human control and computer automation in these systems and how each article describes the degree of reliability and safety in its literature. One of the conclusions they draw is that during the planning and scoping stages, as well as the implementation and monitoring of the application, there are many gaps in the current research. There is also an over-reliance on traditional techniques (such as interviews), and it is proposed to integrate more innovative methods such as The Wizard of Oz. In other words, more creative human-centered design techniques should be adopted to explore the challenges and benefits of educational AI. They also add that it is essential to carry out studies in real contexts to evaluate the effective impact of this type of technology.

Another of the points highlighted by the authors is that these systems must be safe and generate trust, and must incorporate ethical principles, privacy measures, transparency and feedback mechanisms with users. The authors point out that trust is built not only with accuracy, but also by recognizing limitations and educating users about the biases of AI.

Given the wide variety of tools identified, it is essential to understand what types of tools are being designed using a human-centered approach. Due to the time constraints of this master thesis, I will only focus on the tools emerging from the papers identified by Topali et al. (2024) [62]. Still, the results from my feature analysis will be discussed in relation to the findings posed in Topali et al. literature review.

# 3: Methodology

This chapter outlines the methodology adopted in this research: DESMET. The chapter includes a theoretical introduction to the methodology, an explanation on how DESMET was implemented in this study, the rationale behind the selection of the analyzed features and artifacts used, the tools included, and an overview of the research procedure followed.

## 3.1 Theoretical Introduction to DESMET

DESMET is a methodology proposed in 1996 for systematically evaluating software engineering methods and tools. This methodology was a collaborative effort among different researchers funded by the UK Department of Trade and Industry. It is intended to help evaluators in a particular organization to plan and execute an evaluation exercise that is unbiased and reliable. The method is context-dependent, and it can be used to evaluate generic methods, specific approaches, or tools [33].

DESMET identifies three ways of organizing an evaluation exercise: as a formal experiment, as a case study, and as a survey. These methods can be applied to both quantitative and qualitative evaluations. The methodology describes that there are three main categories of evaluation methods [33]:

- *Quantitative evaluation methods:* These methods are based on the assumption that you can identify a measurable property of a software product or process that you expect to change as a result of using the methods/tools you want to evaluate.
- *Qualitative evaluation methods:* These methods are based on identifying the requirements that users have for a particular task/activity and mapping those requirements to features that a method/tool aimed at supporting that task/activity should possess. An evaluator then assesses how well the identified features are provided by a number of alternative methods/tools.

- *Hybrid evaluation methods:* These methods have both quantitative and qualitative elements. The text describes two hybrid methods: qualitative effects analysis and benchmarking.

The DESMET method identifies seven criteria that influence the choice of evaluation method [33]:

1. **Evaluation context:** The context in which the evaluation is being performed, such as the choice of a set of methods/tools for an individual project or evaluating methods/tools for re-sale as part of a product line.
2. **Nature of the expected impact:** The impact of using the method/tool can be either quantitative (e.g. improved productivity or quality) or qualitative (e.g. better process visibility or usability).
3. **Nature of the object to be evaluated:** The object being evaluated can be a tool, a generic paradigm, a specific approach within a generic paradigm, a method/tool combination, or a project support environment.
4. **Scope of impact:** The scope of impact of the method/tool has two major dimensions: product granularity (whether the method/tool applies to the development or maintenance of a software product as a whole or individual parts of the product) and extent of impact (how the effect of the method/tool is likely to be felt over the product/project life-cycle).
5. **Maturity of the item:** The maturity of the method or tool indicates the extent to which there is likely to be information about it readily available.
6. **Learning time:** The time it would take someone to become familiar enough with the method/tool to access its capabilities or to use it effectively.
7. **Evaluation maturity of an organization:** The evaluation capability of the organization, which determines the type of evaluation the organization is able to undertake.

In this master thesis, I will use a hybrid approach because, although most of the categories will be qualitative, there are also some that can be quantitative. For example, if we want to analyze the number of stakeholders involved in HCD processes we will also need to follow a quantitative approach. Moreover, for the dissertation we are doing, the most appropriate method is feature analysis. According to DESMET we have four possibilities [33] (see Table 3.1.

| **Evaluation Method** | **Conditions favouring method** | **Relative Timescales** | **Relative Risk** | **Relative Cost** |
|---|---|---|---|---|
| Feature Analysis - Screening mode | Large number of methods/tools to assess. Short timescales for evaluation exercise. | Short (several weeks) | Very High | Medium |
| Feature Analysis - Case Study | Benefits difficult to quantify. Benefits observable on a single project. Stable development procedures. Tool/method user population limited. Timescales for evaluation commensurate with the elapsed time of your normal size projects. | Long (three plus months) | High | Medium |
| Feature Analysis Experiment | Benefits difficult to quantify. Benefits directly observable from task output. Relatively small learning time. Tool/method user population is very varied. | Short (several weeks) | Low | High |
| Feature Analysis Survey | Benefits difficult to quantify. Tool/method user population very varied. Benefits not observable on a single project. Projects with experience of using the method/tool, or projects prepared to learn about the method/tool. | Medium (several months) | Medium | Medium |

Table 3.1: Feature Analysis [33]

## 3.2 DESMET Implementation

DESMET structures the design of the feature analysis in four different steps:

1. **Identification of features to be analyzed**: This step involves determining the specific features or dimensions that will be the focus of the analysis.

2. **Tool selection**: The evaluated tools have been chosen based on a filtering process derived from the articles included in the SLR by Topali et al [62]. A preliminary screening was conducted by the supervisors to identify relevant tools that matched the focus of this dissertation.

3. **Definition of artifacts used**: Various artifacts support the analysis process, including structured data sheets, interview feedback from tool authors, and normalized datasets.

4. **Procedure conducted**: The evaluation have ben conducted through an iterative process combining both top-down and bottom-up approaches. This included multiple rounds of reading, the incorporation of author feedback, and both qualitative and quantitative analyses.

This section presents one by one how these steps were implemented.

### 3.2.1 Tool Features

While the tool characteristics emerged deductively (top-down), the categories of some features emerged inductively (bottom-up) before the review process. As we analyzed the papers and extracted relevant information, recurring patterns and themes became apparent, which led to the development of the final categories. This bottom-up approach allowed for a more grounded and context-sensitive classification, better reflecting the diversity and nuance of the tools described in the literature.

We defined a set of 42 categories that capture the most important characteristics of each tool. For clarity, we organized the categories into five main groups. These categories were not chosen arbitrarily, but are in line with the objectives outlined in Chapter 1, as they help to understand the tool features, the HC approaches followed along the tool life-cycle, and reflect on the usage and adoption of the tools in educational contexts. In this sense, the categorization provides a structured lens for assessing whether and how current tools respond to the challenges and aspirations defined at the beginning of this research.

- **Tool Basis** - Includes fundamental information about the tool, such as its name, purpose, pedagogical context, and technological aspects.
- **Human-Centered Approach** - Focuses on how stakeholders (e.g., students, teachers, researchers) are involved in tin design, implementation and evaluation phases.
- **Data Management** - Covers aspects related to data collection, storage, processing, and privacy considerations.
- **Tool Evaluation** - Examines how the tool's effectiveness, usability, and impact are assessed.
- **Tool Adoption** - Explores the extent to which the tool is used, its sustainability, and its integration into educational settings.

#### 3.2.1.1 Tool Basis

In this category group, we also divide into two subgroups:

- **Functional Information** - Covers the tool's purpose, target users, pedagogical context, and its contribution to education.

  - **Codification** - Internal coding system for article classification.
  - **Paper/Article** - Paper/Article analyzed.
  - **Authors (of the article/paper)** - List the authors of the article/tool.
  - **Emails** - Authors' contact.
  - **Year of publication** - When the article was published.
  - **Tool Name** - The name of the tool.
  - **Tool Objective** - Objective or purpose for which the tool was developed.
  - **Pedagogical context** - The pedagogical context of a tool refers to the instructional methods in which the tool is used to support learning outcomes.
  - **Year of creation** - When the tool was created.
  - **How long (until when) it has been working** - Duration of the tool's operation.
  - **Type of target user** - Type of target users of the tool (students, teachers, etc.).
  - **Level of education** - Targeted level of education (e.g., primary, secondary, or tertiary education).
  - **Concrete field** - Specific field or subject area of the target user (e.g., science teachers).
  - **Stage of the tool** - Stage of development the tool is currently in (e.g., being designed, under development, under evaluation, or in production).
  - **Contribution type** - How the authors refer to/describe the tool contribution type (e.g., LA dashboard, recommendation system, data gathering tool).

- **Infrastructure** - Focuses on the technological aspects, such as platform type, programming languages, and deployment details.

  - **Platform** - Type of platform on which the tool operates (e.g., web-based, mobile, desktop application).
  - **Embedded/Standalone** - Whether the tool is embedded in another platform or standalone.
  - **If embedded, name of the platform in which it is embedded** - Specify the name of the platform where the tool is embedded, if applicable.
  - **Technology/Programming languages** - Technology or programming languages used to develop the tool.
  - **Is the tool open source? If yes, is there any license?** - Whether the tool is open source and which licenses are used.
  - **Language** - Language(s) in which the tool is available.
  - **User manuals** - Whether user manuals are available for the tool.

  - **User support → What type** - Whether user support is available for the tool.
  - **If the tool is open source, is there software documentation?** - Whether software documentation is available for the tool, if it is open source.

**Human-Centered Approach**

- **Stakeholders involved in the design process** - Who, how many, and how people are involved in this phase, which focuses on understanding the problem and defining requirements.
- **Stakeholders involved in the implementation phase** - The involvement of stakeholders in the co-creation of the tool, including tasks and actions performed.
- **Stakeholders involved in evaluation and testing phases** - The participation of stakeholders in evaluating and testing the tool, whether in a partial or final stage.
- **Total Stakeholders (Who & how many)** - Reports the total number of stakeholders involved, even if their unique participation is unclear.

#### 3.2.1.2 Data Management

- **Data Sources** - The data sources used by the tool (e.g., learning management systems, files, sensors, user input, internal logs, and metrics).
- **Type of Data** - Different types of data collected by the tool.
- **Data Gathering Techniques** - Type of data collection, pull or push (automatically or on demand).
- **Type of Analysis** - Methods of analyzing the data collected:
  - **Descriptive** - Summarizes past data to reveal patterns.
  - **Diagnostic** - Explains causes behind past events.
  - **Predictive** - Uses data to forecast future trends.
  - **Prescriptive** - Recommends actions based on predictions.
- **Data Analysis Techniques** - Mentioned techniques to analyze data used by the tool.
- **Visualization Techniques** - Mentioned visualization techniques included within the tool.
- **Dynamic/Interactive or Static** - The data is static or there is interaction between the user and the system (i.e., dynamic).

- **How does the tool preserve ethics and data privacy? (Original Info)** - Description of the measures taken to ensure privacy, security, and ethical use of data.
- **How does the tool preserve ethics and data privacy?** - Description of the measures taken to ensure privacy, security, and ethical use of data, following the DELICATE checklist [17]:
  - **D - Determination** - Clearly define the purpose and added value of data collection.
  - **E - Explain** - Be transparent about what data is collected and why.
  - **L - Legitimate** - Justify the necessity and legality of the data collection.
  - **I - Involve** - Engage all stakeholders and address privacy concerns.
  - **C - Consent** - Obtain clear and informed consent from data subjects.
  - **A - Anonymize** - Anonymize and aggregate data as much as possible.
  - **T - Technical** - Implement privacy safeguards and monitor data access.
  - **E - External** - Ensure external providers comply with data security and privacy rules.
- **Are these measures embedded in the tool or are the teachers/researchers/... the ones doing it ad-hoc?** - Describe whether the measures are built into the application or whether the user is responsible for these measures.

#### 3.2.1.3 Tool Evaluation

- **Evaluation reported in the paper (yes/no)** - Whether the tool has been evaluated in a research paper.
- **Purpose of Evaluation** - Purpose of the evaluation of the tool.
- **Method of Evaluation** - List the method used to evaluate the tool.

#### 3.2.1.4 Tool Adoption

- **Scope: Only for Research and/or Real Educational Setting** - Indicate whether the tool is intended for research, for application in real educational settings, or both.
- **Evidence of System Adoption** - Provide evidence of the tool's adoption.
- **Availability of the Tool** - Indicate whether the tool is publicly available on the Internet, available upon request, or dependent on an institution.

### 3.2.2 Tool Selection

The tools analyzed in this study were extracted from a filtered subset of papers initially identified in the SLR conducted by Topali et al [62]. Starting from the comprehensive set of articles gathered through the SLR, my supervisors performed a pre-filtering process to select those most relevant for the specific review of tools presented here. The filtered articles are described in Appendix A.

Out of the 43 papers originally considered for this work (see Appendix A):

- Five were eliminated since they do not describe a prototype.
- One was removed as it was found to be a plagiarism of another article already considered in the list.

As a result, the final sample of papers consisted of 37 papers.

A total of 36 unique tools were identified across the 37 papers (see Appendix B). That is because some papers describe the same tools, and others describe more than one tool. More concretely:

- *Grouping*: Some tools were described in multiple papers. In six articles (in pairs of two), the same tool was described. As a result, three tools were extracted from these six papers.
- *Splitting*: In two cases, individual papers described more than one distinct tool, which led to a total of four tools extracted from those two papers.

Additionally, some tools appear in both the "grouped" and "split" categories. For instance, a tool described in multiple papers may also be part of a paper that includes another distinct tool.

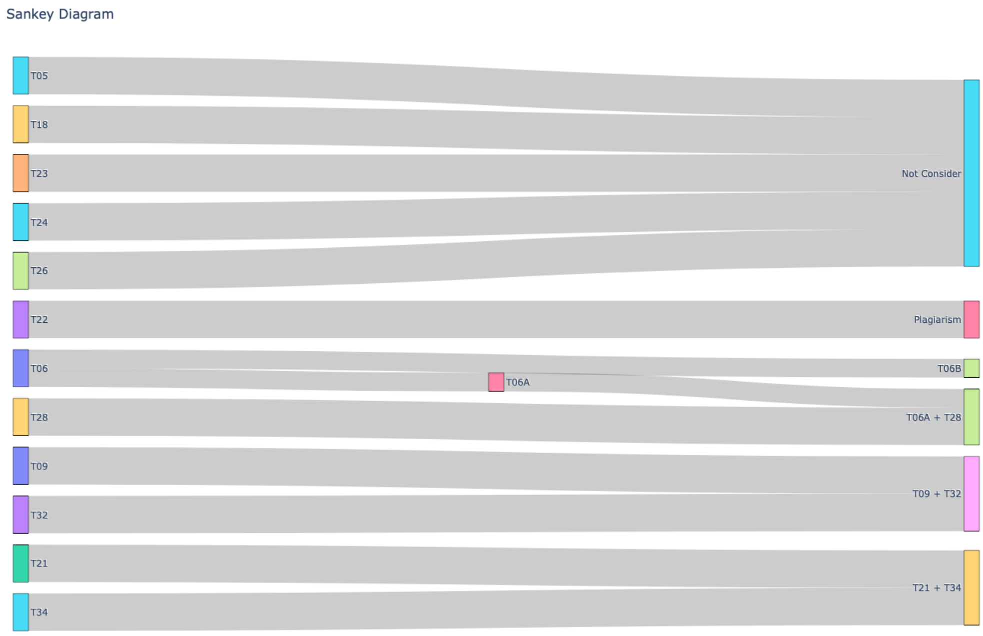



Figure 3.1: Article grouping

### 3.2.3 Artifacts Used

Regarding the artifacts used, a spreadsheet D was employed and organized into four groups of tabs to facilitate the management and analysis of the information collected during the methodological process.

1. The first group (see Figure 3.2) contains the information collected directly by myself after completing the iterations described in the methodology process; that is, the raw data.

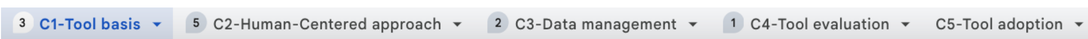



Figure 3.2: Raw Data

2. The second group (see Figure 3.3) includes tabs with comments and feedback provided by the authors. It should be noted that the interview format used with the authors can be found in Appendix B.

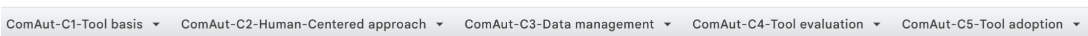



Figure 3.3: Author comments

3. The third group (see Figure 3.4) comprises tabs where the authors' contributions have been integrated into the original data mentioned in point 1, thus combining both sources.


Figure 3.4: Merge

4. Lastly, the fourth group (see Figure 3.5) contains normalized or standardized data prepared for the quantitative and qualitative analyses carried out in this study.




Figure 3.5: Normalized information

In the Appendix C, there are some examples of the content of these different sheets. All content is available on Zenodo [24].

### 3.2.4 Procedure

In Figure 3.6, we can see the main stages of the project, including the contextualization phase, the iterative reading of articles, double-checking with the authors, data consolidation, and the subsequent analysis.

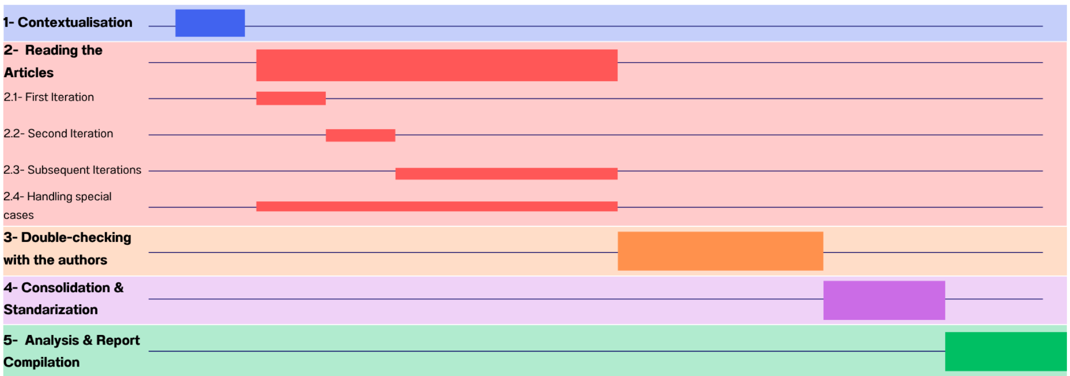



Figure 3.6: Overview of the research procedure

#### 3.2.4.1 Contextualization

In the first phase of this work, I undertook a contextualization stage to build a solid foundation and understanding of the topic scope. This stage involved working with a variety of resources provided by my supervisors, including readings, webinars and relevant articles. The main objective of these activities was to familiarize myself with fundamental concepts such as LA, AIED, as well as to understand the importance of applying people-centered design approaches within this field of research. Among the materials reviewed, recorded webinars stand out, particularly two key presentations that helped with contextualization:

- *Designing Learning Analytics for Humans with Humans* [21].
- *SNOLA Webinar, Learning Analytics for "end-users": from Human-centered Design to Multimodal Data Storytelling* [22].

Moreover, I analyzed in depth a systematic review article entitled 'Designing Human-Centered Learning Analytics and Artificial Intelligence in Education Solutions' [62]. Which is the literature review conducted by my supervisors and from which the articles on which this paper is based are drawn.

I also made a review concerning systematic feature analysis, including methods like DESMET [33], and examples from previous studies. These references helped me identify possible strategies in data collection, analysis tools, and ways of presenting results effectively.

Generally speaking, this step gave me a general view of the research context while, at the same time, laying the required ground to approach successive stages of work with knowledge of what was needed for coherence.

#### 3.2.4.2 Reading the Articles

Having acquired the necessary concepts to continue with the research, I proceeded to read the articles. It happened in a series of iterations. The aim was to evolve and adjust the categorization of tools.

**First Iteration.** The first iteration began with the reading of three articles, suggested by my supervisors, from the initial set. These articles served as the basis for proposing a preliminary classification of the tools. This initial analysis was carried out through the following steps:

- Extraction of key features from the tools described.
- Identification of patterns or similarities between these characteristics.
- Proposal of a first version of categories, based on these similarities.

This first reading resulted in a first version of the categorization. Which was reviewed by my supervisors to ensure its validity and alignment with the overall research objectives.

**Second Iteration.** In the second iteration, five additional articles were read. This analysis made it possible to:

- Adjust the preliminary categories to include aspects that had not been initially considered.
- Eliminate or merge redundant or overlapping categories.
- Ensure that the categories are representative and cover the diversity of tools analyzed.

The refined version of the categories was also reviewed by the directors for approval.

**Subsequent Iterations.** After the second iteration, four further iterations were carried out. In these additional iterations, relevant information continued to be systematically collected from the reviewed articles in order to categorize the tools found more effectively.

As the study progressed and more data were gathered, the categories underwent continuous refinement, ensuring a more precise classification. This process was essential to maintain the consistency and accuracy of the categorization framework.

Moreover, as new insights emerged, it became necessary in some cases to revisit previously analyzed articles. This re-examination allowed for the adjustment and reassignment of information to the updated categories, ensuring that all classifications remained relevant and up to date. The iterative nature of this approach contributed to the robustness and reliability of the study's findings.

#### 3.2.4.3 Handling special cases

During the reading, we found special cases such as plagiarism, articles that do not refer to a specific tool and therefore cannot be considered, and even articles that can be grouped together because they refer to the same tool. The articles that were excluded, together with the reasons for their exclusion, are listed in Appendix A (A.1).

**Detection of plagiarism.** One case of suspected plagiarism was identified in one of the articles during the review process. The following steps were taken to arrive at a fair and transparent resolution of the matter:

- Documentation of the plagiarized section. It was reviewed and documented that the two articles studied were by different authors and dates, and that they did not quote each other. It is found that even the same images and examples from the original article are used.
- Communication with the author. Regarding this, the authors of the article concerned were immediately contacted for remedial action. Evidence of documented proof was provided, indicating there was a case of alleged plagiarism.

These actions were taken in order to follow standards related to publication ethics and maintain the fairness and integrity of the review process.

**Elimination of articles irrelevant to this study.** Articles that did not contain descriptions of relevant tools were identified and removed, ensuring that the analysis focused exclusively on articles useful for the research objectives.

As part of the article selection process for the study, a fundamental criterion was the presence of an artifact or prototype. If, upon analyzing the content of the article, we determined that no artifact or prototype was presented, the article was excluded from the analysis.

**Clustering of related articles.** Cases were found where more than one article discussed the same tool. In these cases, the articles were grouped together, and information on the tool was consolidated to avoid redundancy.

#### 3.2.4.4 Double-checking with the authors the feature analysis

Once the initial analysis had been completed, a debriefing was held with the authors of the articles. As part of this process, I contacted each author individually to share the information collected from their articles, which had been systematically classified based on predefined categories. The purpose of this interaction was to ensure the accuracy and completeness of the data by inviting the authors to review the classification, provide feedback, suggest corrections, or even update the current version of their tool if necessary.

To facilitate this, I sent a personalized email to each author. In the email, I introduced the research context and motivation of this study, explained the methodology used for classifying the extracted information, and included a link to a Google Sheets document where they could review my coding and provide:

- Opinions and comments on the proposed categories and the classification approach used.
- Corrections or clarifications regarding the description of the tools.
- Additional information, including updated versions of the articles or insights into the evolution of the tools.

The emails were sent on January 14, 2025, with a response deadline set for January 31, 2025. This interaction enriched the analysis and ensured that the results accurately reflected the current state of the tools.

Initially, few authors responded, so we proposed a second round of contact by sending a reminder to all those involved. Some of them were interested in holding a meeting to better understand the context and to be able to help in a more precise way. Up to four online meetings were held with different authors. As a result, we managed to get at least 50% responses in which we verified the information collected.

Figure 3.7 shows the two rounds of contact made with authors and the outcomes of these interactions over time. The categories are divided as follows: red indicates no response, yellow represents responses that were received but not completed, and green shows completed responses.

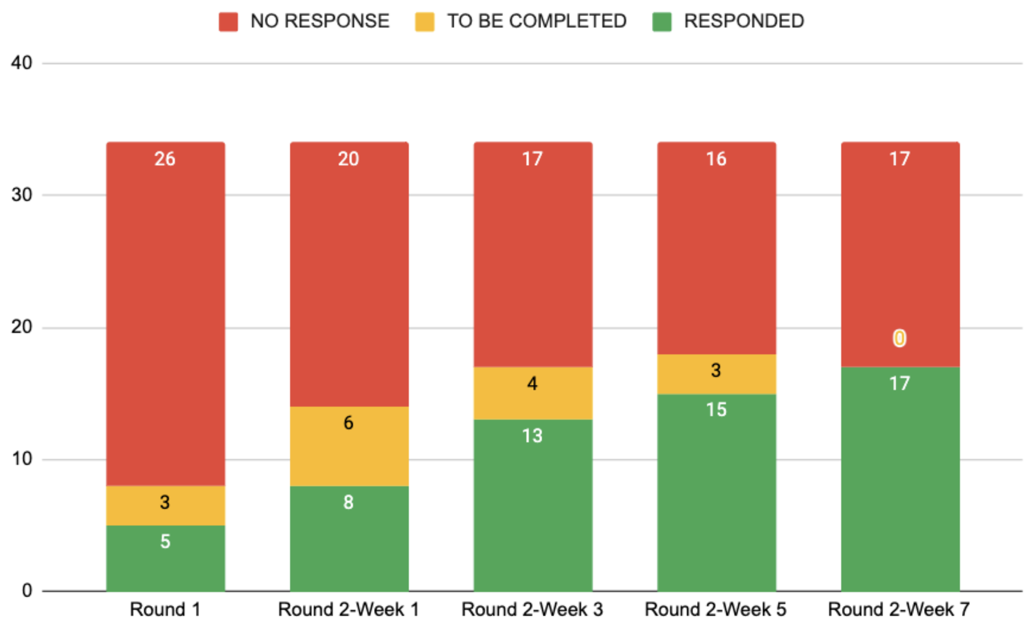



Figure 3.7: Author contact timeline

In Round 1, initial contact was made with 34 authors. Out of these, only 5 responded and completed the process, 3 responded but did not complete it, and 26 did not respond. Following this, a second round of follow-ups was initiated and monitored over several weeks:

- By Week 1 of Round 2, 8 authors had completed their responses, 6 had partially responded, and 20 still had not replied.
- In Week 3, the number of completed responses increased to 13, with 4 incomplete responses and 17 authors still unresponsive.
- By Week 5, 15 authors had responded completely, 3 partially, and 16 remained unresponsive.
- Finally, in Week 7, 17 responses were fully completed, while 17 authors still had not replied.

This interaction enriched the analysis and ensured that the results accurately reflected the current state of the tools.

Figure 3.8 illustrates the nature of the comments received from the authors who responded to our request. Of the 17 responses collected, most were considered substantial

(N = 14), meaning that they included a significant number of comments or inputs that enriched the original information. In contrast, some of the responses were classified as non-substantive (N = 4), as they contained very few comments. Non-substantive responses can be interpreted in two ways: on the one hand, they may indicate that the authors mostly agree with the information provided and see no need for changes. On the other hand, they could suggest that the response was a mere formality. Both interpretations are plausible and highlight the complexity of analazing authors' comments in collaborative review processes.

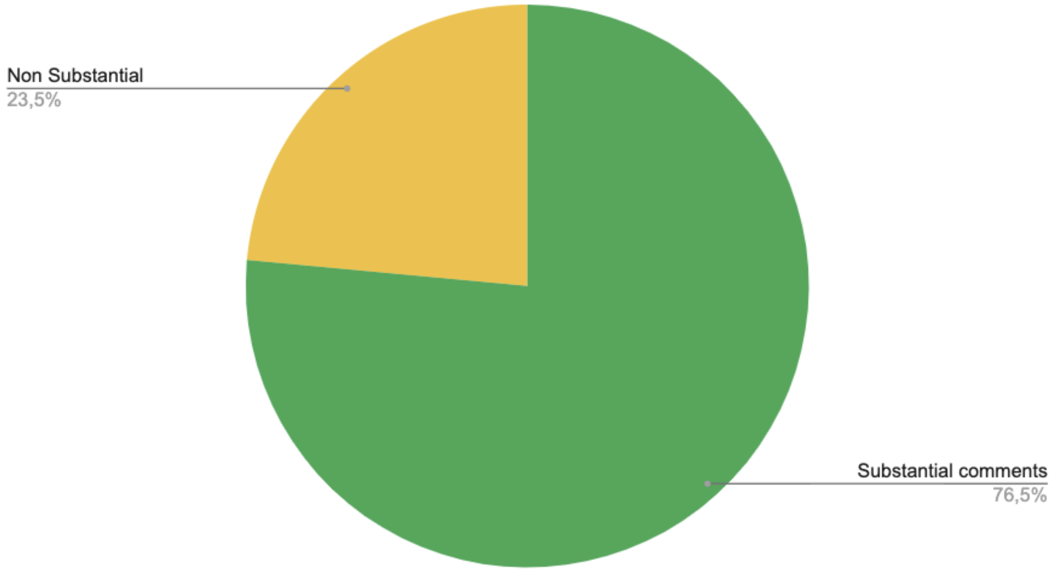



Figure 3.8: Substantiation of comments

#### 3.2.4.5 Consolidation & Standardization

After completing the contact process, one week was dedicated to consolidating the information gathered during the analysis with the feedback and corrections provided by the authors. Once done, the information was standardized to prepare the data for further analysis so that the data could be interpreted in a consistent and meaningful way.

#### 3.2.4.6 Analysis & Report Compilation

The next step was to conduct a detailed category-by-category analysis. This phase focused on reviewing each category separately to identify patterns. By disaggregating the data in this way, it was possible to better understand the key themes and draw more accurate and meaningful conclusions from the information collected. The final phase of the dissertation consisted of a comprehensive review of all the data and perspectives collected in order to draw the main conclusions.

# 4: Results

This chapter presents the results extracted from the analysis of the different categories within the identified tools (see AppendixB). A category-by-category analysis is performed following the groups established in Section 3.1.

## 4.1 Overview of the Analyzed Articles

Regarding the tool development date (see Figure 4.9), out of the 36 tools analyzed, 11 were built between 2016 and 2021, 2 of them before 2010, and one in 2014. This indicates a growing interest in the development of tools linked to HCD principles in the last decade. This may indicate that the field is still evolving.

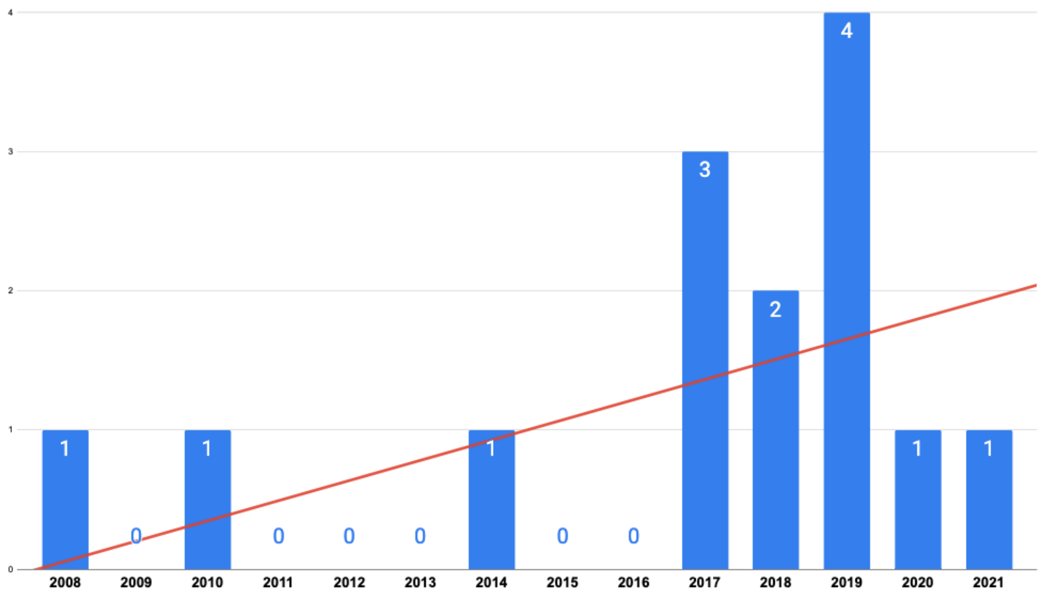



Figure 4.9: Year of creation of the tools

## 4.2 In-depth Results

This section presents the results found according to the five main categories described in Chapter 3.

### 4.2.1 Tool Basis

#### 4.2.1.1 Target Users

Most target users of the analyzed tools are students and/or teachers (N = 34). Only two papers reported other "Educational Users" different from teachers and students, such as school directors (N = 2). Table 4.4 shows the number of analyzed tools according to the target users (i.e., students, teachers, or other stakeholders).

| **Target User** | **Amount** |
|---|---|
| Students | 10 |
| Teachers | 14 |
| Teachers and Students | 10 |
| Others | 2 |

Table 4.2: Stakeholders involved in the design of the tools

Further analyzing the educational level of the target users (see Figure 4.10), we can observe that most of the tools (N = 21) are aimed at higher education (tertiary level). This may indicate a higher availability of digital data in university environments (e.g., due to intensive use of LMS, virtual platforms, etc.), a higher interest in improving performance and data-driven decision making, or a higher technological maturity. The remaining tools correspond to the secondary level (N = 13) and to the primary level (N = 5). There are a few tools that do not report educational level (N= 3). The reasons for a lower development of tools aimed at primary education may be due to less generation of useful data by students, higher reliance on direct teacher intervention, ethical and privacy concerns when analyzing children's data, and/or lower usage of educational technologies at this age.

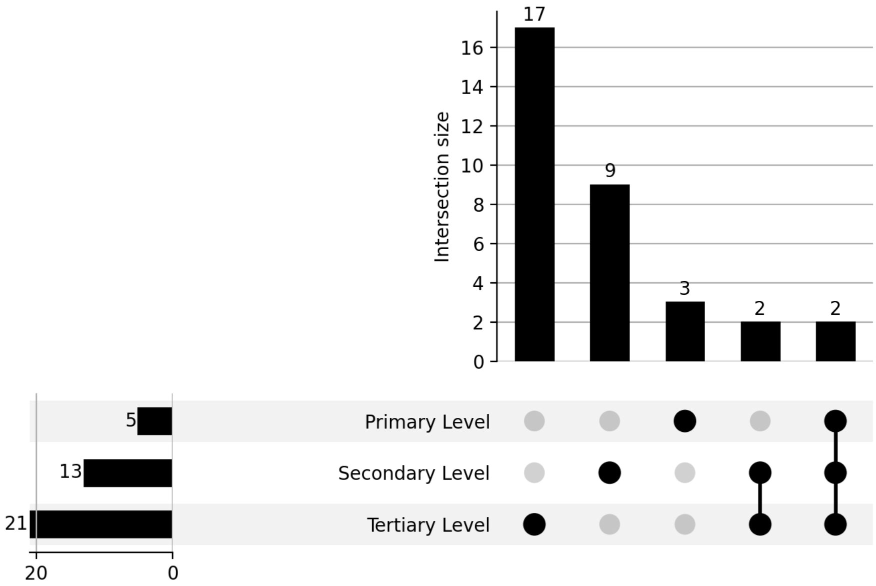



Figure 4.10: Educational level of the target users

#### 4.2.1.2 Pedagogical Context

The inductive analyses of the pedagogical context under which the tools were developed elicited broad areas of interest within educational research and practice. We found 15 different pedagogical approaches and 37 appearances in total among all analyzed tools (see Table 4.3). Some of the tools (N = 11) define their pedagogical context as *collaborative learning*, where students' interactions are often mediated by technology (e.g., forum posts, wiki contributions, computer-mediated discussions, etc.), generating rich digital traces. Usually, these tools are implemented within technological platforms such as LMSs (e.g. Moodle or Canvas), where activities such as forums, group work, discussions or co-assessments are supported.

Also, some of the tools focus on the physical context, i.e. how the environment influences the learning experience (namely, *location-based learning* (N = 1) and *journey-based learning* (N = 1)). Others focus on *competence development*, i.e. the development of cognitive and interpersonal skills through educational interactions (apart from collaborative learning), such as *academic writing* (N = 1) and *problem-based learning* (N = 1). We have also found pedagogical contexts that focus on promoting learner engagement encompassing approaches designed to enhance attention, motivation and active participation (namely, *practice-based learning* (N = 1), *inquiry-based learning* (N = 1), *goal-oriented progress learning* (N = 1), *game-based learning* (N = 1)). Other tools focus on pursuing strategies that include general pedagogical frameworks to guide how learning is structured, such as *blended learning* (N = 2), *recommendation-based learning* (N = 2) or *self-regulated learning* (N =

3). Evidence-based decision-making focuses on the integration of empirical data to support planning and improvement of teaching (e.g., Data-driven learning (N = 3)). Finally, others focus on personalized learning and individual learning processes (namely, *persona-centered learning* (N = 1) and *adaptive learning* (N = 3)), which emphasize tailoring educational experiences to meet the specific needs and characteristics of individual learners.

Finally, for three tools, the authors do not report a clear pedagogical context under which they were developed.

| **Pedagogical Context** | **Appearances** |
|---|---|
| Collaborative Learning | 11 |
| Data-Driven Learning | 3 |
| Not Reported | 3 |
| Self-regulated Learning | 3 |
| Adaptive Learning | 3 |
| Blended Learning | 2 |
| Practice-based Learning | 2 |
| Recommendation-Based Learning | 2 |
| Academic Writing | 1 |
| Game-based Learning | 1 |
| Goal-Oriented Progress Learning | 1 |
| Journey-Based Learning Support | 1 |
| Location-Based Learning | 1 |
| Inquiry-Based Learning | 1 |
| Persona-Centered Learning | 1 |
| Problem-Based Learning (PBL) | 1 |

Table 4.3: Pedagogical contexts supported by the analyzed tools

#### 4.2.1.3 Contribution Type

As depicted in Figure 4.11, the tools were also analyzed according to the purpose for which they were developed. We identified four different groups:

- *Monitoring*: This category includes tools designed to track and visualize user activity or behavior. Dashboards often display data on learning progress or engagement, while wearable devices collect data through physical devices or immersive environments.
- *Recommending & assisting*: These tools provide suggestions or support to users. They can also act as virtual assistants to guide learners or educators through specific tasks.
- *Personalizing*: These tools adapt the learning experience to individual users based on their needs, preferences, or performance. They aim to offer tailored content or pathways that support more effective and efficient learning.

- *Storytelling and journaling*: These tools allow users to reflect on their experiences through storytelling or journaling. They support self-awareness and metacognition by helping learners or educators document and make sense of their learning journey over time.

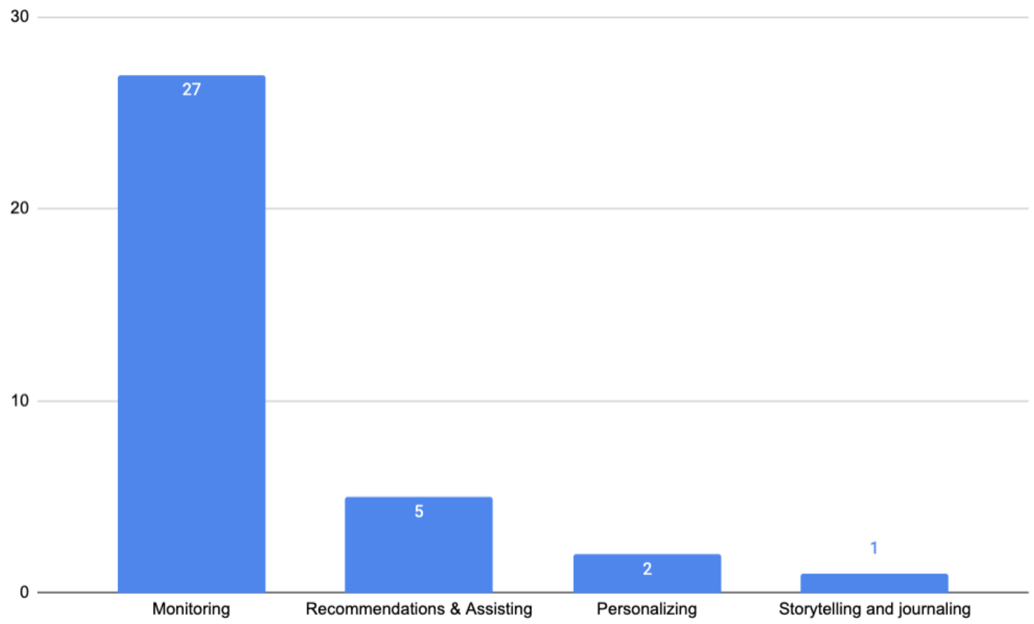



Figure 4.11: Type of contribution groups

Most tools have a monitoring purpose (N = 27). Some of them aims at recommending or assisting the users (N = 5). Few ones were developed to personalize learning (N = 2) and one was created as a journaling tool (N = 1). Finally, one tool does not report its main purpose (N = 1).

We can deduce that priority is given to visualizations and monitoring systems over more adaptive, interactive tools, which are still under development or not yet widely adopted. This reflects a predominant preference for decision support tools. This could be related to limitations in the development, as it is easier to display the information rather than suggesting changes, creating alerts or developing intelligent systems that make autonomous decisions. It might also be related to the fact that the stakeholders prefer having autonomy over the learning situations. Consequently, they choose to monitor the learning analytics and respond as they see fit, rather than relying on autonomous systems.

#### 4.2.1.4 Platform

All papers that mention the platform on which the tool operates (N = 20) specify that it is web-based (N = 17) or that it is embedded in a tool that is also web-based (N =

3). There are 16 tools out of the 36 that do not report a platform. This actually makes sense, because nowadays in education often promotes bring your own devices approaches, requiring tools to be compatible with different devices, and the easiest method is to do it through a web browser. However, it is important to note that some tools may also take the form of mobile apps to support ubiquitous learning, allowing access beyond traditional web platforms.

#### 4.2.1.5 Embedded/Standalone

Some of the tools are embedded in a learning environment or in another tool (N = 11). Some are classified as standalone (N = 12), since they are not embedded in other systems. The remaining are considered unreported, as neither the paper nor later the authors determined whether they are embedded or not (N = 13). This equal distribution between embedded, standalone and unreported tools suggests that there is no dominant method of implementation in terms of integration.

The tools embedded within other systems are often integrated into educational platforms such as Petel (a free online learning environment available to more than 1,000 high school teachers), dotLRN (an open-source, collaboration-oriented learning management system used in universities worldwide), and WILLOW (a free-text computer-assisted assessment system), among other examples.

#### 4.2.1.6 Programming language

Out of the 36 tools analyzed in this study, we were able to obtain information about the programming language used in 18 cases. Figure 4.12 shows that the predominant programming languages used to develop them were JavaScript, HTML and CSS. These results are in line with the results from the mentioned platform analysis since most of the tools are web-based. Web languages aside, there are no patterns or standards regarding programming for human-centered learning analytics tools.

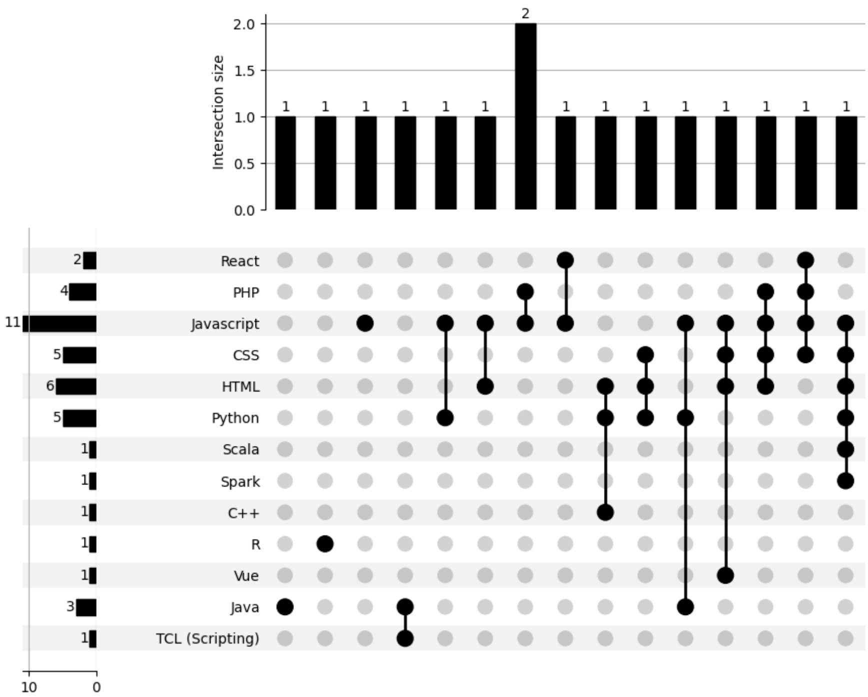



Figure 4.12: Programming language

#### 4.2.1.7 Open Source

As reported in Figure 4.13, some of the tools analyzed are open source (N = 10) and some are not (N = 3). For the rest (N=23), we were unable to obtain such information.

Most of the ten open source tools do not specify a license (N = 6), while a few of them do (N = 4):

- Two mention *GNU Affero General Public License v3.0 (AGPLv3)* as a license. It requires source code and modifications to be publicly available. Ideal for web software.
- One tool uses *MIT Permissive License*, which allows reuse, modification and commercial use without obligation to share changes.
- Another tool applies *Creative Commons BY-SA (CC-BY-SA)*, which is commonly used for content rather than code. Allows reuse with attribution and equal licensing.

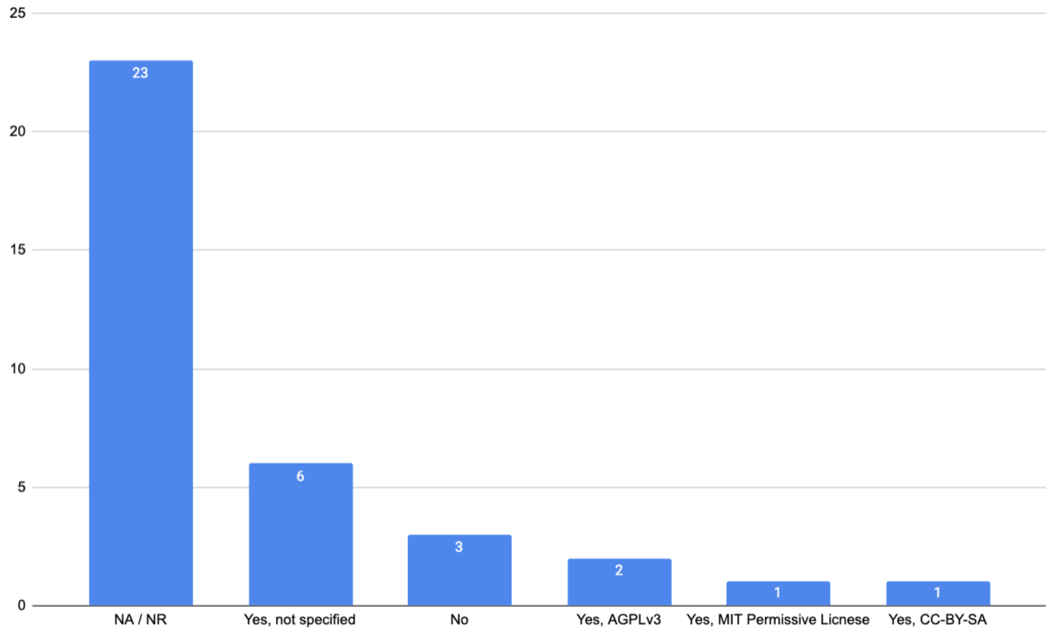



Figure 4.13: Open source tools

#### 4.2.1.8 Tool Language

As we can see in Figure 4.14, most of the tools analyzed are available in English (N = 24), which clearly positions it as the dominant language. Some tools are available in more than one language (N = 7). Also, there are some tools that do not report language (N = 9). If the tools were primarily in minority or local languages, their adoption and transferability to other countries or regions could be more limited, potentially reducing their impact and usability in international contexts.

Language combinations are minimal (maximum 2 tools at some multilingual intersection). Moreover, languages such as German, Spanish, Estonian and Georgian appear only 1 or 2 times, suggesting a low representation of tools adapted to non-English-speaking linguistic contexts.

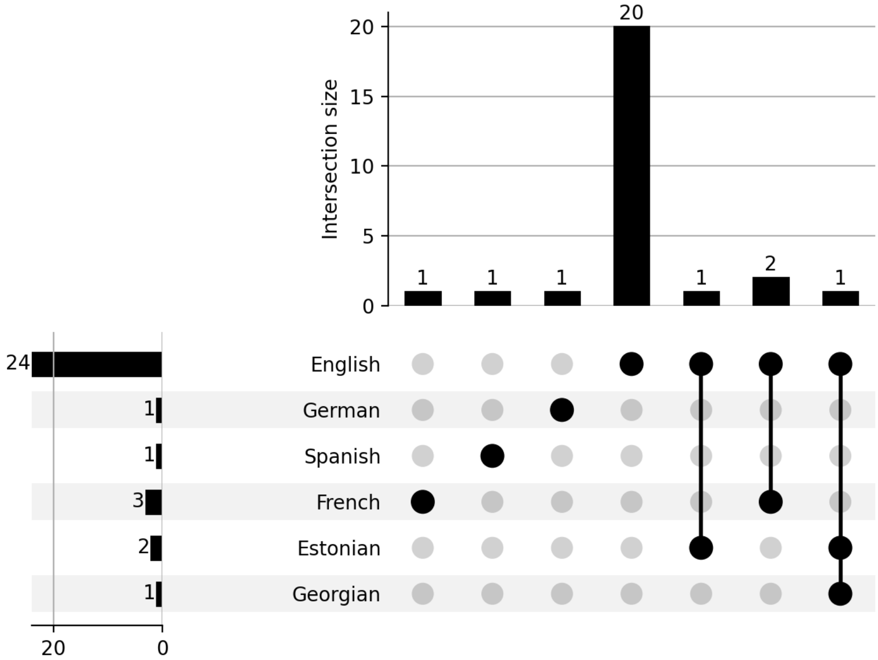



Figure 4.14: Tool languages

#### 4.2.1.9 Support and Documentation

We have checked if the papers refer to user documentation or user manuals, user support, or software documentation, which are independent categories inside the analysis:

- Only a few tools report user documentation (N = 6). Most of them do not report (N = 30).
- Only a few tools report having or having had user support (N = 6), but most do not report information (N = 30).
- Only a few tools report having software documentation (N = 5), but most of them do not report information (N = 31).

The absence of documentation and support suggests that many of these tools may still be in a prototype or research phase.

Moreover, with only five tools reporting software documentation, opportunities for reuse or customization, especially by the academic or open source communities, are limited. Additionally, the fact that only six of the 36 tools report that they have user documentation or provide user support may complicate adoption by end-users.

### 4.2.2 Human-Centered approach

This section analyzes how each of these stakeholders is involved in the design, prototyping/implementation, and evaluation/testing phases. As we can see in Figure 4.4, a wide variety of stakeholders were found to be involved in the tools analyzed.

| **Stakeholder** | **Appearances** |
|---|---|
| Teachers | 22 |
| Students | 17 |
| Researcher | 8 |
| Educational Expert | 8 |
| Technical Developers | 4 |
| Project Manager | 5 |
| External Experts | 2 |
| Designer | 2 |
| Observer | 1 |
| School Principal | 1 |
| School Comitee Member | 1 |
| Parents | 1 |

Table 4.4: Number of times these stakeholders are mentioned during HCD in the analyzed tools

#### 4.2.2.1 Design Phase

All tools except one report information about stakeholder involvement during the design phase (N = 35). As we can see in Figure 4.15, teachers (N = 22) and students (N = 17) are the stakeholders most frequently involved in the design phase, reflecting a clear orientation towards end-users. This trend is aligned with the HCD principles, which prioritize the participation of the main users, as emphasized by conceptual contributions and guidelines such as the principles of human-centered design proposed by the Interaction Design Foundation and standards like ISO 9241-210:2019, which may inform future studies and increase the effectiveness of stakeholder involvement [62].

Technical and expert involvement is less present in the design phase. Profiles such as technical developers (N = 4), project managers (N = 5), researchers (N = 8) and educational experts (N = 8) appear less frequently, but are important in specific combinations, especially when more specialized approaches are required.

Stakeholders such as parents, principals, observers or school committee members are poorly represented (only one appearance each), indicating that they have little role in the design phase.

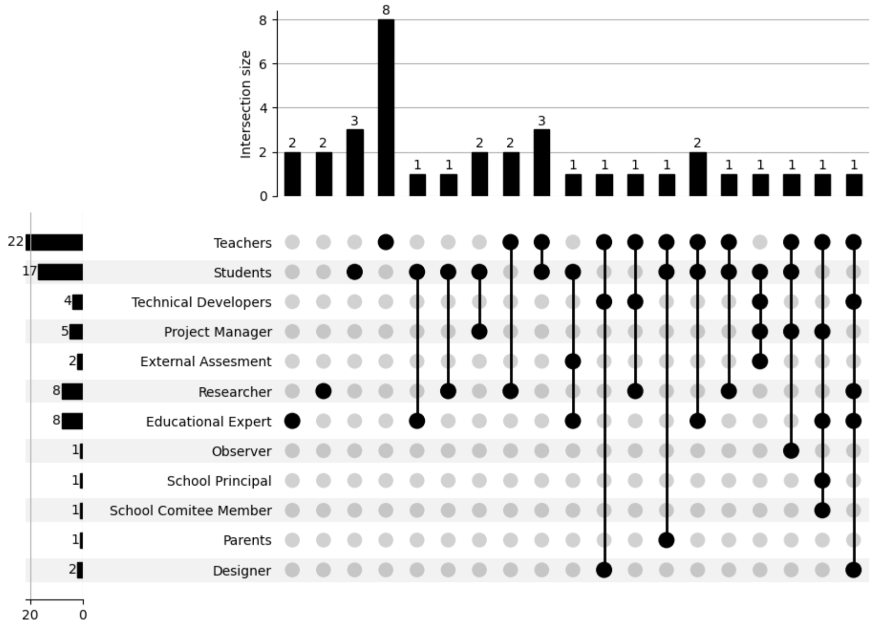



Figure 4.15: Stakeholders involved in the design phase

As we can see in Figure 4.16, interviews (N = 15) and surveys (N = 13) are the most frequently used methods, indicating a strong focus on directly understanding users' needs and opinions. Workshops (N = 8) and focus groups (N = 10) are other popular methods, showing that collaborative group activities are valued for creating solutions or validating ideas with real users.

Although there is a wide variety of reported methods (N = 21), many were used only once. Methods such as brainstorming, sketching or creative sessions such as 'superpower' or storytelling appear rarely, which could indicate that the design of the tools has a basic idea already established before starting the design. In other words, the fundamental objective of the tool may usually be known before the design of the tool is started.

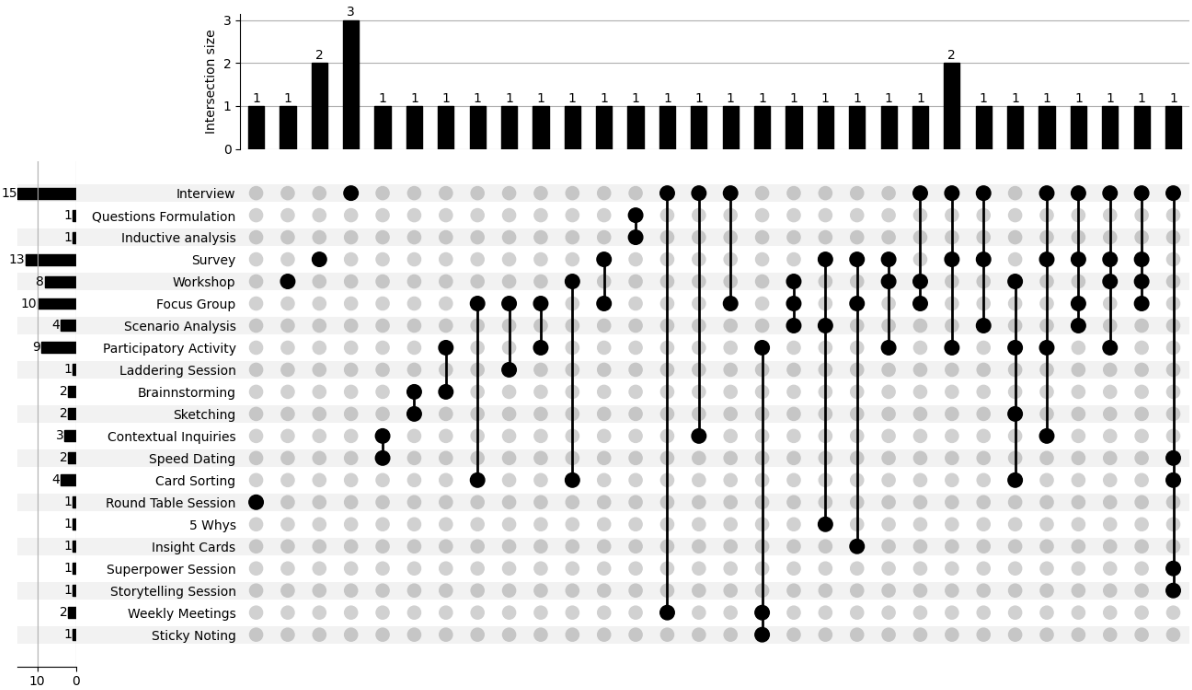



Figure 4.16: Ways of stakeholder involvement in the design phase

The participatory methods used in the studies can be grouped into several categories (see Figure **??**). First, there are methods that help researchers really get to know users and their needs, such as interviews, contextual enquiries, laddering sessions and the 5 whys. Then there are methods devoted to gathering more specific information, such as surveys or activities where participants help formulate the questions. On the other hand, to involve people more directly in the design process, activities such as collaboration sessions, workshops, focus groups, round tables and regular meetings are used. To spark creativity and explore new ideas, techniques such as brainstorming, sketching, storytelling, and scenario planning come into play, sometimes even with playful approaches such as 'superpower' sessions. There are also activities aimed at organizing all opinions and making sense of them, such as card sorting, sticky notes and the use of perception cards. Finally, some studios use light analysis techniques to bring everything together and guide their design decisions in a practical way.

#### 4.2.2.2 Prototyping/Implementation Phase

While for most tools I found information about the stakeholder involvement during the prototyping/implementation phase (N = 27), for some of them I did not (N = 9). As we can see in Figure 4.17, teachers (N = 14) and students (N = 10) are the most involved stakeholders in this phase. However, we can also see that designers (N = 5) and technical developers (N = 3) are mentioned fewer times, but similarly often than in the design phase. This may indicate that the technical aspects are either less visible in studies, or their roles are more supportive/behind the scenes at this stage.

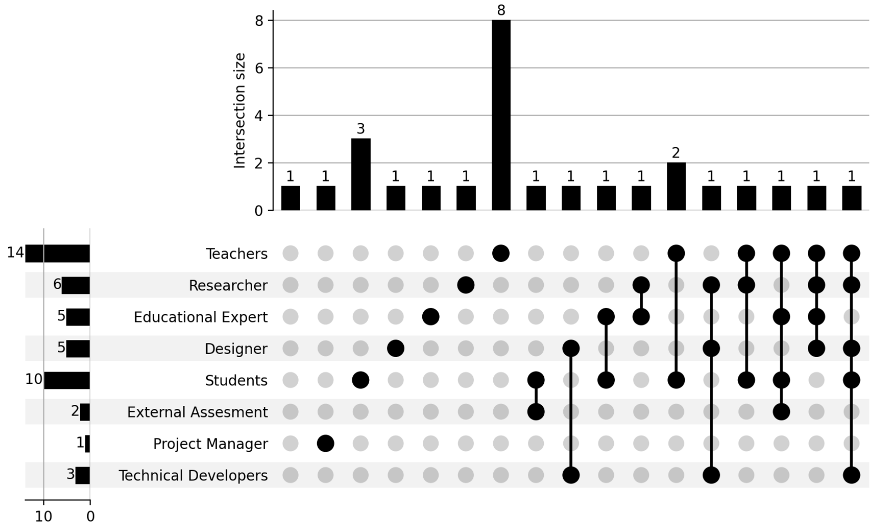



Figure 4.17: Stakeholders involved in prototyping/implementation phase

When referring to "Prototype design session", we mean low, mid and high fidelity prototype designs, including paper prototypes, sketching, cards, boards, comic boarding, etc. As we can see in Figure 4.18, the prototype design sessions are the preferred way of involving users (N = 18). The reason why prototype design sessions are the most common method of involving users is that engaging stakeholders throughout all phases of the tool's life cycle is a core principle of HCD.

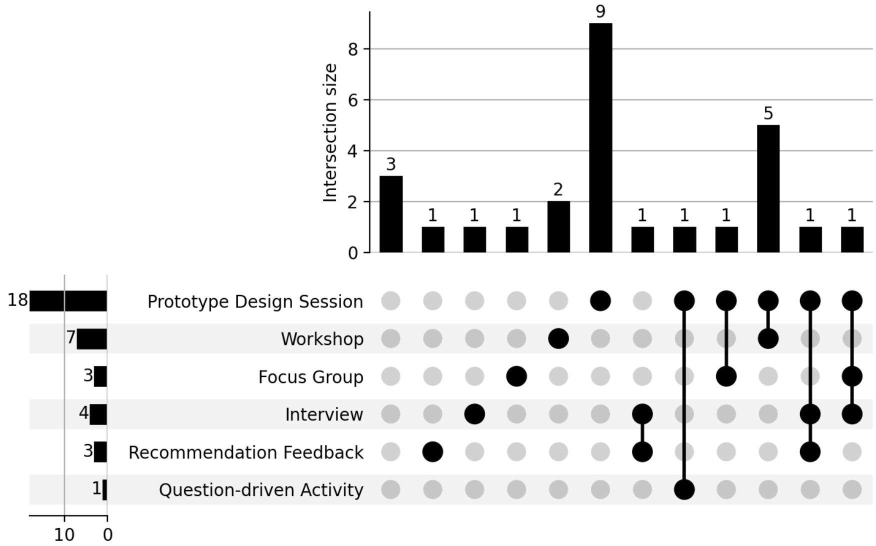



Figure 4.18: Ways of stakeholder involvement in the prototype phase

#### 4.2.2.3 Evaluation/Testing Phase

In the evaluation phase, if it is reported (N = 25), the stakeholders included are always the target users. But, in Figure 4.19, we can see that in the evaluation phase it is common to mix formal experiments (quantitative) with interviews and surveys (qualitative or mixed methods). This combo helps check if the design choices work both in terms of data and user experience.

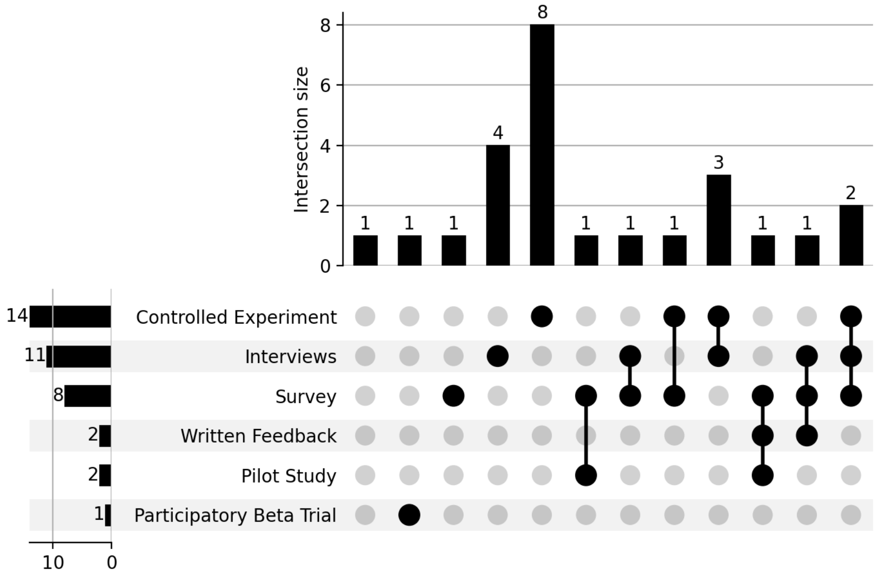



Figure 4.19: Ways of involving stakeholders in the evaluation phase

## 4.2.3 Data Management

### 4.2.3.1 Data Sources

As can be seen in Figure 4.20, most tools use information from learning management systems as their main source of data (N = 19), and some of them use the data directly entered by the stakeholders (N = 10).

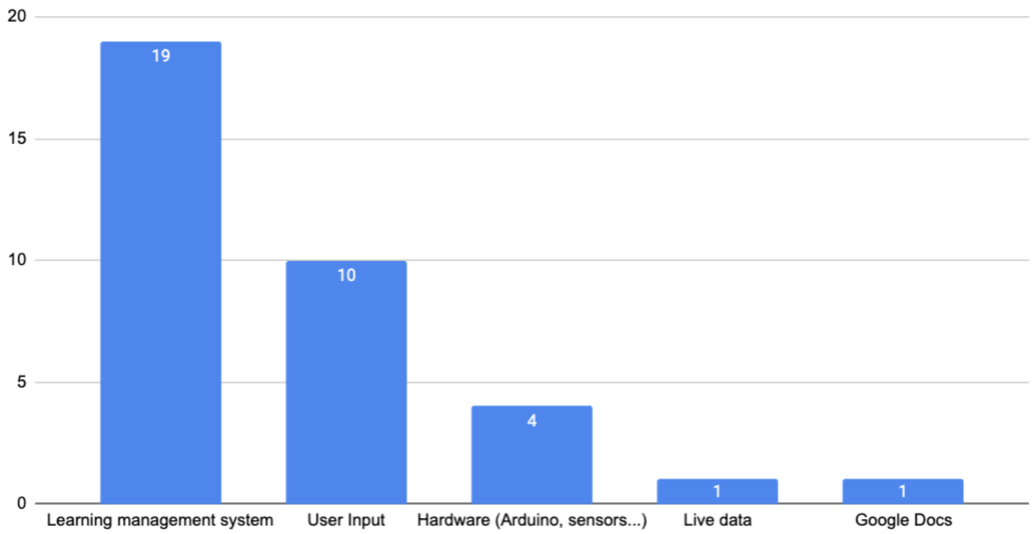



Figure 4.20: Ways of involving stakeholders in the evaluation phase

Hardware-based data (e.g. Arduino, sensors) appears as a third option from which to obtain information for LA tools. This result suggests that this technology is less used in education. Finally, live data and cloud collaboration tools (e.g. Google Docs) are underutilised in the reviewed tools. There are a few tools that do not report information (N = 3).

#### 4.2.3.2 Data Types

Of the 36 tools, 32 specify the type of data they use. There are 4 tools for which we have not been able to identify this data. These are the mentioned data types that the tools collected:

- *Logs:* Activity logs, sequential logs, real-time event data, and behavioral data are used extensively. These logs capture user interactions, navigation patterns, task completion, and system state.
- *Numerical Data:* Commonly includes scores, progress metrics, assessment results, and indicators. Indicates a focus on quantifiable outcomes like performance, progress, and engagement.
- *Text Data:* Includes written content, feedback, lesson plans, explanations, and visitor notes. Other examples are teacher reflections, field notes, and facilitator observations.
- *Audio/video data:* Some tools use video/audio (e.g. voice interaction, class interaction videos).
- *Sensor Data:* Includes physiological, physiological sensors, AR overlays, localization.

The frequency of each data type can be observed in Figure 4.22.

#### 4.2.3.3 Data Gathering Techniques

Pull/on-demand is the dominant model (N = 27). So, most systems require the user to actively request or trigger data collection (usually the teacher). This can include manual report generation, form submissions, or clicking to retrieve results. This limits the system's ability to respond in real time or offer adaptive feedback without user input. Few tools explicitly mentioned the use of push/automatic methods (N = 4), and some of them push user/system recommendations via alerts/messages. There were some tools that do not report information about this topic (N = 5).

#### 4.2.3.4 Data Treatment

For this category we have followed the types of data treatments mentioned by the Society for Learning Analytics Research [59]:

- *Descriptive:* Summarizes past data to reveal patterns.
- *Diagnostic:* Explains causes behind past events.
- *Predictive:* Uses data to predict future trends.
- *Prescriptive:* Recommends actions based on predictions.

We found that descriptive analysis is the most common type of data analysis (N=26), see Figure 4.21. This suggests that most tools are focused on summarizing what has already happened, such as tracking progress or usage patterns. Diagnostic analysis is also frequently implemented (N = 19), sometimes overlapping with descriptive methods, thus showing that these tools often combine both analyses to explain patterns.

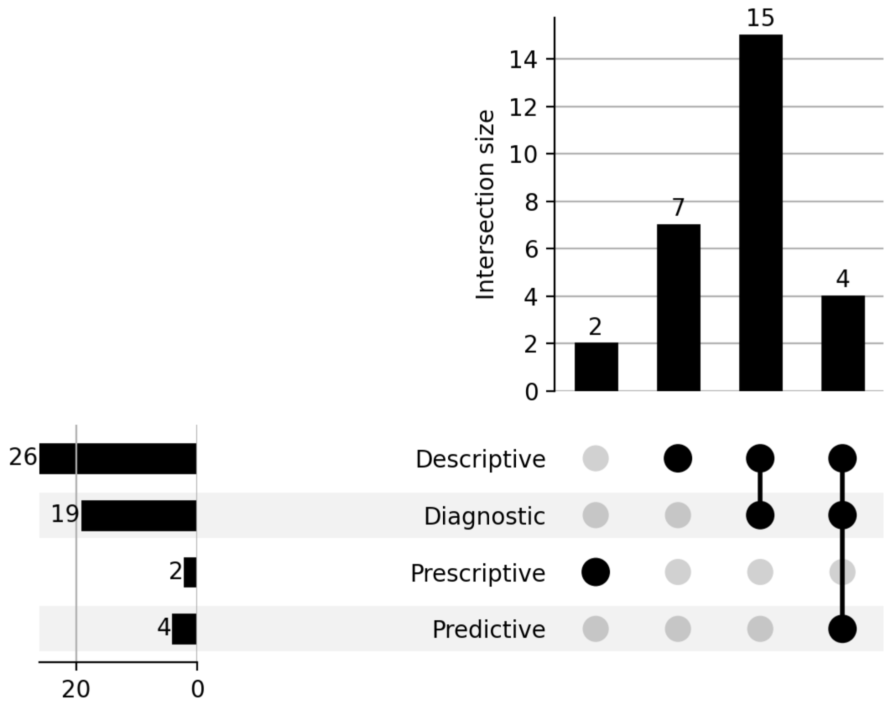



Figure 4.21: Types of data analysis

Current tools rely primarily on descriptive and diagnostic analyses to understand learners' past behavior. However, there is significant untapped potential in predictive and prescriptive approaches that could move educational technology towards more personalized support systems. There were some tools that do not report information about this topic (N = 8).

#### 4.2.3.5 Data Analysis Techniques

For this category there are 14 tools reporting Data Analysis Techniques, and therefore 22 do not report information. Although all 36 tools were classified within the field of Learning Analytics, 9 of them also make use of Artificial Intelligence models (e.g., machine learning, temporal models), highlighting the intersection between both domains. We find the following data analysis techniques during the tools review, understood as the way in which the data is analysed:

- *Machine learning and AI models:* Techniques like decision trees, Bayesian Knowledge Tracing (BKT), and clustering with explainable AI show the integration of intelligent systems.

- *Data mining:* Frequent use of educational data mining, interaction mining, process mining and multi-source mining. This indicates a strong interest in discovering patterns from large datasets.

- *Statistical analysis:* Approaches like descriptive statistics, uni-variate/bi-variate analysis, and mean-based forecasting are more traditional statistical methods.

- *Text and content analysis:* Text analytics and content analysis reflect a need to interpret qualitative or unstructured data (e.g. student writing, teacher feedback). Text analysis usually refers to computational or linguistic processes to extract patterns in texts of considerable volume, usually using tools such as natural language processing or sentiment analysis. In contrast, content analysis involves categorically classifying and interpreting communication content, such as themes or keywords to understand underlying meanings or trends.

- *Temporal models:* Techniques like temporal analytics, predictive stability models.

- *Real-Time analysis:* Real-time clustering and detector models suggest adaptive systems that respond to student behavior.

Figure 4.22 shows a cross analysis of data sources, data types and data analysis techniques. Those with information reported in these categories were considered (N = 14). It should be noted that learning management systems are the predominant category within data sources. In data types, logs and numerical data are the most frequent and in data analysis, there is a predominance of approaches based on machine learning and AI models.

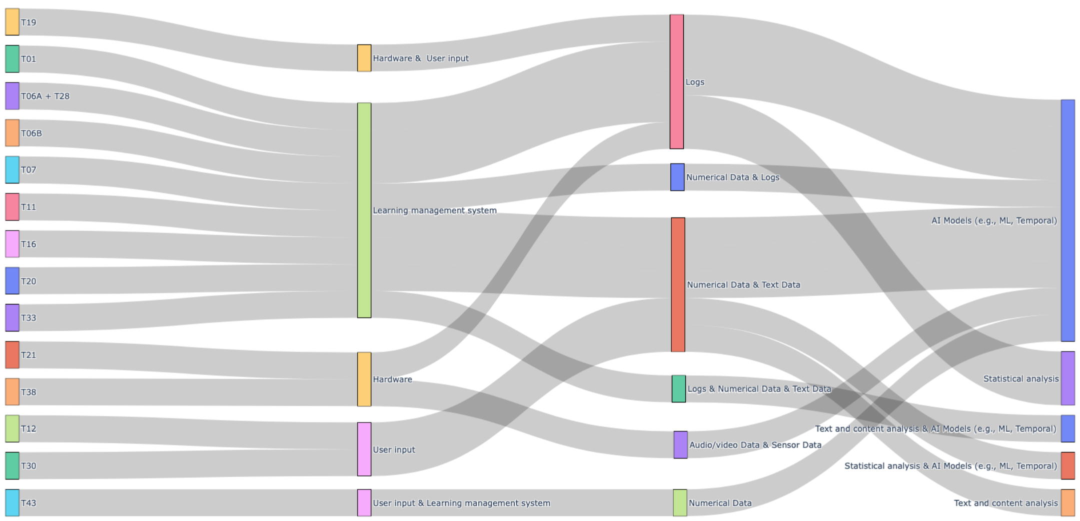



Figure 4.22: Cross analysis of data sources, data types and data analysis techniques

#### 4.2.3.6 Visualization Techniques

This category refers to graphic techniques or visual elements integrated into the tool to represent data, patterns or insights. Almost all the tools analyzed have some type of data visualization (N = 30). Only 4 tools do not report this data.

- *What is displayed throughout all the tools?*:

  Indicators represent key metrics such as performance, progress, engagement... They often include data such as student locations, activity levels, or scores.

- *How is the information displayed?*:

  - *Diagrams and graphical representations*: We have found a wide variety of diagrams such as:bar charts, radial tidy trees, node-edge (proxy) visualizations, skill maps, planet charts and gamified buttons, annotated student work previews, tag clouds, gradient meters, timelines, SNA (Social Network Analysis) graphs, and map views with student locations. Found in various combinations with indicators and filters.
  - *Storytelling and cards*: Several tools use data storytelling, cards, or narrative elements to make insights more digestible or actionable.
  - *Alerts and notifications*: Present in tools offering real-time updates, warnings, or recommendations for action.

- *Where is it displayed?*: Mainly dashboards. These combine multiple indicators, charts, and interactive elements. Often allow for filtering/sorting by student or time range, so users can control the data or customize their views. Visual elements like progress bars, timeline evolution, and calendar views help monitor ongoing activity.

Most tools are interactive (N = 26), indicating that tools are looking for user-centered systems as they require the interaction of the user to display the desired content. Results support the idea that interactivity is now a basic expectation for tools in the HCD domain, as the predominance of interactive tools suggests that designers prioritize systems that actively engage users and adapt to their needs, thereby improving the overall user experience. Furthermore, there is only one tool that reports to be static (Tool T20 B). Finally, there were some tools that do not report information about this topic (N = 9).

#### 4.2.3.7 Data Privacy

For this analysis we borrowed the DELICATE checklist [17]. This checklist offers a structured approach to managing data in a way that respects user rights and promotes transparency, accountability, and trust. The checklist covers the following items:

- *D - Determination*: Clearly define the purpose and added value of data collection.

- *E - Explain*: Be transparent about what data is collected and why.
- *L - Legitimate*: Justify the necessity and legality of the data collection.
- *I - Involve*: Engage all stakeholders and address privacy concerns.
- *C - Consent*: Obtain clear and informed consent from data subjects.
- *A - Anonymize*: Anonymize and aggregate data as much as possible.
- *T - Technical*: Implement privacy safeguards and monitor data access.
- *E - External*: Ensure external providers comply with data security and privacy rules.

Only half of the tools (N = 18) mention measures to ensure the privacy of the information. As we can see in Figure 4.23, the dimensions: *explain*, *legitimate*, *involve*, *consent* and *anonymize* are present in seven tools each, suggesting that they are dimensions commonly applied in the tools analyzed. *Determination* appears only in five and *Technical* and *External* are the least common, present in only three tools.

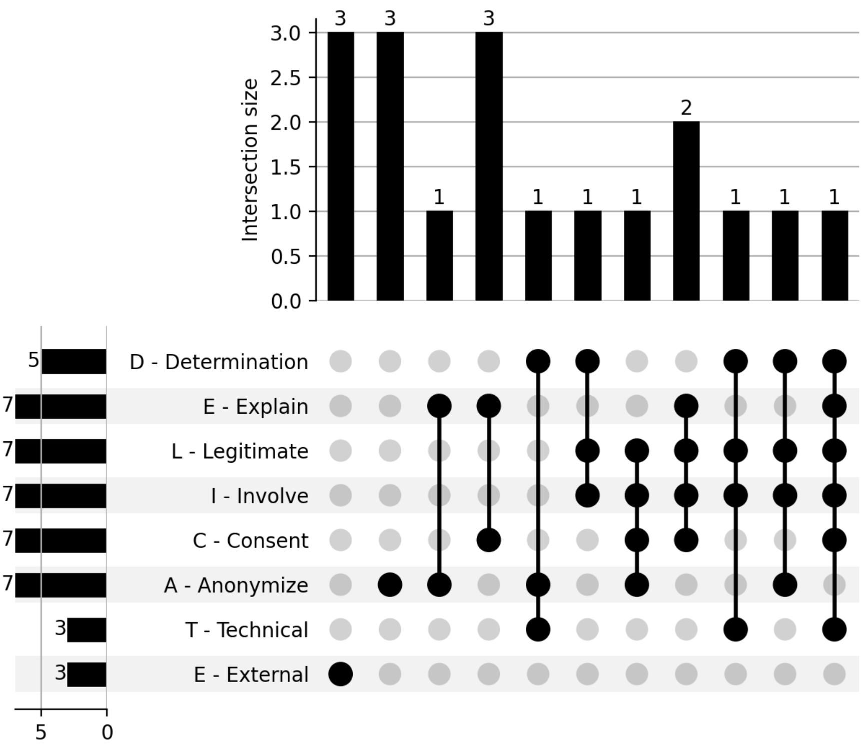



Figure 4.23: DELICATE checklist in the analyzed tools

Figure 4.23 shows that not all tools cover the full checklist, but many apply combinations of some items. In fact, the intersections show that there are common patterns of application of these principles, which may reflect common practices or constraints in tool design.

Only 14 of the 36 tools mentioned how they preserve data privacy or how it is secured. However, most of these tools (N = 12) describe built-in/embedded data privacy and security mechanisms to grant security. A few describe that they also have ad-hoc mechanisms like confidentiality clauses (N = 2).

### 4.2.4 Tool Evaluation

As reported in Section 4.2.2.3, most of the tools analyzed report an evaluation with end-users, using a range of methods including interviews, surveys, usability tests, and participatory trials (N = 23). All other tools report no evaluation (N = 13).

Most evaluations prioritize understanding, tool acceptance, user experience, and visualization usability. But, usability is the most consistently evaluated dimension across the tools, which is often paired with studies on visualization design, which reflects the importance of UI/UX in education tools.

On the other hand, the dimensions identified for the evaluation of the tools are as follows:

- *Usability:* The ease with which users can learn, navigate, and effectively use a tool or system without errors or frustration.
- *User experience (UX):* The overall feelings, perceptions, and satisfaction a user has when interacting with a tool, including emotional and cognitive responses.
- *Tool acceptance:* The willingness and intention of users to adopt and continue using a tool, influenced by perceived usefulness and compatibility with their needs.
- *Interpretability / actionability:* The extent to which users can understand the information presented and use it to make informed decisions or take meaningful actions.
- *Transparency / translucency:* How clearly a system reveals its processes, data sources, and algorithms to users, fostering trust and understanding. For example, LAT-EP, which is specifically designed to evaluate and promote the clear, understandable, and transparent use of learning analytics systems, ensuring users see how data are processed and used.
- *Engagement / motivation:* The degree to which users are interested, involved, and motivated to interact with the tool and pursue related tasks or goals.

Figure 4.24, out of the 23 tools reporting evaluation, shows the most commonly evaluated dimensions in the analysed tools. We find that *User Experience* (N = 11), *Usability*

(N = 9), *Tool Acceptance* (N = 9), and *Interpretability / Actionability* (N = 8) are the most frequent. In contrast, *Engagment / Motivation* (N = 3) and *Transparency / Translucency* (N = 1) are the least considered dimensions. The most frequent combination of dimensions evaluated includes *User Experience*, *Usability*, *Tool Acceptance* and *Interpretability / Actionability* (N = 4).

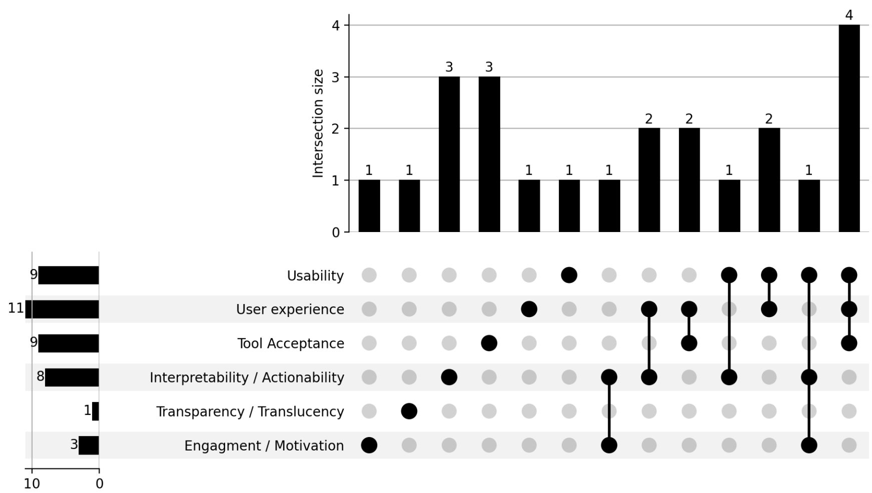



Figure 4.24: Dimensions considered in the evaluations

## 4.2.5 Tool Adoption

### 4.2.5.1 Tool scope: research vs real educational setting

The tools analyzed show a fairly even distribution in terms of their intended scope of application, with some designed solely for research (N = 13), another ones for application in real educational settings (N = 10) and the rest aim to cover both (N = 13). Some tools do not. This suggests that, although most tools are still at the experimental or developmental stage, many are being designed with real-world application in mind.

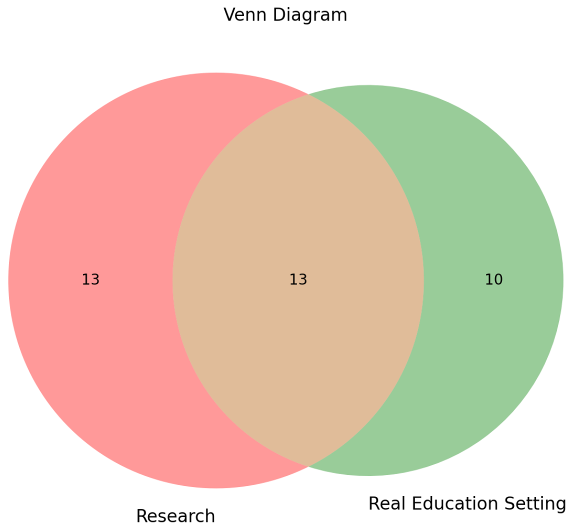



Figure 4.25: Scope of the tools

#### 4.2.5.2 Evidence of System Adoption

In Figure 4.26 we can see that most of the tools analyzed in this thesis are in a stage related to prototype development (N = 24). We can also see that some of the tools have been put in a production environment (N = 9).

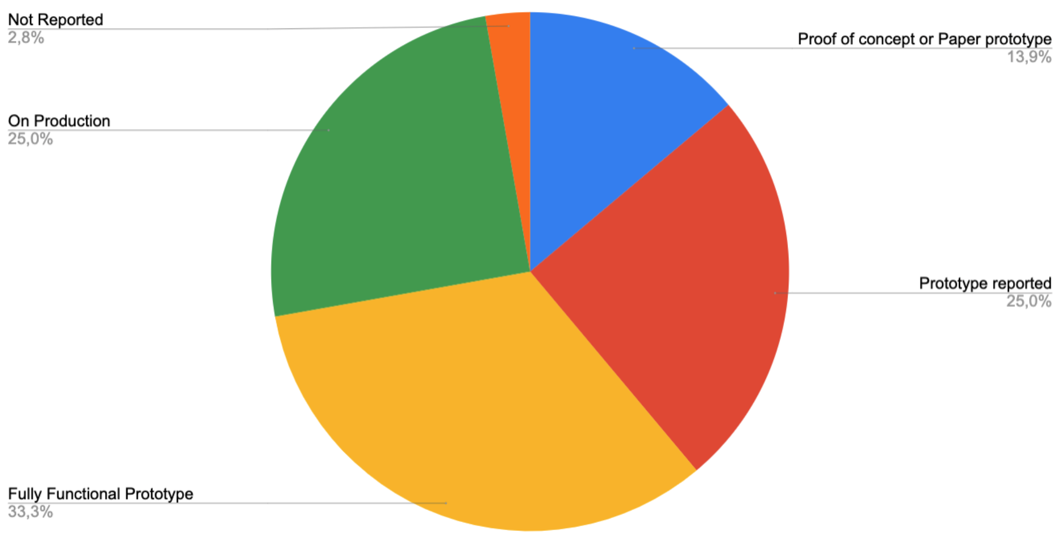



Figure 4.26: Classification according to stage of the tool

Only 13 of the 36 tools analyzed report evidence of system adoption, and at least 6 of them were used with significant numbers of students or in multiple real-world educational contexts, including universities, schools and institutional platforms. For example, some tools were deployed in up to 18 classes or reached platforms with over 4,000 users, while others report semester-based usage involving around 90 students per term.

# 5: Discussion

This chapter presents a comprehensive discussion of the research findings. It begins by revisiting the main objectives of the study, followed by a comparison of the results with existing literature and related work. Based on the findings, a set of recommendations is proposed to inform future practice or research. Finally, the chapter outlines the limitations encountered during the study, providing context for the interpretation of results and suggestions for future research.

## 5.1 Objectives

As reported in Section 1.2, given the current lack of systematic analyses of LA and AIED tools created following human-centered principles, this master thesis poses a number of research questions to better understand the features of 36 tools extracted from the publications analyzed in a previous systematic literature review by Topali et al. [62]. Here, we answer each of these questions:

- *What are the common characteristics of the tools identified?* The analysis of the 36 tools identified reveals several common characteristics. While all tools were considered by the authors as LA tools, the data analysis techniques reveal that 9 of them use AI models such as machine learning ones.

  A majority of these tools (21 out of 36) target higher education, focusing primarily on tertiary-level learning environments. Collaborative learning is the most frequently defined pedagogical context, mentioned by 11 tools.

  The most commonly used tools are dashboards, which focus mainly on monitoring learners. From the learner's point of view, they provide information on their own progress, helping them to self-regulate and reflect on their learning. From the teacher's perspective, these tools provide real-time data that enable educators to identify students who may need additional support, allowing for timely and targeted interventions. Often, these tools feature interactive visualizations and user-friendly interfaces, which make them easy to use and encourage data-driven decision-making in educational settings.

From the technical point of view, regarding implementation and deployment, most tools that specify their platform (20 tools) are web-based or embedded within web-based systems, with JavaScript, HTML, and CSS being the predominant programming languages used for their development.

Regarding data management, the review reveals that while some tools are monomodal, 3 draw from more than one data source and 15 from several data types, leading to a variety of data analysis techniques. In terms of ethics and data privacy, these considerations are explicitly mentioned in only half of the tools (18 out of 36).

- *Which stakeholders, when and how were involved the the tool life-cycle?* This study reveals that stakeholders are involved in the different phases of the tool life cycle: design, prototyping/implementation and evaluation. The design phase shows the highest level of stakeholder involvement, with almost all tools (35 out of 36). In this phase, teachers and students are the most frequently involved, and participation methods such as interviews and surveys predominate. During the prototyping and implementation phase, stakeholder involvement decreases slightly (N = 27), but teachers and students are still the most involved. Activities in this phase focus on design sessions using various levels of prototypes. In the evaluation or testing phase (N = 25), stakeholders, mainly end-users, continue to be included and mixed methods (quantitative experiments with qualitative surveys and interviews) are used to assess both technical performance and user experience.

  Overall, the data support the conclusion that stakeholder involvement is recognized as essential throughout the development process, although the depth and diversity of engagement are not always the same.

- *Is there any evidence about the adoption of the tools?*

  The majority of tools (23 out of 36) report having undergone evaluation involving end-users, many tools appear to be designed as proofs of concept or prototypes (N = 14) (see Figure 4.26, and are often developed for specific research purposes rather than for sustained use or widespread adoption. Also, it is noteworthy that while user involvement seeks to better tailor the solutions to the contextual requirements and user needs, as well as to raise reliability and trustworthiness of the systems, most evaluations do not assess the achievement of these goals.

  A significant limitation is the lack of reporting on key aspects such as licensing, software documentation, or user manuals. Interestingly, many tools lack accessibility to the code, with only 10 detected cases where the authors published them open-source. Similarly, only a minority provide user documentation (6 tools) or software documentation (5 tools). User support is scarcely reported, with just 6 tools indicating its availability. This limitation significantly hampers the reusability, dissemination, and uptake of the tools by the broader educational or open-source communities.

  Moreover, most of the tools reviewed are available in only one or two languages, which limits their accessibility in multilingual or international educational settings. This lack of language support may reflect a limited focus on internationalization. On a positive note, the majority of tools (23 out of 36) report having undergone evaluation involving end-users, employing diverse methods such as interviews, surveys, usability tests, and participatory trials.

## 5.2 Findings Comparison

This section discusses the tool analysis presented in this master thesis in relation to the findings described in the systematic literature review carried out by Topali et al. (2024) [62], from which the tool selection emerged.

The review also touches upon the importance of adopting human-centered approaches where stakeholders are actively involved in the design, development, and evaluation of LA/AIED solutions. The results of the systematic literature review show that more than two-thirds of the papers involve stakeholders in the design of the solutions, but fewer papers involve them during ideation and prototyping, and the majority do not report any evaluation. On the other hand, the tool analysis reported in this thesis gives a more positive view where 35 out of the 36 of the tools have involved stakeholders in the design phase, 27 out 36 in the prototype/implementation phase, and 24 out of 36 in the evaluation. This difference is due to our explicit focus on tools (excluding methodologies and other kinds of theoretical contributions), plus the additional information provided by the authors of the papers where the tools were presented.

We can also see that both in the review and in the analysis carried out there is a diversity of actors involved. It is important to highlight that a wide range of stakeholders were engaged, including IT specialists, school administrators, and developers, indicating that Human-Computer Interaction approaches necessitate involvement from individuals outside of the primary users. However, with the diverse group of stakeholders identified, there is a potential risk of catering to numerous and conflicting needs. However, teachers and students are the most involved, while others play supporting or contextual roles. Perhaps more consideration should be given to involving other actors, such as families or educational institutions, but in my opinion, probably small-size projects may tend to simplify the involvement of secondary stakeholders.

Another conclusion drawn from the literature review was that despite evaluation plays a crucial role in determining the acceptance of research papers for publication, most of the reviewed papers did not report any assessment of their LA/AEID proposals, especially in real-world studies. Thus, the authors hypothesize that the proposals may still be in their early stages. To shed light on this issue, upon conducting an initial analysis of their development stage, this dissertation reveals that the majority of these solutions have reached the mockup stage. Following this, there are a few experimental prototypes, and only a small number of them were fully functional tools by the time the papers were written.

## 5.3 Recommendations

The tool analysis reported in this thesis leads to some recommendations that may help LA/AIED researchers and developers, as well as stakeholders seeking for LA/AIED solutions. My main lesson learnt is that, before designing functionalities, it is essential to clarify the specific educational problem to address and how the tool will bring real value to the actors involved (e.g., posing questions as does it cover a real problem? How many actors can benefit from your tool and how?). Thus, engaging stakeholders in HCD processes to shape the tool from the very beginning could greatly help.

For me, the failure to clearly specify the documentation and type of licensing is a missed opportunity because if it were done correctly it could greatly facilitate the adoption and evolution of these tools. Therefore, a key recommendation is for the research community to place more emphasis on sustainable development and sharing of LA tools beyond experimental or short-term applications. Make sure that your tool can be easily reused and adapted, i.e. open source. Even contact authors of similar works who can contribute their experiences, or even collaborate. They may have open source tools that can be reusable as well. In other words, think about scalability and maintenance.

Another important recommendation is to continue to involve stakeholders not only in the early design phases as most of the work reviewed does, but also throughout the development and evaluation phases. This continuous involvement helps to adapt interfaces to user preferences, thus improving the overall usability of the systems. In addition, any new tool should prioritize the development of clear user guides to facilitate wider adoption and ease of use. In addition, I would encourage future research in AL and AEID to include evaluation processes, especially in real-world educational settings, as this helps to validate the usefulness and impact of the proposed tools and increases their chances of being adopted in practice.

Privacy and data management is another critical aspect to consider during development. Given that only half of the tools reviewed explicitly address privacy measures, future designs should embed strong privacy protections from the outset to ensure compliance and build user trust. Define from the beginning how data is collected, processed and stored, and communicate this transparently to users. From my experience and in my field of work this is called *security by design*.

To improve the inclusivity and broader applicability of LA tools, it is important to consider their adaptability to diverse linguistic and cultural contexts. Currently, most tools lack support for multilingual or culturally adaptive interfaces. Adopting established standards like i18n (internationalization) [68]) could help developers design tools that are easier to adapt across different languages and educational environments, thereby enhancing accessibility and global usability.

Overall, these recommendations arise directly from the patterns observed in the study and aim to improve the practical impact, usability, and adoption of learning analytics tools through comprehensive stakeholder engagement, clear documentation, configurability, and robust privacy practices.

## 5.4 Limitations

Several limitations can be remarked from this dissertation. For example, many authors provide detailed explanations and include illustrative figures, the lack of practical interaction meant that some functional or experiential aspects of the tools may have been overlooked or misinterpreted.

Another limitation of this study is related to the author contact process. An attempt was made to reach out to the authors of all 36 tools to gather additional information or clarification. However, responses were received from only 18, which may have limited the completeness or accuracy of certain details in the analysis.

One limitation of this study is that it is based on a Systematic Literature Review (SLR) published in early 2024. Given the increasing popularity of Human-Centered Design (HCD) throughout the past year, especially due to the growing hype around the topic, this review may not capture the most recent developments or emerging trends up to the present date.

Another potential limitation is that, although the initial analysis was carried out collaboratively as part of earlier research efforts, the final review and categorization of the papers were conducted by a single researcher. This individual perspective may have introduced personal bias. Ideally, each paper would have been categorized by multiple reviewers to ensure triangulation and improve the reliability of the results. To help address this, the authors of the tools were contacted for clarification, but only 18 out of 36 responded.

Finally, a further limitation may lie in the focus of the study. The review has a strong emphasis on Learning Analytics (LA), while Artificial Intelligence (AI) is less prominently addressed. This imbalance may be due in part to a selection bias stemming from the keywords used during the paper identification process, which may have favored LA-related literature over AI-driven approaches.

# 6: Conclusions & Future work

This chapter presents the final reflections of the research. It begins with a brief summary of the work carried out, highlighting the overall process and methodology followed. The main findings are then revisited, along with key recommendations that align with the initial objectives. A concise overview of the study's limitations is provided to contextualize the results and recognize areas of improvement. The chapter also outlines potential directions for future work, suggesting how this research could be extended or refined. Finally, a personal reflection is offered, discussing lessons learned about the topic and the methodological process undertaken throughout the study.

## 6.1 Brief Summary of the Work Done

The work began with a contextualization phase, which involved a review of key literature, webinars and previous studies in order to place myself in the context required for the research. From there, it was decided to follow a methodology inspired by DESMET, which allowed for a structured approach to evaluate and analyze software tools through a systematic analysis of features.

The categorization of the tools was carried out using both deductive and inductive coding, progressively refined through iterative reading of the selected articles. Over several iterations, relevant features were extracted, patterns were identified and categories were continuously adjusted to improve clarity and coherence.

A key component of the study was the contact with the authors of the reviewed papers to validate the extracted information. Two rounds of outreach were conducted, with a significant number of authors providing feedback that was later integrated into the final analysis. After consolidating the data, a category-by-category analysis was performed to identify trends and key findings.

## 6.2 Main Findings

Firstly, five areas were identified as relevant to frame the posed research questions: (1) the basis of the tool; (2) the human-centered approach; (3) the data management; (4) the evaluation; and, (5) the adoption. It was observed that the most recurrent tools are dashboards, these visualizations allow both learners to reflect and self-regulate and teachers to detect needs and implement interventions in real time, thanks to intuitive and interactive data representations that facilitate data-driven decision-making.

In terms of stakeholder involvement, it was found that they are present in all phases of the life-cycle of the tools: design, implementation and evaluation. The greatest involvement is in the design phase, especially by teachers and students through interviews and surveys that serve to collect the requirements and functionalities of the tools. Finally, the analysis shows that the field of LA is still at an early stage of maturity. Many tools are prototypes developed in research contexts and lack key elements such as documentation, licensing or user guides. This lack of information limits their re-usability and scalability, pointing to the urgent need to promote more sustainable and open development in this field.

Although all the tools analyzed (see appendix B) are positioned as Learning Analytics (LA) solutions, nine of them incorporate Artificial Intelligence (AI) techniques to analyze the data.

## 6.3 Future Work

- **Reaching out again to the authors who did not respond:** Their input could provide valuable clarifications or additional insights about the tools and approaches discussed in their publications. This would improve the overall accuracy and depth of the analysis.
- **Expand the analysis by including the papers reviewed by Alfredo et al. (2024)** [4]: As cited in the Introduction and Related Work sections, this would help to ensure broader coverage and alignment across related research efforts.
- **Update and refine the search queries used in Topali et al. (2024)** [62]: Given the significant number of new publications on HCLA and HCAI since 2024, updating the queries will help ensure that recent developments are accurately captured.
- **See how the tools evolve:** Many of the tools analyzed appear to be still in the early stages of development. It would therefore be interesting to monitor them over time to see how they mature, how they are improved, and what real impact they end up having. This would help to better understand where the HCLA and HCAI field is going.
- **Direct testing of tools:** In the future, it would be very useful to be able to access and test tools directly, rather than just relying on what the articles tell. Getting

hands-on experience, seeing how they work, how they are used, and how they feel, would allow for a much better assessment of aspects such as user experience, design, or actual functionalities.

- It would be valuable to develop a global framework for HCAI/HCLA researchers. Such a framework could guide developers through the key steps necessary to improve the adoption and impact of their tools, incorporating best practices such as co-design by stakeholders, transparent documentation, licensing, or thorough evaluation in real-world contexts.

## 6.4 (Personal) Lessons Learned about the Topic/Methodological Process

While analyzing the tools, a few key lessons and challenges became evident. First, as the classification of the tools progressed iteratively, the categories employed to analyze them evolved and adapted over time. This was mainly during the first iterations. While this allowed for a more refined and context-sensitive analysis, it also required repeated review and re-analysis of earlier documents, which significantly increased the time and effort required. Secondly, as most of the tools could not be tested directly, the analysis relied entirely on descriptions provided in the literature.

One of the lessons learned about a literature review versus a tool review is that, in my opinion, the two are complementary. I would even say that they are dependent, as without the literature review conducted by my supervisors it would not have been possible to identify articles that fit the field of study of this dissertation. While SLRs are effective in identifying general trends and the overall state of the art, these findings can sometimes be quite broad or generic.

In my opinion, the authors' involvement is a crucial aspect of the research process. However, coordinating and contacting all the involved authors proved to be quite complex. It is not always straightforward to find a valid email address for communication. Many times, the contact information provided in articles is outdated or missing altogether. In addition, some authors do not have public profiles where their current contact details can be found, which I fully understand, making it difficult to establish communication. These obstacles highlight the difficulties in contacting them directly, which can impact on feedback during the study and waiting times. During the contact, a three-week period was established in which we allowed time to respond, but given the low response rate and in the quest for double-checking, we extended the deadline further and further. Thus, while very enriching, this methodological decision was significantly time-consuming.

But the most important challenge of this work was dealing with highly technical academic articles. Many of the papers reviewed were complex and written at a level of detail that required sustained concentration. The difficulty was not simply to read them, but to really understand the content and make sure that no relevant information was missed, as any small detail could determine the classification or tool assessment. This has required patience and critical thinking to ensure that the conclusions drawn were accurate and well-founded.

In my opinion, artificial intelligence in education can be compared to a car, which in the hands of a responsible and civic-minded driver, it becomes an effective and powerful tool for advancing progress, enhancing learning and supporting both teachers and learners. However, when misused or guided by the wrong intentions, it can pose risks and even become a threat to educational integrity and equity. Just as a car needs standards, training, and ethical behavior to be safe and effective, AI requires thoughtful application and critical reflection to serve its purpose in education. We can even go further with this analogy: how are cars designed? They are co-designed with the end users, who dictate what features are needed, where to place indicators, or how to represent interfaces. It is then the responsibility of developers and researchers to adapt laws and standards to meet those user needs. Similarly, in educational AI, involving stakeholders in the design process ensures that tools are both useful and aligned with real-world requirements and ethical considerations.

# Appendices

# Appendix A

# SLR Articles

In this appendix are listed the articles extracted from the literature review conducted by my supervisors, and they serve as the foundation for the development of this work.

This section also includes articles that were reviewed but excluded for reasons such as a lack of relevant tool descriptions or evidence of plagiarism, in order to ensure the integrity and relevance of the analysis.

| **Title** | **Author** | **Included / Excluded** |
|---|---|---|
| Make It Personal!" - Gathering Input from Stakeholders for a Learning Analytics-Supported Learning Design Tool [55] | Schmitz M., Scheffel M., van Limbeek E., Bemelmans R., Drachsler H. | Included |
| A Multi-Stakeholder Perspective of Analytics for Learning Design in Location-Based Learning [47] | Pishtari, G; Rodriguez-Triana, MJ; Valjataga, T | Included |
| Action-oriented, accountable, and inter(active) learning analytics for students [35] | Knight S., Anderson T.D. | Included |
| Adapting Learning Analytics Dashboards by and for University Students [43] | Oliver-Quelennec, K; Bouchet, F; Carron, T; Casalino, KF; Pincon, C | Excluded After Review |
| Assessing post-hoc explainability of the BKT algorithm [70] | Zhou T., Sheng H., Howley I. | Included |
| Co-design of a Learning Analytics Tool by Computer Scientists and Teachers: The Difficult Emergence of a Common World [46] | Person J., Vidal-Gomel C., Cottier P., Lecomte C. | Excluded After Review |

| **Title** | **Author** | **Included / Excluded** |
|---|---|---|
| Co-Designing a Real-Time Classroom Orchestration Tool to Support Teacher-AI Complementarity [29] | Holstein, K; McLaren, BM; Aleven, V | Included |
| Co-Designing for Privacy, Transparency, and Trust in K-12 Learning Analytics [2] | Ahn, J; Campos, F; Nguyen, H; Hays, M; Morrison, J | Included |
| Communicating learning analytics: Stakeholder participation and early stage requirement analysis [9] | Chalvatza F., Karkalas S., Mavrikis M. | Included |
| Design a Dashboard for Secondary School students to Support Mastery Learning in a Gamified Learning Environment [30] | Hou X., Nagashima T., Aleven V. | Included |
| Design and usability testing of an in-house developed performance feedback tool for medical students [50] | Roa Romero Y., Tame H., Holzhausen Y., Petzold M., Wyszynski J.-V., Peters H., Alhassan-Altoaama M., Domanska M., Dittmar M. | Included |
| Design Considerations for Data-Driven Dashboards: Supporting Facilitation Tasks for Open-Ended Learning [6] | Beheshti, E; Lyons, L; Mallavarapu, A; Wallingford, B; Uzzo, S | Included |
| Designing for Complementarity: Teacher and Student Needs for Orchestration Support in AI-Enhanced Classrooms [28] | Holstein, K; McLaren, BM; Aleven, V | Excluded After Review |
| Designing Human-Centered Learning Analytics Dashboard for Higher Education Using a Participatory Design Approach | Revano T.F., Garcia M.B. | Excluded After Review (Plagiarism) |
| Designing in context: Reaching beyond usability in learning analytics dashboard design [1] | Ahn J., Campos F., Hays M., Digiacomo D. | Included |
| Designing LADs That Promote Sensemaking: A Participatory Tool [52] | Sadallah, M; Gilliot, JM; Iksal, S; Quelennec, K; Vermeulen, M; Neyssensas, L; Aubert, O; Venant, R | Included |
| Designing translucent learning analytics with teachers: an elicitation process [38] | Martinez-Maldonado, R; Elliott, D; Axisa, C; Power, T; Echeverria, V; Shum, SB | Included |

| **Title** | **Author** | **Included / Excluded** |
|---|---|---|
| Developing a learning analytics dashboard for undergraduate engineering using participatory design [34] | Knight D.B., Brozina C., Stauffer E.M., Frisina C., Abel T.D. | Excluded After Review |
| Developing a teacher dashboard for use with intelligent tutoring systems [3] | Aleven V., Xhakaj F., Holstein K., McLaren B.M. | Included |
| Development of Actionable Insights for Regulating Students' Collaborative Writing of Scientific Texts [27] | Hoffmann, C; Mandran, N; D'Ham, C; Rebaudo, S; Haddouche, MA | Included |
| Empowering Teachers with AI: Co-Designing a Learning Analytics Tool for Personalized Instruction in the Science Classroom [42] | Nazaretsky, T; Bar, C; Walter, M; Alexandron, G | Included |
| How do students want their workplace-based feedback visualized in order to support self-regulated learning? Initial results and reflections from a co-design study in medical education [63] | Treasure-Jones T., Dent-Spargo R., Dharmaratne S. | Included |
| Human-centered design of a dashboard on students' revisions during writing [13] | Conijn R., Van Waes L., van Zaanen M. | Included |
| Impact of using learning analytics in asynchronous online discussions in higher education [39] | Martinez, JPC; Catasus, MG; Fontanillas, TR | Included |
| Inspiration Cards Workshops with Primary Teachers in the Early Co-Design Stages of Learning Analytics [67] | Vezzoli, Y; Mavrikis, M; Vasalou, A | Included |
| Involving teachers in learning analytics design: Lessons learned from two case studies [40] | Michos, K; Lang, C; Hernandez-Leo, D; Price-Dennis, D | Included |
| Learning analytics dashboards: The past, the present and the future [66] | Verbert K., Ochoa X., De Croon R., Dourado R.A., De Laet T. | Excluded After Review |
| Learning analytics features for improving collaborative writing practices: insights into the students' perspective [32] | Kilińska D., Kobbelgaard F.V., Ryberg T. | Included |
| Learning analytics made in France: the METAL project [7] | Brun A., Bonnin G., Castagnos S., Roussanaly A., Boyer A. | Included |
| Opening the black box of practice-based learning: Human-centred design of learning analytics [65] | Valkanova N., Cukurova M., Berner A., Avramides K., Mavrikis M. | Included |

| Title | Author | Included / Excluded |
|---|---|---|
| Our Journey: Designing and utilising a tool to support students to represent their study journeys [14] | Coughlan, T; Lister, K; Freear, N | Included |
| Service Design of Artificial Intelligence Voice Agents as a Guideline for Assisting Independent Toilet Training of Preschool Children [31] | Huh J., Ann S., Hong J., Cui M., Park J.Y., Kim Y., Sim B., Lee H.-K. | Included |
| Student Centred Design of a Learning Analytics System [16] | Quincey, E. et al | Included |
| Taylor, the Disability Disclosure Virtual Assistant: A Case Study of Participatory Research with Disabled Students [36] | Lister, K; Coughlan, T; Kenny, I; Tudor, R; Iniesto, F | Included |
| TeachActive Feedback Dashboard: Using Automated Classroom Analytics to Visualize Pedagogical Strategies at a Glance [5] | Al Zoubi, D; Kelley, J; Baran, E; Gilbert, SB; Ilgu, AK; Jiang, S | Included |
| The Multimodal Matrix as a Quantitative Ethnography Methodology [8] | Buckingham Shum S., Echeverria V., Martinez-Maldonado R. | Included |
| The Question-driven Dashboard: How Can We Design Analytics Interfaces Aligned to Teachers' Inquiry? [48] | Pozdniakov, S; Martinez-Maldonado, R; Tsai, YS; Cukurova, M; Bartindale, T; Chen, P; Marshall, H; Richardson, D; Gasevic, D | Included |
| Towards the Co-Design of a Teachers' Dashboards in a Hybrid Learning Environment [45] | Ouatiq, A; Riyami, B; Mansouri, K; Qbadou, M; Aoula, ES | Included |
| User centered approach for learning analytics dashboard generation [15] | Ines D., Jean-Marie G., Sebastien I. | Included |
| User-centred design and educational data mining support during the recommendations elicitation process in social online learning environments [53] | Santos, OC; Boticario, JG | Included |
| Contextualising Learning Analytics with Classroom Observations: a Case Study [20] | Eradze, M; Rodriguez-Triana, MJ; Milikic, N; Laanpere, M; Tammets, K | Included |
| Practical guidelines for designing and evaluating educationally oriented recommendations [54] | Olga C. Santos and Jesus G. Boticario | Included |

| **Title** | **Author** | **Included / Excluded** |
| --- | --- | --- |
| Semantically Annotated Lesson Observation Data in Learning Analytics Datasets: a Reference Model [19] | Eradze, Maka and Rodríguez-Triana, María and Laanpere, Mart | Included |

Table A.1: SLR articles extracted from [62]

*Appendix B*

# Tool Classification

This appendix lists the different tools, with their coding and the articles to which they refer. The *Tool information* in Table B.1 referes to Tool Codification - Name of the Tool (if it is reported) - Brief Summary of the tool. Only tools that refer to articles that have finally been included in the analysis are listed. See appendix A, included articles.

| **Tool Information** | **Article** |
| --- | --- |
| T01 - GrouPer - A dashboard that supports group-level analysis and task assignment. | Empowering Teachers with AI: Co-Designing a Learning Analytics Tool for Personalized Instruction in the Science Classroom (Nazaretsky et al.) [42] |
| T02 - Question-driven Dashboard - A monitoring tool designed to help teachers oversee synchronous online activities and provide real-time feedback to students. | The Question-driven Dashboard: How Can We Design Analytics Interfaces Aligned to Teachers' Inquiry? (Pozdniakov et al.) [48] |
| T03 - Level-Up - A tool to give feedback on the day-to-day education of medical students. | Design and usability testing of an in-house developed performance feedback tool for medical students (Roa Romero et al.) [50] |
| T04A - TILE (teacher inquiry tool) - Support teacher inquiry in Technology-Enhanced Learning (TEL) activities with learning analytics | Involving teachers in learning analytics design: Lessons learned from two case studies [40] |
| T04B - inILDE (community awareness dashboard) - Support community awareness in online teacher communities | Involving teachers in learning analytics design: Lessons learned from two case studies [40] |

| **Tool Information** | **Article** |
|---|---|
| T06A + T28 - DtP, discovering the platform - It teaches how to use the dotLRN platform to novice users. It defines simple activities to make use of the different platform services. | Practical guidelines for designing and evaluating educationally oriented recommendations [54] & User-centered design and educational data mining support during the recommendations elicitation process in social online learning environments [53] |
| T06B - EBIFE, which is its Spanish abbreviation, 'Search strategies in the Web with Educational Goals' - Provide adaptive navigation support in order to guide the students in their interaction. This is meant to foster a proactive attitude of the student which facilitates the usage of Willow without the teacher support. | Practical guidelines for designing and evaluating educationally oriented recommendations [54] |
| T07 - METAL - METAL is the name of the project, and the project lead to several tools, some of which were related to Learning Analytics: a teacher and a student dashboard with various indactors and recommendations of learning activities. An open-source Learning Record Store (LRS) has also been designed, and a charter for responsible and ethical use of educational data defined. | Learning analytics made in France: the METAL project [7] |
| T08 - Our Journey - It is a tool to accompany students on their school journey. This involves both educational and everyday life activities, for example emotions, difficulties, events or comments. It is initially intended to support students with disabilities. | Our Journey: Designing and utilising a tool to support students to represent their study journeys [14] |
| T09 + T32 - Observata - The tool aims to analyze and visualize the combination of digital traces with real classroom observations by designing a learning analytics model for lesson observations. This model provides insights into the connection between the learning context, teacher intentions, and the data gathered from multiple sources during the learning activity. | Semantically Annotated Lesson Observation Data in Learning Analytics [19] & Contextualising Learning Analytics with Classroom Observations: a Case Study [20] |
| T10 - NR - Design a LAD to show teachers indicators and visualizations of collaborative writing (CV) activities of their students | Development of Actionable Insights for Regulating Students' Collaborative Writing of Scientific Texts [27] |

| **Tool Information** | **Article** |
|---|---|
| T11 - NR - Tool in which students choose a series of motivations to fulfill throughout the course. The dashboard displays progress indicators, statistics on the progress of objectives and predictions around a timeline. | Student Centered Design of a Learning Analytics System [16] |
| T12 - NR - Research and design a mobile/tablet learning dashboard to support learning activities in a museam exhibition | Design Considerations for Data-Driven Dashboards: Supporting Facilitation Tasks for Open-Ended Learning [6] |
| T13 - It is a methodology - Describe a case study in which teachers participate in an LA co-design approach to an existing tool. The main objective is to enhance the use of Inspiration Cards (technology and domain cards) as a design methodology. | Inspiration Cards Workshops with Primary Teachers in the Early Co-Design Stages of Learning Analytics [9] |
| T14 - Interactive Alchemy - Provide algorthmic undestanding to teachers and students of the Bayesian Knowledge Tracing (BKT) system | Assessing Post-hoc Explainability of the BKT Algorithm [70] |
| T15 - TeachActive - This tool is an automated feedback system based on classroom analytics that focuses specifcally on encouraging active learning strategies. | TeachActive Feedback Dashboard: Using Automated Classroom Analytics to Visualize Pedagogical Strategies at a Glance [5] |
| T16 - myPAL - Tool to store and manage feedback for self-regulated learning (SRL) in the workplace (WBA), as it is provided and potentially used in the context where students (medicine students in this case) need to become more self-reliant. | How do students want their workplace-based feedback visualized in order to support self-regulated learning? Initial results & reflections from a co-design study in medical education [63] |
| T17 - 3 prototype names: Zoom-in, Timeline, Reporting - Design process of analytics for LD features (as dashboards) in the context of location-based learning | A Multi-Stakeholder Perspective of Analytics for Learning Design in Location-Based Learning [47] |
| T19 - PELARS - This tool is intended to help and understand the students/teachers involved in practical activities. The main objective is to help teachers to see what all the students are doing in order to try to help them. | Opening the Black Box of Practice-Based Learning: Human- Centered Design of Learning Analytics [65] |

| **Tool Information** | **Article** |
|---|---|
| T20 - These are not the actual names, but they have called the two dashboards: for the next day (prepare classes) and for field situations (class monitoring). - The tool is a teacher dashboard of intelligent tutoring software focused on realistic classroom scenarios. It allows both class monitoring and help to prepare future classes. | Developing a teacher dashboard for use with intelligent tutoring systems [3] |
| T21 + T34 - These are not the actual names, but they have called the four visualizations as: social proxy,physical proxy,arousal proxy and timeline proxy - The tool presents 4 types of visualizations showing indicators of social, physical, affective, and epistemic aspects of the activity captured while teams of students practiced clinical skills in a simulated environment. | Designing translucent learning analytics with teachers: an elicitation process [38] & The Multimodal Matrix as a Quantitative Ethnography Methodology [8] |
| T25 - PaDLAD - The tool is a dashboard centered in Learning persona (which is a hypothetical student who is representative of a certain number of potential students, teachers...) | Designing LADs That Promote Sensemaking: A Participatory Tool [52] |
| T27 - Taylor - The tool aims to address the administrative burden faced by students with disabilities | Taylor, the Disability Disclosure Virtual Assistant: A Case Study of Participatory Research with Disabled Students [36] |
| T29 - NR - The dashboard is specifically aimed at visualizing and interpreting students' writing processes. This focus is relevant for writing instruction, where understanding the process can be as important as the final product. | Human-Centered Design of a Dashboard on Students' Revisions During Writing [13] |
| T30 - It is not titled, it is an adaptation of the SCRAM . - The objective of the tool is to communicate quality indicators to stakeholders by summarizing and visualizing data collected through student and parent surveys. | Communicating Learning Analytics: Stakeholder Participation and Early Stage Requirement Analysis [9] |
| T31 - NR - The tool aims to create a learning platform and associated learning analytics that are tailored to the needs of students | Action-oriented, Accountable, and inter(Active) Learning Analytics for students [35] |

| **Tool Information** | **Article** |
| --- | --- |
| T33 - DIANA 2.0 (DIalogue ANAlysis versión 2.0) - This tool provides teachers with actionable data to monitor and assess asynchronous online discussions, aiming to improve student engagement, reduce dropout rates, and refine teaching strategies for better learning outcomes. | Impact of using learning analytics in asynchronous online discussions in higher education [39] |
| T35 - NR - The goal of the teacher dashboard is to promote informed decision making by providing information about student data. | Towards the Co-Design of a Teachers' Dashboards in a Hybrid Learning Environment [45] |
| T36 - Ddongddong (Poop Poop in English) - AI voice agent to help preschool children go to the toilet alone | Service Design of Artificial Intelligence Voice Agents as a Guideline for Assisting Independent Toilet Training of Preschool Children [31] |
| T37 - NR - The main objectives of the LA4LD tool are to create personalized dashboards for both students and teachers. Improving learning processes. | "Make It Personal!" - Gathering Input from Stakeholders for a Learning Analytics-Supported Learning Design Tool [55] |
| T38 - Lumilo - The tool's goal is to improve teaching and learning in the classroom by providing teachers with real-time feedback on student learning through augmented reality (AR) glasses. | Co-Designing a Real-Time Classroom Orchestration Tool to Support Teacher–AI Complementarity [29] |
| T39 - edshigt - The primary goal is not merely the creation of dashboards but fostering a deep understanding of diverse users and their specific practices. | Designing in Context: Reaching Beyond Usability in Learning Analytics Dashboard Design [1] |
| T40 - NR - Tool to visualize student interactions at 3 different levels (individual, class or department). | User Centered Approach for Learning Analytics Dashboard Generation [15] |
| T41 - NR - The objective of the tool described is to develop a data sharing and privacy prototype specifically tailored for the K-12 educational context. | Co-Designing for Privacy, Transparency, and Trust in K-12 Learning Analytics [2] |
| T42 - NR - The tool aims to facilitate collaborative writing (Google Docs) by providing relevant analytics features. | Learning analytics features for improving collaborative writing practices: insights into the students' perspective [32] |

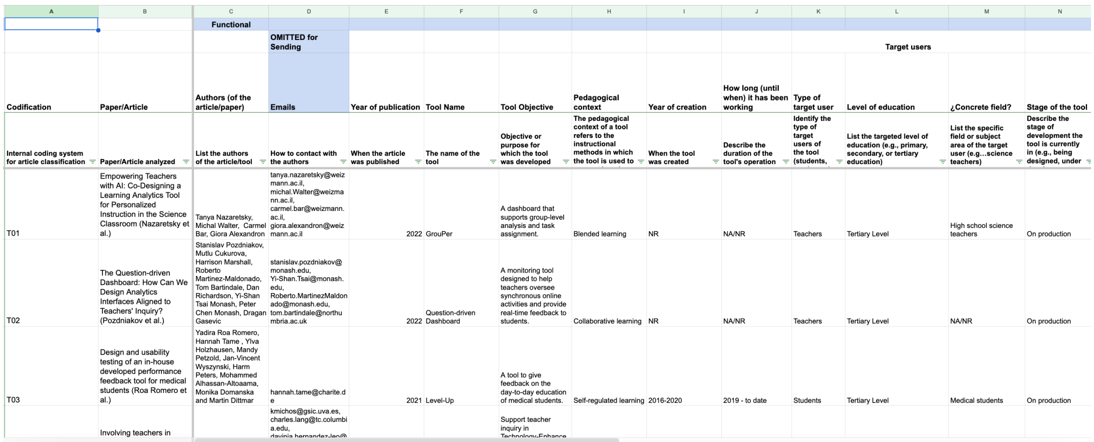
| **Tool Information** | **Article** |
|---|---|
| T43 - Gwynnette Dashboard - The objective of the dashboard is to help students learn better and feel more positive about their learning progress in Gwynnette (which is a tool designed to help students learn algebra through a gamified intelligent tutoring system) | Design a Dashboard for Secondary School students to Support Mastery Learning in a Gamified Learning Environment [30] |

Table B.1: Analyzed tools

# Appendix C

# Spreadsheet

This appendix presents a series of screenshots illustrating how the data and information were organized and managed within the spreadsheet used throughout this study. This visual documentation complements the methodological description and offers additional clarity on the practical handling of the research artifacts. All content is available on Zenodo [24].



| A | B | C | D | E | F | G | H | I | J | K | L | M | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Functional | | | | | | | | | | | |
| | | | OMITTED for Sending | | | | | | | Target users | | | |
| Codification | Paper/Article | Authors (of the article/paper) | Emails | Year of publication | Tool Name | Tool Objective | Pedagogical context | Year of creation | How long (until when) it has been working | Type of target user | Level of education | ¿Concrete field? | Stage of the tool |
| Internal coding system for article classification | Paper/Article analyzed | List the authors of the article/tool | How to contact with the authors | When the article was published | The name of the tool | Objective or purpose for which the tool was developed | The pedagogical context of a tool refers to the instructional methods in which the tool is used to | When the tool was created | Describe the duration of the tool's operation | Identify the type of target users of the tool (students, | List the targeted level of education (e.g., primary, secondary, or tertiary education) | List the specific field or subject area of the target user (e.g...science teachers) | Describe the stage of development the tool is currently in (e.g., being designed, under |
| T01 | Empowering Teachers with AI: Co-Designing a Learning Analytics Tool for Personalized Instruction in the Science Classroom (Nazaretsky et al.) | Tanya Nazaretsky, Michal Walter, Carmel Bar, Giora Alexandron | tanya.nazaretsky@weizmann.ac.il, michal.Walter@weizmann.ac.il, carmel.bar@weizmann.ac.il, giora.alexandron@weizmann.ac.il | 2022 | GrouPer | A dashboard that supports group-level analysis and task assignment. | Blended learning | NR | NA/NR | Teachers | Tertiary Level | High school science teachers | On production |
| T02 | The Question-driven Dashboard: How Can We Design Analytics Interfaces Aligned to Teachers' Inquiry? (Pozdniakov et al.) | Stanislav Pozdniakov, Mutlu Cukurova, Harrison Marshall, Roberto Martinez-Maldonado, Tom Bartindale, Dan Richardson, Yi-Shan Tsai Monash, Peter Chen Monash, Dragan Gasevic | stanislav.pozdniakov@monash.edu, Yi-Shan.Tsai@monash.edu, Roberto.MartinezMaldonado@monash.edu, tom.bartindale@northumbria.ac.uk | 2022 | Question-driven Dashboard | A monitoring tool designed to help teachers oversee synchronous online activities and provide real-time feedback to students. | Collaborative learning | NR | NA/NR | Teachers | Tertiary Level | NA/NR | On production |
| T03 | Design and usability testing of an in-house developed performance feedback tool for medical students (Roa Romero et al.) | Yadira Roa Romero, Hannah Tame , Ylva Holzhausen, Mandy Petzold, Jan-Vincent Wyszynski, Harm Peters, Mohammed Alhassan-Altoaama, Monika Domanska and Martin Dittmar | hannah.tame@charite.de | 2021 | Level-Up | A tool to give feedback on the day-to-day education of medical students. | Self-regulated learning | 2016-2020 | 2019 - to date | Students | Tertiary Level | Medical students | On production |
| | Involving teachers in | | kmichos@gsic.uva.es, charles.lang@tc.columbia.edu, | | | Support teacher inquiry in | | | | | | | |

Figure C.1: Example of Tool Basis sheet

| | A | B | C | D | E |
|---|---|---|---|---|---|
| 1 | | | | | |
| 2 | | | | | **Overall figures of stakeholder involvement** |
| 3 | **Codification** | **Stakeholders involved in design process** | **Stakeholders involved in implementation phase** | **Stakeholders involved in evaluation and testing phases** | **Total Stakeholders (Who & how many)** |
| 4 | Internal coding system for article classification | **Who, How many and How people are involved in this design phase. This stage is understood as understanding the problem and making requirements.** | **Who, How many and How people are involved in this implementation phase. Understanding this stage as tasks/actions of co-creation with stakeholders** | **Who, How many and How people are involved in this evaluation and testing phase. Understanding this stage as an evaluation of a partial or final tool, i.e. something concrete** | **Total number of participants reported (unclear if they are unique or not)** |
| 5 | T01 | High-school science teachers (5) - Semi-structured interviews | 1-Physics and biology science teaching researchers, educational data scientists, UX/UI designers, and teachers - Moc-kup design<br>2-High schol science teachers (12) - Experiment/workshop | High school Biology teachers (48) - Workshop/controlled experiment | 65 teachers |
| 6 | T02 | Teachers (15) - Interviews, Lightweight inductive analysis, Questions formulation | Based on most commonly teachers question, but they are not involved in the prototype | Teachers - Interviews | 15 teachers |
| | | Technical | | | |

Figure C.2: Example of HCD Approach sheet

A1 fx

| | A | B | C | D | E | F | G | H | I | J |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | | | | | | | | | |
| 2 | | | | | **Data analysis techniques** | | **Data visualization techniques** | | | |
| 3 | **Codification** | **Data sources** | **Type of data** | **Data gathering techniques** | **Type of analysis** | **Data analysis techniques** | **Visualization techniques** | **Dynamic/interactive or static** | **How does the tool preserve ethics and data privacy?** | **Are these measures embedded in the tool or are the teachers/researchers/ ... the ones doing it ad-hoc?** |
| 4 | Internal coding system for article classification | **List the data sources used by the tool (e.g., learning management systems, files, sensors, user input...)** | **List the diferent types of data collected by the tools** | **Describe the type of data collection, pull or push (automatically or on demand)** | **Methods of analyzing the data collected: -Descriptive: Summarizes past data to reveal patterns. -Diagnostic: Explains causes behind past events. -Predictive: Uses data to forecast future trends.** | **Mentioned techniques to analyze data used by the tool** | **Mentioned visualization techniques included within the tool** | **The data is static or there is interaction between the user and the system (i.e., dynamic)** | **Description of the measures taken to ensure privacy, security and ethical use of data. DELICATE CHECKLIST: D - Determination: Clearly define the purpose and added value of data collection. E - Explain: Be** | **Describe whether the measures are built into the application or whether the user is responsible for these measures** |
| 5 | T01 | Learning management system | Numerical (task completion status) and sequential logs (actions) | Pull/On demand | Descriptive, Diagnostic | Real-time clustering algorithm with an explainable-AI scheme | Filters, group visualizations, indicators, task assignment | Dynamic/interactive | NA/NR | NA/NR |
| 6 | T02 | Live online activity data | Real-time event data | Pull/On demand | Descriptive, Diagnostic | NR | Data Storytelling | Dynamic/interactive | ANONYMISE | NA/NR |
| 7 | T03 | Learning management system | Activity logs, student progress, exam results... | Pull/On demand | Descriptive, Diagnostic | NR | Visualizations, charts, indicators, status progress | Dynamic/interactive | DETERMINATION: Clear purpose of securing data ANONYMISE: No personal data saved in live server TECHNICAL: Personal hashes on a separate internal server | Embedded |
| 8 | T04A | Learning management system | Logs, student feedback (google forms) | Pull/On demand | Descriptive | NR | Bar plots, visualizations, indicators, radial tidy tree | NA/NR | E-Explain, C-Consent | NA/NR |
| | | Learning management | | | | | | | | |

Figure C.3: Example of Data Management sheet

F8 fx

| | A | B | C | D |
|---|---|---|---|---|
| 1 | | | | |
| 2 | | | **Summative Evaluation** | |
| 3 | **Codification** | **Evaluation reported in the paper (yes/no)** | **Purpose of evaluation** | **Method of evaluation** |
| 4 | Internal coding system for article classification | **Whether the tool has been evaluated in a research paper** | **Purpose of evaluation of the test** | **List the method used to evaluate the tool** |
| 5 | T01 | Yes | Evaluate teachers performance | Performance was evaluated in a controlled experiment with a non-parametric Wilcoxon sum rank test |
| 6 | T02 | Yes | "Validation of visualisations" and "Validation of full-interface" | Interviews |
| 7 | T03 | Yes | 1-Usability test<br>2-Tool acceptance / user experience | 1-Test in which time per task and non-critical errors are measured.<br>2-Comments/opinions during the test and with a survey with qualitative and quantitative questions |
| 8 | T04A | Yes | Whether it supports data-informed teacher inquiry | Interviews, questionnaires, teacher online comments |
| 9 | T04B | Yes | Whether it supports community awa | Design-based research with 3 cycles |

Figure C.4: Example of Tool Evaluation sheet

Q10 fx

| | A | B | C | D |
|---|---|---|---|---|
| 1 | | | | |
| 2 | | | | |
| 3 | **Codification** | **Scope: only for research and/or real educational setting** | **Evidence of system adoption** | **Availability of the tool** |
| 4 | Internal coding system for article classification | **Indicate whether the tool is intended for research, for application in real educational settings, or both** | **Provide evidence of the tool's adoption** | **Indicate wheter the tool is publicly available on Internet, available under request or dependent of an institution** |
| 5 | T01 | Both | Yes, integrated in PeTel. | It is dependent on the platform where are used |
| 6 | T02 | Real education setting | Yes, A fully functional version of the question-driven interface was deployed in an authentic university context as part of a unit of study in Information Technologies Research Methods at Monash University. | They report that is an open source, https://gitlab.com/action-lab-aus/zoomsense |
| 7 | T03 | Real education setting | Yes, LevelUp enjoys wide acceptance and meets the need for improved student feedback on the Charité's modular curriculum. | It is not dependant, It is an open source application and It can be adapted to other universities. |

Figure C.5: Example of Tool Adoption sheet

# Appendix D

# Author Contact

This appendix shows how the information is sent to the authors so that they can add, modify or extend the information collected during the analysis.

The format consists of four columns, in which the category being evaluated is named and explained, the information found is presented and a space is left for them to give their opinion.

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| 1 | Category | Category Description | Gathered Information | Author Comments | | |
| 2 | Codification | Internal coding system for article classification | T01 | | | C1-Tool basis |
| 3 | Paper/Article | Paper/Article analyzed | (Nazaretsky et al.) | | | C2-Human-Centered approach |
| 4 | Authors (of the article/paper) | List the authors of the article/tool | Tanya Nazaretsky, Michal Walter, Carmel Bar, Giora Alexandron | | | C3-Data management |
| 5 | Year of publication | When the article was published | 2022 | | | C4-Tool evaluation |
| 6 | Tool Name | The name of the tool | GrouPer | | | C5-Tool adoption |
| 7 | Tool Objective | Objective or purpose for which the tool was developed | A dashboard that supports group-level analysis and task assignment. | | | |
| 8 | Pedagogical context | which the tool is used to support learning outcomes. | Blended learning | | | |
| 9 | Year of creation | When the tool was created | NR | | | |
| 10 | How long (until when) it has been working | Describe the duration of the tool's operation | NA/NR | | | |
| 11 | Type of target user | Identify the type of target users of the tool (students, teachers...) | Teachers | | | |
| 12 | Level of education | education) | Tertiary | | | |
| 13 | ¿Concrete field? | teachers) | High school science teachers | | | |
| 14 | Stage of the tool | designed, under development, under evaluation, or in production) | Functional version integrated into PeTel | | | |
| 15 | Contribution type | gathering tool) | Learning Analytics Dashboard | | | |
| 16 | Platform | web-based, mobile, desktop application) | Web-based | | | |
| 17 | Embedded/Standalone | standalone | Embedded | | | |
| 18 | it is embedded | applicable | 1000 high school sci- ence teachers in Israel. | | | |
| 19 | Technology/Programming languages | tool | NA/NR | | | |
| 20 | licence? | Indicate whether the tool is open source | NA/NR | | | |
| 21 | Language | List the language(s) in which the tool is available | English | | | |
| 22 | Are there user manuals? | Indicate whether user manuals are available for the tool | NA/NR | | | |
| 23 | If there is user support -> What type | Indicate whether user support is available for the tool | NA/NR | | | |
| 24 | documentation? | is open source | NA/NR | | | |
| 25 | Stakeholders involved in design process | requirements. | High-school science teachers (5) - Semi-structured interviews | | | |
| 26 | Stakeholders involved in implementation phase | phase. Understanding this stage as tasks/actions of co-creation with stakeholders | scientists, UX/UI designers, and teachers - Moc-kup design 2-High schol science teachers (12) - Experiment/workshop | | | |
| 27 | testing phases | final tool, i.e. something concrete | High school Biology teachers (48) - Workshop/controlled experiment | | | |
| 28 | Total Stakeholders (Who & how many) | not) | 65 teachers | | | |
| 29 | Data sources | systems, files, sensors, user input, internal logs and metrics...) | Learning management system | | | |
| 30 | Type of data | List the diferent types of data collected by the tools | Numerical (task completion status) and sequential logs (actions) | | | |
| 31 | Data gathering techniques | demand) | Pull/On demand | | | |
| 32 | Type of analysis | -Prescriptive: Recommends actions based on predictions. | Descriptive, Diagnostic | | | |
| 33 | Data analysis techniques | Mentioned techniques to analyze data used by the tool | Real-time clustering algorithm with an explainable-AI scheme | | | |
| 34 | Visualization techniques | Mentioned visualization techniques included within the tool | Filters, group visualizations, indicators, task assignment | | | |
| 35 | Dynamic/interactive or static | system (i.e., dynamic) | Dynamic/interactive or static | | | |
| 36 | privacy? | privacy rules. | NA/NR | | | |
| 37 | it ad-hoc? | the user is responsible for these measures | NA/NR | | | |
| 38 | Evaluation reported in the paper (yes/no) | Whether the tool has been evaluated in a research paper | Yes | | | |
| 39 | Purpose of evaluation | Purpose of evaluation of the test | Evaluate teachers performance | | | |
| 40 | Method of evaluation | List the method used to evaluate the tool | non-parametric Wilcoxon sum rank test | | | |
| 41 | educational setting | real educational settings, or both | Both | | | |
| 42 | Evidence of system adoption | Provide evidence of the tool's adoption | Yes, integrated in PeTel. | | | |
| 43 | Availability of the tool | under request or dependent of an institution | It is dependent on the platform where are used | | | |

Figure D.1: Format in which we have submitted information to authors

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