EdTech Scan

An Exploratory Analysis of Equity, AI and Effectiveness in Widely Used EdTech Tools in Dutch Higher Education

let's change
YOU. US. THE WORLD.

THE HAGUE
UNIVERSITY OF
APPLIED SCIENCES

EdTech Scan

An Exploratory Analysis of Equity, AI and Effectiveness in Widely Used EdTech Tools in Dutch Higher Education

Authors*
Marleen Sharpe-Biesheuvel, Manika Garg, Theo Bakker

Department
Research Group for Learning Technology & Analytics

Date
13 Apr 2026

Project type
Research report

Version
1.0

*Marleen Sharpe-Biesheuvel conducted the literature review, developed the EdTech Scan, collected and analysed the information about the tools investigated, and wrote the report. Manika Garg and Theo Bakker contributed to the conceptual definition and methodological design of the exploratory study, and provided substantive feedback on successive versions of the manuscript. All authors approved the final version of the report.

Disclaimer

This report presents an exploratory analysis based exclusively on publicly available information about EdTech tools. The aim is to examine what is visible and verifiable in public documentation, not to assess the actual performance or effectiveness of tools in practice.

It is important to note that additional forms of evidence (such as pilot studies, customer-specific evaluations, or internal analyses) may exist but are not publicly disclosed due to confidentiality, approval processes, or institutional ownership.

Furthermore, the scan was conducted in 2025. As EdTech tools and their documentation evolve rapidly, new features, evidence, or transparency practices may have emerged since the time of analysis.

Therefore, the absence of publicly verifiable information in this report should not be interpreted as the absence of evidence or developments in practice. The findings reflect transparency and public accountability at the time of the scan, rather than a comprehensive or current evaluation of tools.

Summary

This exploratory study investigated the extent to which public values such as equity, transparency around AI and effectiveness are visible and verifiable in commonly used EdTech tools, based on publicly available information. The EdTech Scan was developed and applied as a framework for reflection.

The analysis shows that public information on these themes is generally fragmentary and implicit. Equity, AI use and effectiveness are rarely explicitly elaborated at the functional level, but appear scattered in general claims, design principles or policy documentation. Assessment based on public sources is therefore possible, but has clear limitations. These limitations also include the fact that relevant evidence and documentation may exist but are not publicly accessible, for example due to confidentiality or institutional constraints.

The extent to which public values can be assessed is strongly related to the function and positioning of a tool. Not every criterion is equally relevant or visible for every tool. Missing information often points to implicit assumptions in the design. In other cases, it remains unclear to what extent considerations regarding use, interpretation and risks are explicitly assigned to the tool or assumed to be the responsibility of users and institutions.

Across the themes examined, transparency appears to be a crucial prerequisite. Without insight into how the tool works, how data is used and how it is substantiated, it is difficult to interpret claims of effectiveness, critically assess AI applications or make inclusive choices. In particular, when it comes to effectiveness, traceable evidence at the functional level is rarely publicly available. Substantiation is often based on plausibility and contextual preconditions.

The EdTech Scan is not an assessment tool, but a tool for structuring public information, making assumptions explicit and supporting the discussion about values, risks and substantiation. Responsible use of EdTech therefore requires not only the choice of tools, but also conscious considerations, transparency and cooperation between educational institutions, suppliers and sector organisations.

Table of contents

1. Introduction

Digital technology has become inextricably linked to higher education. Digital learning resources (Educational Technology, hereinafter EdTech) increasingly support testing, interaction, learning pathways and feedback. At the same time, there is a growing awareness that the use of technology is not neutral. Both educational institutions and EdTech suppliers make design and implementation choices that can have direct consequences for public values such as equity, transparency and trust.

Although there is increasing international attention for public values and the responsible use of technology, in practice there is often a lack of shared, workable frameworks for assessing EdTech tools. Evaluation often focuses on technical or commercial aspects, or takes place in a fragmented manner within individual projects and institutions. Collaboration between educational institutions, researchers and developers remains limited, partly due to diverging interests, paces and infrastructures (Kucirkova, 2025).

What is particularly lacking in this context is a practical framework for reflection that helps institutions and suppliers to explicitly consider public values at the level of concrete EdTech tools, based on publicly available information. It is precisely this information that forms the primary basis for decision-making in selection, procurement and implementation processes, but it often appears to be fragmentary, implicit or difficult to interpret.
In practice, educational institutions are under increasing pressure. Teachers are increasingly calling for support in the use of new digital tools, while institutions have limited capacity, budget and expertise to carefully assess and implement these technologies. At the same time, policy frameworks and regulations expect institutions to take responsibility for public values such as equity, transparency and responsible data use. EdTech suppliers also navigate these tensions. They are increasingly being asked for transparency about algorithms, substantiation of effectiveness and attention to inclusion, while these forms of accountability are not always embedded as standard in product development or public communication.

Within this context, The Hague University of Applied Sciences' Learning Technology & Analytics Research Group developed the EdTech Scan as an exploratory reflection framework. The aim of this exploratory study is to gain insight into the extent to which and the manner in which commonly used EdTech tools in Dutch higher education can be publicly assessed in terms of public values, based on publicly accessible information. In doing so, it explicitly explored where a compact, standardised reflection is sufficient and where further interpretation or guided application appears to be necessary.

The EdTech Scan is structured around three thematic perspectives: equity, AI and algorithms, and effectiveness. Each theme is elaborated in key questions, reflection frameworks and practical points for attention that guide the analysis. The scan is explicitly not an assessment or certification tool, but is intended as an aid to clarify relevant questions, structure considerations and support the discussion about public values.

The development of the EdTech Scan is in line with existing initiatives and frameworks, such as the SURF algorithm register (Vermaas, 2023), the European AI Act and the Dutch 3E model for evidence-informed evaluation (Garg & Bakker, 2025). Inspiration has also been drawn from the EdTech Evidence Movement (Kucirkova, 2022, 2025), in which transparency and substantiation are seen as preconditions for both ethically responsible use and sustainable market development. In a broader sense, the scan fits within the movement towards public values and responsible digitisation, as expressed in the Responsible Tech discussion paper (SURF, 2023).

In addition, the EdTech Scan ties in with initiatives such as the Collaborative Trust Framework (Collaborative Trust Framework, n.d.), which focuses on long-term collaboration between educational institutions and EdTech providers, with an emphasis on freedom of choice, shared responsibility and transparency (‘EdTech, not AdTech’). By systematically organising and interpreting public information, the scan acts as a link between national strategies and the practical work of teachers, information managers, educational advisors, purchasers and suppliers.

2. Methodology

The aim of this exploratory study is to gain insight into how public values are visible and verifiable in commonly used EdTech tools, based on publicly available information. The analysis does not focus on determining the actual functioning or impact of tools, but on the way in which suppliers publicly account for themes such as equity, AI and effectiveness.
The EdTech Scan was used as a framework for reflection to systematically organise and analyse this public information. The research is exploratory in nature and does not aim to rank or make a final judgement on individual tools, but to identify patterns, gaps and recurring assumptions at field level.

2.1 Selection of tools

The examined set of EdTech tools consists of eleven commonly used tools in Dutch higher education. The selection is based on the ten most frequently ticked applications in SURF's Educational Applications Collaboration Platform (SPEA), supplemented with one additional tool to increase the spread of function types. The selection was made in the summer of 2025.

The set includes both domain-specific EdTech tools (such as testing, feedback or learning platforms) and generic digital applications that are widely used in educational contexts. The tools have not been selected for comparison or to make statements about individual products, but serve as case studies to explore the extent to which public values are made publicly transparent within different types of EdTech. The list of tools is included in Appendix 1: Tools studied in this exploratory study.

2.2 Delimitation and analysis framework

The analysis is limited to features that are visible in the design, documentation and public communication of the tool. Internal documentation, contractual agreements, implementation strategies and actual use within institutions are outside the scope of this exploratory study.

The EdTech Scan is structured around three main themes:

- Equity, with a focus on accessibility, differentiation, inclusivity and support;
- AI and algorithms, with a focus on transparency, bias, privacy and human oversight;
- Effectiveness, with a focus on the type of publicly available evidence.

Criteria have been formulated for each theme to guide the analysis. These criteria are not intended as a checklist that every tool must meet, but as analytical lenses to structure public information and make it comparable. Not every criterion is equally relevant or visible for every tool; the absence of information is therefore explicitly included as an analytical observation.

2.3 Data collection

Data collection was carried out through systematic desk research. Public sources were consulted for each tool, including:

- product documentation and help articles,
- policy and compliance pages,
- white papers and blogs from suppliers,
- publicly available statements on AI, privacy and accessibility.

Where available, external sources have also been included, such as independent reports or scientific publications cited by suppliers themselves. No interviews, surveys or internal datasets have been used.

The focus on publicly available information is not merely a practical limitation, but a conscious choice. This information forms transparency, accountability and informed decision-making by institutions, teachers and students.

2.4 Analysis and interpretation

The information collected has been summarised in concise analytical descriptions for each tool and each criterion. These descriptions have not been translated into scores or final assessments, but have been used as input for a thematic analysis at field level.

In chapter 4, recurring patterns, differences and gaps are described on this basis, without making any statements about the good or poor functioning of individual tools. The analysis focuses on what is made publicly visible, how explicitly this is done, and where assumptions or ambiguities remain.

2.5 Limitations of the exploratory study

This exploratory study has a few limitations. Because only publicly available information was used, internal processes, actual use and context-specific effects remain outside the scope. In addition, the analysis is a snapshot; public documentation can change over time.
However, these limitations are inherent to the chosen perspective. The study does not claim to be exhaustive, but aims to reveal what is and is not transparent based on publicly available documentation. It is precisely this limitation that makes it possible to make statements about transparency, verifiability and the division of roles between suppliers and institutions.
An important limitation of this study is that it only considers publicly available information. In practice, additional forms of evidence (e.g. pilot studies, customer-specific evaluations, or internal analyses) may exist but are not publicly disclosed due to confidentiality, approval procedures, or institutional ownership. As a result, the absence of publicly verifiable evidence should not be interpreted as absence of evidence in practice.

2.6 Accountability for AI use in this research

To support the exploratory application of the reflection framework, generative AI tools (ChatGPT – OpenAI, Claude – Anthropic, and Gemini – Google) were used as analytical aids to structure and summarize publicly available information.

AI was deployed with a clearly defined and limited purpose: to accelerate the initial organization of large volumes of public documentation per criterion. All AI-generated summaries and preliminary interpretations were reviewed, compared, and where necessary corrected or supplemented by the researchers.

Repeated analyses and the use of different models did not always produce identical outcomes. This variation was not treated as a judgment about the tools under review, but as an indication that certain criteria or guiding questions might still contain ambiguities. Differences between model outputs were therefore used to refine and sharpen the reflection framework.

The use of generative AI entails methodological considerations. Large language models operate probabilistically, and their training data, selection mechanisms, and internal weighting processes are not fully transparent. This limits the traceability of generated interpretations. For that reason, AI outputs were not presented as findings in themselves, but used solely as support for structuring and preliminary analysis.

ChatGPT (versions 4o and 5.2) was also used in structuring and editing this report, under the responsibility of the authors.

3. Conceptual and analytical framework

In the following three sections, we explain the three main themes of the scan: equity, AI and algorithms, and effectiveness. For each theme, the underlying values, assessment criteria and key questions are elaborated, with reference to relevant literature and frameworks.

3.1 Equity

Equity is a fundamental public value in education, but comes under pressure when technological systems implicitly reproduce existing inequalities. Digital resources can contribute to equity, for example by enabling flexible learning or by removing barriers for students with support needs. At the same time, those same resources can reinforce exclusion, for example when they only function well for students with stable access to technology, strong language skills or sufficient digital confidence.

The EdTech Scan is in line with a widely supported vision of equity as more than just access to education or learning resources. It also involves fair support, understandable interfaces, cultural representation and making structural barriers visible. In line with the vision document “AI en Kansengelijkheid: Visie op de impact van AI op kansengelijkheid in het vervolgonderwijs” *(AI and Equity: Vision on the impact of AI on equity in further education)* (Bakker et al., 2024), equity is understood as a multidimensional issue that touches on the design, implementation and use of EdTech.

International frameworks (such as Dickson's TAXI model,(2022) emphasise the importance of experiential equity and identity equity: the extent to which technology does justice to differences in learning experience, background and self-image. Technological innovation without attention to social differences risks reinforcing existing inequality (Onderwijsraad, 2022). The Universal Design for Learning (UDL) principle is a broadly applicable approach to making education accessible and inclusive. UDL is based on flexibility in learning objectives, instruction and assessment, so that students with diverse needs can participate fully (ECIO, 2021).

In order to make equity not only normative but also analytically manageable, the EdTech Scan translates these broad principles into four core criteria: accessibility, differentiation, inclusive content and support. These criteria function as analytical lenses: they reveal which aspects of equity are explicitly addressed by suppliers and where assumptions, implicit choices or 'blind spots' remain in public documentation.

One key question has been formulated for each criterion to guide the scan. These are included in Table 1.

Criterion	Key question
Accessibility	To what extent is the tool accessible to students with varying physical, cognitive and digital abilities (e.g. compatibility with assistive devices, multimodality, comprehensibility of the interface)?
Differentiation and personalisation	Does the tool offer options for tailoring learning content, pace or feedback to differences between students, and is this explicitly explained?
Inclusivity and cultural sensitivity	Does the tool and documentation explicitly focus on inclusive and culturally sensitive content, language use and representation?
Support & guidance	Does the tool actively support teachers and/or students in learning and using it, taking into account differences in starting situations and support needs?

Table 1: Key questions for the criteria of the theme of equity

3.1.1 Accessibility

Accessibility means that the tool can be used by students with different support needs, limitations or digital skill levels. The scan looks at functional characteristics such as compatibility with assistive technology, subtitles, clear navigation and understandable language use.

An EdTech tool must be usable by all students, regardless of device, disability or digital literacy. Limited accessibility increases existing inequality and can exclude students with support needs. Accessibility goes beyond technical compatibility; ease of use and support for tools such as screen readers, subtitles and alternative text also play a crucial role (Dickson, 2022). In addition, accessibility also includes cognitive and linguistic barriers, such as complex language, unclear navigation or a lack of support for students with reading difficulties (Seale, 2013).

Accessible design features, such as adjustable font size, transcripts and content in multiple formats (text, audio, image), directly contribute to equity. They ensure that students with visual, auditory or motor impairments can also participate fully in education. Research also shows that such facilities support all students. Think of subtitles that are useful when reviewing course material, or simple navigation for students who study on the go or in noisy environments (Dommett et al., 2022; Mullin et al., 2021).

This aligns with the principle of Universal Design for Learning (UDL): technology designed with diversity in mind from the outset offers multiple routes to learning and helps remove barriers for all students (ECIO, 2021).

A widely used standard for digital accessibility is the Web Content Accessibility Guidelines (WCAG) (W3C, 2024), which focuses on four design principles:

- **Perceivable** – Information is perceivable in multiple forms (e.g. text, audio, image, subtitles).
- **Operable** – The tool can be operated using various aids, such as keyboard navigation or screen readers.
- **Understandable** – The interface and language are clear, logical and predictable.
- **Robust** – The tool works reliably on different devices and browsers.

Key question for the scan:
Is the tool designed according to accessibility principles (perceivable, operable, understandable, robust), for example with multimodal content, screen reader support and clear navigation?

Accessibility goes beyond technology
Accessibility in this scan primarily refers to functional accessibility for students with support needs, such as compatibility with screen readers, subtitles or keyboard navigation. However, accessibility goes beyond technology: cognitive, social and cultural aspects also play a role (McAlvage & Rice, 2018). This broader interpretation is included in the reflection, but falls outside the direct assessment of tools.

3.1.2 Differentiation and personalisation

Differentiation and personalisation refer to the extent to which a tool adapts learning paths, instruction or feedback to the characteristics or progress of individual students. Differentiation focuses on providing appropriate support for different learning needs; personalisation emphasises individual preferences or routes.

The aim of differentiation and personalisation is to provide each student with optimal support in achieving equal learning outcomes (Baker & Hawn, 2022; ECIO, 2021; Onderwijsraad, 2022). Digital technology makes it possible to automatically adapt explanations or practice material to a person's prior knowledge or learning pace, so that students are neither overburdened nor underchallenged. Think of adaptive systems that offer extra instruction when mistakes are made, or advanced material once the basics have been mastered. This type of adaptive technology can be effective, but only if students receive targeted support (Du Plooy et al., 2024).

The Universal Design for Learning (UDL) principle is also relevant here. It states that education becomes more accessible when diversity is taken into account in its design and implementation from the outset.

The ECIO guidance document (2021) on this subject emphasises the importance of flexible and inclusive education, with a focus on variation in instruction, interaction and assessment.
It is important that adjustments for students are also explainable and transparent. A system that makes adjustments 'under the surface' without visible logic can unintentionally lead to exclusion or mistrust. Both students and teachers must be able to understand what differentiation is based on and when it is appropriate to deviate from it.

Key question for the scan:
Does the tool offer opportunities to tailor learning content, pace or feedback to differences between students, and is this explicitly explained?

3.1.3 Inclusivity and cultural sensitivity

An inclusive tool offers recognisable content, avoids stereotyping and is in line with different cultural, linguistic and social backgrounds.

EdTech tools can promote equity when they are designed with cultural diversity and inclusion in mind. Tools that implicitly assume a single dominant norm in language use, examples, imagery or interface can alienate students from other backgrounds. Think of exclusively Western names or male figures in examples. This one-sidedness can lead to subtle forms of exclusion, even if this is not intentionally meant. This criterion is particularly relevant for tools with suggested or built-in content. For platforms where teachers provide their own content, this shifts to educational practice.

An inclusive design allows students to identify with the material, increases their sense of connection and contributes to motivation and learning performance (Gay, 2010; Hammond, 2015). In concrete terms, this means that a tool contains diverse perspectives and representations, avoids stereotypes and leaves room for cultural recognition. Examples include multilingualism, gender-inclusive language and case studies from different contexts. Cultural sensitivity also concerns the accessibility of language and images, and an interface that feels intuitive to a wide range of users (Bakker et al., 2024; Dickson, 2022).

Social and cultural background influences how students experience education, especially for students who are the first in their family to study. Research shows that explicitly acknowledging this background can contribute to motivation, engagement, and self-confidence (Stephens et al., 2014). Inclusive EdTech can play a role in this by making room for recognisable perspectives, acknowledging differences, and creating a sense that everyone's experience matters.

Key question for the scan:
Does the tool and documentation explicitly focus on inclusive and culturally sensitive content, language use and representation?

Illustrative example from the literature: social background as a strength
In a study, new students were presented with a panel of stories from senior students from diverse backgrounds (Stephens et al., 2014). By explicitly mentioning how social background influences study experiences, differences were normalised. This led to better study results and a stronger sense of connection, especially among students who were the first in their family to study. These types of interventions demonstrate how important it is for EdTech and educational practices to make room for multiple perspectives.

3.1.4 Support and guidance

The criterion of support and guidance refers to the presence of features that help students in the learning process, such as hints, explanations or feedback. It also examines whether teachers and students receive sufficient support to use the tool effectively and independently.

Support and guidance in EdTech refers to built-in features or facilities that actively help students with their learning (through explanations, feedback, hints or guidance) and to mechanisms that facilitate the use of the tool by both students and teachers.

Even the best EdTech tool is of little use without appropriate support. Tools that offer active guidance, such as immediate feedback, contextual hints or scaffolding, can make all the difference, especially for students with less prior knowledge, confidence or support at home. This type of support is essential to prevent personalised learning from exacerbating existing inequalities: students with fewer self-regulation skills are otherwise at risk of getting stuck or dropping out (Dumont & Ready, 2023). Adaptive technologies that offer targeted support can lead to significant learning gains in further education, but only if that support is relevant to the content and timely (Du Plooy et al., 2024).

Feedback quality also plays a role: it is not enough that feedback is provided; it must be concrete, explainable and tailored to the learning process (Hattie & Timperley, 2007). Good support prevents students from getting stuck or discouraged, thereby increasing the likelihood that all students will achieve their learning goals (Dumont & Ready, 2023).

In addition, teachers and students also need guidance to learn how to work with EdTech. Clear explanations within the tool and accessible help functions are essential for the fair and effective use of technology. This teaches teachers to use EdTech consciously and inclusively, and enables students to start using the tool independently and with confidence more quickly.

Support goes beyond cognitive assistance. Explicitly acknowledging social background can contribute to motivation, self-confidence and a stronger sense of belonging. EdTech can play a role in this by not only guiding students in terms of content, but also by strengthening socio-psychological safety, for example through recognisable examples, reflective prompts or inclusive language (Stephens et al., 2014).

Key question for the scan:
Does the tool actively support teachers and/or students in learning and using it, taking into account differences in starting situations and support needs?

3.1.5 Overall overview of equity

Table 2Table 2 summarises the criteria as an overview; the application follows in chapter 0.

Criterion	Basic conditions	Reinforcing characteristics	Warning signs
Accessibility	Tool demonstrably complies with WCAG principles (perceivable, operable, understandable, robust). Support for screen readers, subtitles, clear navigation.	Adjustable display options (contrast, font size), multimodal content (text/audio/video), transcripts, language level tailored to target audience.	Only usable with certain devices or connections. Complex language use without explanation. No support for reading or assistive devices.
Differentiation & personalisation	Tool offers multiple difficulty levels or pace options. Teacher can influence or disable personalisation.	Adaptive feedback, tailor-made learning paths, dashboards for teacher insights. Transparent logic behind choices (explainable).	Invisible algorithms determine learning path without explanation. Systematically lower expectations for certain groups due to bias. No possibility to adjust.
Inclusivity & cultural sensitivity	Images and language use are neutral and	Diversity in names, cases, examples.	Only Western/white/cisnormati

Criterion	Basic conditions	Reinforcing characteristics	Warning signs
	avoid stereotyping. No exclusive norm culture.	Multilingual options. Gender-inclusive language. Cultural recognition in content and interface.	ve imagery. English-language standard interface without adaptation. Users are addressed with implicit assumptions.
Support & guidance	Users receive explanations about functions. Basic feedback and help are available within the tool.	Scaffolding, direct feedback, just-in-time hints. Digital coaching functionality. Built-in tutorials or guided learning paths.	No support unless the user actively seeks help. Information is 'hidden'. Feedback is vague, generic or absent.

Table 2: Complete overview of criteria for equity

3.2 AI and algorithms

EdTech tools can use AI and algorithms to adapt learning paths, make predictions or personalise content. This technology can be visible, as in adaptive systems that select practice material, but can also work in the background, for example in dashboards, automatic assessments or content recommendations.
AI in EdTech takes many different forms: from simple algorithms that calculate scores or determine sequences, to advanced systems that learn independently and generate new content. This variation, and the often implicit nature of AI functionality, makes it difficult for users and institutions to understand where and how automation influences learning.

To get a handle on this variation, it is useful to look at both the role of the system and the degree of automation. For the role of the system, we use the Detect-Diagnose-Act framework (Molenaar, 2022) :

- Detect: the system recognises relevant data, such as answers and behaviour.
- Diagnose: determining where the learner is in the learning process at that moment, but also predicting their development in the near future.
- Act: acting on this information by informing the user (teacher or student), for example through a dashboard, or by actually acting on that information: giving feedback or adapting teaching materials.

Six levels are distinguished for the extent to which control shifts from the teacher to the system, based on the model for self-driving cars (Molenaar, 2022). This is a scale from 0 to 5:

- (0) Teacher only (no technology)
- (1) Teacher assistance (technology supports, teacher remains responsible),
- (2) Partial automation (teacher monitors)
- (3) Conditional automation (system performs multiple tasks, involves teacher if necessary)
- (4) High automation (system acts independently, teacher does not need to monitor continuously)
- (5) Full automation (complete system control without human intervention).

The numbering starts at '0' because in that case no technology is used at all.

However, these classifications are not entirely adequate for generative AI. Unlike adaptive learning systems, generative applications rely less on learning data and function more often as creative or organisational assistants. That is why we combine these frameworks with the three-part classification of Belkina et al (2025), which distinguishes three main functions for generative AI in further education:

- Cognitive partner: rewriting, brainstorming, asking for explanations
- Organising assistant: study planning, structuring notes
- Learning object: learning to use AI itself, as part of digital literacy.

Combining these classifications creates a broader analytical framework for interpreting AI applications in EdTech. At the same time, they make it clear that understanding the role, degree of automation and function does not automatically lead to an understanding of responsible use.

AI systems can help with learning and organising, but they also entail risks. These include opaque decisions, bias and loss of autonomy (Bakker et al., 2024; Onderwijsraad, 2022). These risks affect not only effectiveness, but also equity. This is all the more true when systems implicitly assume that all students function in the same way or have access to the same resources (Bakker et al., 2024; Vesna et al., 2025).

In order to make this variation in AI applications not only conceptually but also analytically manageable, we have translated these frameworks into four criteria for the EdTech Scan. These criteria serve as analytical lenses to reveal how suppliers of EdTech tools publicly account for their use of AI and algorithms, and where ambiguities, assumptions or gaps remain in design and documentation.

The criteria focus explicitly on the characteristics of the tool itself: what is made visible, what is explained, and what scope for action is supported for users.

The four criteria are:
- Transparency and explainability
- Bias and fairness
- Privacy and data use
- Human oversight

These four criteria are based on guidelines from the European AI Act, the SURF algorithm register, the vision document on AI and equity (Bakker et al., 2024) and recent scientific literature on responsible and explainable use of AI in education (including Holstein et al., 2018; Selwyn & Pangrazio, 2022). Each criterion is accompanied by a definition, followed by the context and a key question that guides the analysis in the scan. Table 3 summarises these key questions as used in the EdTech Scan.

Criterion	Key question (scan)
Transparency	Is the use of AI or algorithms made explicit, and is it explained what the system does, when it intervenes and for what purpose?
Bias & fairness	Is there publicly available information about possible bias, fairness considerations or limitations of data and models?
Privacy & data use	Is it clear what (personal) data is used, for what purpose, and how privacy and data protection are safeguarded?
Human oversight	Is the role of teachers or users in monitoring, adjusting or intervening in the system explicitly described?

Table 3: Key questions regarding the criteria for the theme of AI and algorithms

3.2.1 Transparency and explainability

Transparency is about visibility: is it clear to users that an algorithm or AI is exerting influence, where this is happening and for what purpose? Explainability is about comprehensibility and scope for action: can users understand why a result is achieved, based on what data and logic, and what they can do with it (e.g. adjust, correct or contest it)? The scan checks whether this information is publicly available, formulated in an understandable way and usable for students and teachers.

AI and algorithms can play a role in EdTech tools in how information is displayed, decisions are made, and users are guided. For users, it is often not explicitly visible that an algorithm is running, let alone how it works. Institutions also do not always have an overview of which systems exert influence where (Vermaas, 2023). This can lead to black-box-like situations. In addition, EdTech tools can be part of 'algorithmic supply chains', in which models are developed, trained and maintained by third parties (Cobbe et al., 2023). This makes both transparency and explainability particularly challenging.

Transparency starts with visibility: knowing that an algorithm influences, for example, the order of exercises, the feedback given or the learning path proposed. This visibility also requires demarcation: which parts of the tool are (partly) automated, for what purpose, and for whom. This is relevant for both complex AI applications and relatively simple systems (level 1 of Molenaar, 2022), such as dashboards that automatically assign a 'risk score' to students (Hill et al., 2018). Without explicit visibility, the presence of algorithmic control can go unnoticed, even though it does have an effect on choices, interpretations or behaviour.

Explainability goes beyond making it visible that a system exerts influence. It requires that users be able to understand how and why outcomes are achieved: what data is used, what logic or decision rules apply, what assumptions are built in, and what limitations or uncertainties are at play. It is also crucial that explanations are tailored to the role of the user. Explanations can be too technical, abstract or non-committal, placing the burden of interpretation on teachers or students and making risks less visible (Nazaretsky et al., 2022). Explainability therefore also requires translation into the context of the user.

Explainability only becomes meaningful when users can actually do something with the information: compare alternatives, adjust settings, object, or engage in discussion about the use of the system. This also applies to non-AI systems: as soon as a system influences how a student is perceived (by themselves or by others), it is important that it is clear on what that judgement is based and what scope for action exists.

A lack of explainability can lead to misuse, excessive dependence, or exclusion. Research shows that students regularly follow the outcomes of AI systems without critically understanding them, unless they are explicitly supported in learning to interpret how the system works (Selwyn & Pangrazio, 2022). Explainability is therefore also linked to design choices in the literature: information provision and scope for action must be taken into account from the outset (explainability by design).

Transparency and explainability are related to acceptance and responsible use, but they are not the same thing. Whereas transparency reveals where a system has an impact, explainability helps users understand why and how that impact works, including goals and limitations. The ISTAM model (Intelligent Systems Technology Acceptance Model) underlines this by distinguishing between, among other things, insight into decision-making, clarity about goals and visibility of limitations (Vorm & Combs, 2022).

Regulations also set requirements that affect both transparency (visibility) and explainability (comprehensibility and usage information). The European AI Act (2024) sets requirements for documentation and the provision of information to users about the use, functioning and limitations of AI systems. Initiatives such as the SURF algorithm register show how this can be implemented in educational contexts: they provide insight into where algorithms are used, for what purpose and based on what data.

Key question for the scan:
Is the use of AI or algorithms made explicit, and is it explained what the system does, when it intervenes and for what purpose?

3.2.2 Bias detection and mitigation

Bias refers to systematic prejudices in AI and algorithms that can lead to unequal treatment of users. Fairness means that a tool does not structurally disadvantage any groups based on characteristics such as language, background or previous performance. The scan checks whether the tool has been tested for bias and whether monitoring or correction mechanisms are built in.

AI systems learn from data, and that data is rarely neutral. When algorithms are trained on historical educational data, existing inequalities and biases can be unintentionally reproduced. This risk also applies to EdTech tools. For example, research shows that systems give less positive feedback on non-Western names, or unfairly underestimate students from minority groups (Baker & Hawn, 2022; Vesna et al., 2025).

Bias in algorithms can take various forms. Sometimes bias is visible, such as in selective recommendations. In other cases, bias is more subtle: systems that assume the 'average student' may exclude students who deviate from this, such as first-generation students, students with disabilities or students of colour. The literature emphasises that such forms of bias do not necessarily stem from deliberate discrimination, but from, for example, skewed training data (input), a model design that does not take sufficient account of diversity (throughput) or incorrect interpretation or application of the results (output) (Baker & Hawn, 2022; Kennisnet, 2020; Onderwijsraad, 2022).

This risk can increase in personalised learning in particular. If a system predicts that a student can handle a lower level and automatically links this to simpler material, this can lead to a self-fulfilling prophecy (Pijpers, 2022; Weissburg et al., 2025). Such predictions can 'anchor' both teachers and students in a lower level of expectation (Bauer & Gill, 2024). Bias then becomes not only an ethical problem but also a didactic obstacle: it limits students' learning opportunities without this being visible or open to discussion (Bauer & Gill, 2024).

Scientific literature confirms these risks. Previous research indicates that educational AI systems are not always systematically tested for bias, making it difficult for institutions and teachers to recognise differences in outcomes between subgroups (Baker & Hawn, 2022; Holstein et al., 2019). Practical research shows that bias monitoring and iterative adjustments based on usage data can lead to fairer outcomes (Boateng & Boateng, 2025; Holstein et al., 2019; Idowu et al., 2024).

The AI Act (2024) states that education-related AI applications that assess performance or monitor students are considered 'high risk'. These systems must be demonstrably tested for fairness. It is important to actively monitor the outcomes, including possible differences between subgroups, for example in terms of language, background or accessibility. In other words: 'no fairness without awareness' (Bakker, 2024).

Key question for the scan:
Is there publicly available information about possible bias, fairness considerations or limitations of data and models?

> Also note whether bias analysis is carried out structurally or only once at launch. Are subgroups included in the evaluation? Are there procedures for users to report problems?

3.2.3 Privacy and data security

This criterion concerns the extent to which users understand what data is collected, how it is stored, shared and used. The scan assesses not only legal compliance (such as GDPR), but also the comprehensibility of privacy information and the degree of control users have over their own data.

EdTech tools collect and process personal data: from test results and click behaviour to study progress and learning styles. Especially with AI applications, this data collection can be intensive and long-term. If students continuously provide input to systems that make predictions, adapt content or analyse behaviour, this raises fundamental questions about privacy, ownership and control.

An important principle is that students must know what data is collected about them, for what purpose, and what happens to it. This is not only a matter of legal consent, but also of clear communication. Important questions include:

- Who has access to the data?
- Is data shared with third parties?
- Can students view, correct or have their data deleted?

Previous research shows that students often do not know how their data is processed, even if they have formally agreed to it (Prinsloo & Slade, 2017). This may also be unclear to teachers. With AI, data is also used to train or adjust models. This sometimes happens outside the institution's view, for example with commercial providers. The aforementioned 'black box within the black box' caused by EdTech suppliers using third-party models makes this even more complex (Cobbe et al., 2023).

The General Data Protection Regulation (GDPR) provides a legal framework: institutions must be transparent about data collection, formulate explicit objectives and take appropriate security measures. But legislation alone is not always sufficient. A tool may comply with the GDPR legally, but still be unclear, one-sided or difficult for students and teachers to follow in practice.

According to the AI Act (2024), extra vigilance is required for AI applications in education. Certainly when systems are used to classify, predict or guide students, it must be possible to trace who is responsible for the decisions that follow from that data.

Key question for the scan:
Is it clear what (personal) data is being used, for what purpose, and how privacy and data protection are guaranteed?

> Ensure that students know what data is being collected, where it ends up, and whether they have control over it. Legal documents are not sufficient if they are not understandable.

3.2.4 Human oversight

Human oversight means that users (especially teachers and supervisors) can understand, nuance or correct the system's decisions. The scan tests whether there is explicit room for human control and whether this role is practically feasible within the design of the tool.

AI in education is generally positioned as a supportive tool. Studies show that AI systems can also take on co-decision-making roles, such as systems that automatically assess homework, suggest learning paths or issue risk signals (Molenaar, 2022). The issue of human oversight is not only about the possibility of intervention, but also about the degree of autonomy granted to the system.

The six levels of automation discussed earlier (Molenaar, 2022) range from full human control (level 0) to full system control (level 5). As the level of automation increases, so does the importance of safeguards for meaningful human oversight.

For systems that function conditionally or fully automated (levels 3-5), it is therefore essential that users (students and teachers) can understand why a system makes a particular decision and that they can check, nuance or correct that decision where necessary.

Human oversight is also important from the perspective of equity. AI systems have no insight into personal circumstances, motivation or cultural context, and are limited in their ability to interpret exceptions or complex learning processes. Without adequate supervision, AI outcomes can appear objective, when in reality they are based on assumptions or incomplete data (Bakker et al., 2024).

Regulations also underscore this importance. The AI Act (2024) stipulates that AI systems in education must be subject to 'meaningful human oversight'. This implies more than formal involvement: users must be able to understand why a system acts the way it does and be able to adjust its actions. For example, can a teacher adjust the suggested learning path? Can a study advisor see what a risk score is based on? Is there an explanation for automatically generated feedback?

The literature indicates that this type of oversight is not a given in educational practice. Studies show that teachers use AI systems without understanding the underlying logic, which limits their ability to intervene (Holstein et al., 2018). Other studies point to the risk of *automation bias,* whereby users follow the system's recommendations because they are perceived as sophisticated or objective, even when they are not appropriate(Kahn et al., 2024).

Human supervision is therefore also a didactic issue. AI can provide support, but cannot replace what makes a teacher unique: recognising nuance, assessing emotions and guiding students with diverse needs. The added value of generative AI in higher education depends heavily on its didactic embedding. Tools that function as 'cognitive partners' (Belkina et al., 2025) only offer learning gains when students are given clear frameworks for use, feedback and assessment. Without this guidance, AI is more likely to lead to superficial use than to in-depth learning (Holstein et al., 2018).

Key question for the scan:
Is the role of teachers or users in controlling, adjusting or intervening in the system explicitly described?

Also check whether users understand why a system makes a particular recommendation. An override option is of little value without insight into the underlying logic.

3.3 Effectiveness

Effectiveness is a crucial but complex theme in the evaluation of EdTech. The question of whether a tool actually contributes to better education cannot be answered unequivocally, because effectiveness is not limited to measurable learning outcomes. Aspects such as usability, pedagogical embedding, trust and effects on well-being or collaboration also play a role.

Although there is increasing international attention for evaluating the effectiveness of EdTech, there is no widely supported standard that does justice to the diversity of educational contexts and applications. This makes it difficult for educational institutions to substantiate and justify their choices. At the same time, there are various forms of evidence in circulation, ranging from marketing claims and design principles to practical experiences and scientific research. A framework that organises and clarifies these different types of evidence can contribute to more evidence-informed decision-making (Lindroos Cermakova et al., 2024).

3.3.1 Effectiveness in the context of EdTech

In order to identify different forms of evidence of effectiveness, this scan uses the Dutch 3E Framework developed within the Research Group (Garg & Bakker, 2025). This model was developed to support educational institutions and suppliers in classifying evidence about the impact of technology on learning within the Dutch educational context. It distinguishes between three types of evidence: bronze, silver and gold.

In this exploratory study, the 3E model is used as a classification framework for types of evidence in publicly available sources. The model is explicitly not intended as a rating scale for the effectiveness of tools. No systematic determination has been made as to the level of evidence for individual functionalities with, and no statements are made about causal effects. The aim is to provide insight into what kind of evidence is publicly available, how specific this evidence is, and where room for interpretation or gaps arise.

3.3.2 Levels of evidence in public sources

The 3E model distinguishes between three types of evidence, which differ in nature, robustness and degree of specificity. Table 4 shows how these levels of evidence are interpreted in the context of this exploratory study.

Level of evidence (3E)	Type of substantiation	Minimum required specificity	Examples of public sources
Source	Argumentative/plausible	Description of operation and intended purpose, without empirical testing	Product documentation, white papers
Silver	Empirical, context-specific	Results linked to specific application or target group	Pilots, case studies
Gold	Independent/scientific	Methodologically transparent research, traceable to specific application	Peer-reviewed studies, independent evaluations

Table 4: Interpretation of levels of evidence within the 3E model

This classification shows that evidence differs not only in strength, but also in the extent to which it is specified for concrete applications. It is precisely this specificity that is relevant for weighing and interpreting claims of effectiveness.

3.3.3 Functionality and context

Effectiveness is always context-dependent. Whether and how a technology contributes to learning, well-being or collaboration depends on factors such as the target group, didactic embedding and usage situation. In many public sources, however, effectiveness claims remain generically formulated, without explicit links to specific applications or functions.

This exploratory study therefore does not make any statements about the effectiveness of tools as a whole. The analysis focuses on the extent to which public sources specify and substantiate effectiveness claims, and on the types of evidence used to do so. This approach prevents generic claims from being overestimated and highlights where interpretation remains necessary.

In recent literature, the concept of an *evidence portfolio* has been introduced in this context as a way of considering different forms of substantiation — such as theoretical assumptions, practical experiences and research results — in a coherent manner and continuing to update them over time (Garg & Bakker, 2025; International Centre for EdTech Impact, 2025). The evidence portfolio is not presented as an assessment tool, but as an emerging frame of reference that can contribute to a shared understanding of evidence of effectiveness and to a more consistent discussion about effectiveness within the EdTech domain.

Key question for the scan:
What type of evidence of effectiveness is publicly available for (parts of) the tool: theoretical basis (bronze), practical experience/empirical evidence (silver), or robust causal evidence (gold)?

4. Results

In chapter 3, explicit criteria and key questions were formulated for each theme. In this results chapter, the findings are presented thematically and in an integrated manner, rather than per criterion. This choice was made to avoid repetition and to reveal patterns across criteria.
To ensure consistency with the assessment framework, the findings for each theme are summarised in an overview table showing the dominant pattern for each criterion. The criteria thus remain analytically guiding, without determining the text structure of this chapter.

This chapter describes patterns that become apparent when the findings on the tools examined are viewed in conjunction with each other. The aim is not to compare individual tools, but to provide insight into recurring characteristics, gaps and differences at field level. Detailed tool-specific observations are included in the appendices.

4.1 Equity

This section describes patterns in how equity is publicly addressed within the EdTech tools examined. The analysis focuses on four interrelated criteria: accessibility, differentiation and personalisation, inclusivity and cultural sensitivity, and support and guidance. The findings are based on a systematic analysis of publicly available documentation and functionality descriptions.

4.1.1 Accessibility

Attention to accessibility is explicitly present in public documentation for the majority of the tools examined. Accessibility is mainly addressed through technical and functional aspects, such as compatibility with assistive devices, compliance with accessibility guidelines, or general usability principles.

However, this focus is often limited to basic provisions. Public information about limitations, exceptions or context-dependent barriers is generally limited. Accessibility is therefore primarily positioned as a technical prerequisite, rather than as part of a broader vision of equal opportunities in learning.

4.1.2 Differentiation and personalisation

Most tools allow for differentiation and personalisation in the form of configurable settings, choices in pace, order or types of feedback. These forms of adaptation can usually be set in advance and are highly dependent on the didactic choices of teachers or institutions.

Adaptive or dynamic personalisation during use is found in a smaller proportion of the tools and is rarely explicitly linked to equity. Public documentation usually does not make clear on the basis of which assumptions or data differentiation takes place, nor what consequences this may have for different groups of students.

4.1.3 Inclusivity and cultural sensitivity

Inclusivity and cultural sensitivity are rarely explicitly operationalised within the tools examined. Public documentation contains few indications that these aspects have been included as independent design principles in the development of functionalities.

Where inclusivity is mentioned, it is usually done so indirectly, for example through general references to flexibility, diversity in working methods or deployment options in different educational contexts. Concrete elaboration at the level of language use, representation, standardisation or cultural assumptions remains largely absent.

4.1.4 Support and guidance

Support and guidance are present in almost all tools in a functional or instrumental form, for example through feedback mechanisms, instructions or aids. This support focuses primarily on the use of the tool or the performance of tasks, and less on guidance of the learning process itself.

The extent to which support contributes to equal opportunities depends heavily on how tools are used and embedded in educational practices. Public documentation generally offers little insight into how support works differentially for students with varying needs or skills.

4.1.5 Equity – Summary of patterns

The above findings describe how different aspects of equity are publicly addressed within the EdTech tools studied. In order to position these findings in context and relate them to the analytical framework, the dominant patterns per criterion are summarised in Table 5.

Criterion	Dominant pattern	Primary role for
Accessibility	Technical and functional implementation; limited clarification of boundaries	Tool
Differentiation & personalisation	Pre-configurable; rarely adaptive	User / institution
Inclusivity & cultural sensitivity	Rarely explicitly addressed	User/institution
Support & guidance	Instrumental; learning process guidance outsourced	User / institution

Table 5: Overview of equity results

4.2 AI and algorithms

This section describes patterns in how AI and algorithmic functionalities are publicly accounted for within commonly used EdTech tools. The analysis does not focus on the technical quality of systems, but on the extent to which institutions and users can gain insight into the use, functioning and risks of AI-supported functions based on public information.

4.2.1 Transparency and explainability

AI-supported functionalities are present in all the tools studied, but are not always explicitly identified as such. In almost all tools, automation is functionally visible, for example through feedback, signals or dashboards. At the same time, in the majority of tools it remains unclear whether and how AI or algorithms play a role in this; explicit explanations of the underlying logic, assumptions or decision rules are often lacking.

To the extent that public documentation on AI use is available, it generally focuses on the purpose and output of functionalities. Insight into how outcomes are achieved (such as the data used, weightings or decision logic) remains limited. Explanations tend to be descriptive and abstract, and are rarely tailored to different user roles such as students, teachers or administrators.

Transparency and explainability therefore focus primarily on the *what* of functionalities, and much less on the *how* and *why* of the outcomes of the algorithms.

Some tools provide feature-level transparency documentation (e.g. descriptions of functionality, scope, and user control per feature). However, this does not typically extend to model-level or architectural explanations.

4.2.2 Bias and fairness

Public attention to bias in AI-supported functionalities is limited within the tools examined. No explicit information was found in the public documentation about possible distortions in algorithmic outcomes or about differences in effects between user groups.
Where bias is mentioned, it is usually in general terms and without reference to specific functionalities or applications. Bias is mainly positioned as a general risk of AI systems or as the responsibility of external model suppliers, while public information about systematic bias testing, fairness audits or monitoring of differential effects is lacking.

Even when suppliers indicate that they assess or adjust AI outcomes internally, it remains unclear on the basis of which criteria this is done and which forms of inequality are taken into account. These processes are rarely publicly transparent and cannot be traced back to specific functions or usage situations within the tool.

Bias is not explicitly investigated or monitored in most tools. At the same time, it remains unclear how fairness or possible differences in effects between user groups are taken into account, as these aspects are rarely addressed publicly.

4.2.3 Privacy and data use

Information about privacy and data use is publicly available for all tools examined, usually in the form of privacy statements and GDPR documentation. This documentation focuses primarily on legal compliance, data processing and responsibilities between the supplier and the institution.

However, AI-specific explanations of data use remain limited for the majority of tools. Public information about which data is used for algorithmic functions, the extent to which user data contributes to training or improving models, and what forms of reuse take place is often vague or absent. As a result, it remains unclear how AI functionalities relate to broader data flows within and outside the tool.

It is generally difficult for students and teachers to trace the role their interactions play in algorithmic processes. Privacy information is rarely tailored to these user roles and offers little insight into the specific implications of AI-supported use, such as automatic analysis, profiling or feedback.

Privacy and data use are therefore well documented at the system and institutional level, but offer limited insight into the role of data in AI functionalities that are relevant to users and to the interpretation of algorithm outcomes. In some cases, suppliers provide more detailed feature-level descriptions of data use (e.g. per AI functionality). However, these are often distributed across documentation sources and not always easily traceable for users.

4.2.4 Human oversight

Public documentation on human oversight of AI-supported functionalities in most of the tools examined focuses primarily on the general division of responsibilities and the positioning of AI as a support tool. It is often emphasised that AI does not make autonomous decisions, but supports users in analysis, feedback or organisation.

Concrete information about how and when human intervention is provided or supported remains limited in public sources. Documentation generally contains few specific indications about situations in which AI outcomes must be critically assessed, ignored or adjusted, or about the role of users in identifying potential risks.

When human oversight is mentioned, it is often at an abstract level, for example in terms of 'supportive use' or 'human-in-the-loop'. This leaves it unclear how oversight is conceived or facilitated in practice based on the design of the tool.

4.2.5 AI and algorithms: summary of patterns

The above analysis shows how public accountability for AI and algorithmic functionalities is spread across the various criteria. In order to make the relationship between transparency, bias, privacy and human oversight explicit, the dominant patterns for each criterion are summarised below. Table 6 provides a concentrated picture of recurring patterns and sources of uncertainty, without making any statements about the quality or desirability of individual tools.

Criterion	Pattern	Where is the ambiguity?
Transparency & explainability	Visibility of output, limited explanation of operation	Logic, assumptions, decision rules
Bias & fairness	Bias considered an implicit risk; rarely explicitly tested or monitored	Subgroups, differential effects
Privacy & data use	Legally and institutionally defined; limited insight for students	Granularity, reuse, AI training
Human oversight	Pre-organised; little support for contextual intervention	Signalling, timing and level of supervision

Table 6: Overview of results for AI and algorithms

4.3 Effectiveness

This section describes patterns in how the effectiveness of EdTech tools is publicly substantiated. Effectiveness is understood here as the extent to which publicly available information provides insight into the tool's contribution to learning processes. The analysis focuses on the type and traceability of the available evidence, not on determining actual impact.

4.3.1 Defining effectiveness

For most of the tools examined, effectiveness is not claimed across the entire product range, but is implicitly linked to the intended use or to individual functionalities. Many tools position themselves as facilitating or conditional: they support educational processes such as organising, communicating, practising or measuring, whereby any learning or educational effects depend on didactic design and context of use. Only a small proportion of the tools explicitly focus on learning or skills development as their primary goal.

4.3.2 Type of publicly available evidence

The type of publicly available evidence for effectiveness is predominantly limited in nature. For the majority of tools, the substantiation consists mainly of theoretical explanations, design principles or references to generally recognised didactic insights. Empirical research is available for a few tools, but in most cases it focuses on user experiences, perceptions or acceptance by students and teachers. These studies provide indicative insight into how tools are experienced and used, but rarely make an explicit distinction between the effects of specific tool functionalities and broader didactic or organisational factors.

In some cases, suppliers provide publicly accessible research overviews (e.g. collections of academic studies or case-based evidence). However, these are not always systematically structured or directly traceable to specific functionalities within the tool, and were therefore only partially captured within this scan.

4.3.3 Traceability and specificity

So far effectiveness claims are supported by empirical research, for most tools these remain limited in their traceability to specific functionalities. Public sources generally do not make it clear which parts of a tool contribute to observed effects, for which target groups this applies, or under what circumstances these effects occur. This makes it difficult to compare tools or interpret claims at the functional level.

Even when empirical research is available, it often concerns studies in which tool use is closely intertwined with didactic activity. In such cases, it is difficult to determine to what extent observed effects can be attributed to specific tool functionalities, or to the chosen working method, the role of the teacher or the educational context. Effectiveness is therefore often legitimised through plausibility and alignment with existing pedagogical literature, rather than through traceable evidence of the effectiveness of specific tool functionalities.
In some cases, empirical evidence is available at a broader product or use-case level (e.g. collections of studies or success cases), but remains difficult to map directly to specific functionalities analysed in this study.

4.3.4 Role of context and preconditions

Public documentation regularly emphasises that effectiveness depends on preconditions such as design, guidance, didactic choices and user skills. However, these preconditions are rarely explicitly included when effectiveness is described or substantiated, making it difficult to assess claims independently of the context in which the tool is used.

4.3.5 Effectiveness – Summary of patterns

The above findings describe how the effectiveness of EdTech tools is publicly substantiated and positioned. In order to link these observations to the analytical framework used and the 3E model, the dominant patterns for each aspect are summarised below. Table 1Table 7 shows how effectiveness claims relate to public verifiability, without making any statements about actual impact.

Aspect	Pattern	Implication for verifiability
Delineation of effectiveness	Function-oriented, not product-wide	Comparison only meaningful within function type
Type of effect	Usually facilitating or conditional	Learning impact context-dependent
Available evidence	Predominantly theoretical or indicative	Causal evidence rarely appropriate or claimed
Preconditions	Mentioned, but not included in effectiveness claim	Effectiveness cannot be assessed separately from use

Table 7: Overview of effectiveness results

5. Discussion

This scan shows that EdTech tools vary greatly in terms of function, design and context of use. This also means that not every criterion is equally applicable to every tool. In this chapter, we reflect on the limitations and possibilities of the instrument, the interrelationships between the themes investigated, and broader observations about transparency, trust and inclusion. We also look ahead: what does this scan require of institutions, policymakers and developers working with EdTech?

5.1 Differences between tools and their public verifiability

This exploratory study shows that EdTech tools vary greatly in function, design and context of use, and that these differences have direct consequences for the extent to which public values are publicly assessable. Not every criterion is equally relevant or visible for every tool. Some criteria are strongly linked to didactic functionality, while others mainly relate to technical or organisational characteristics. This leads to deliberate 'gaps' in assessment profiles: the absence of information is not necessarily a shortcoming but often reflects the nature and positioning of the tool.

The analysis in chapter 4 shows that public information about equity, AI and effectiveness is rarely available in a complete or systematic manner at the functional level. Instead, these themes often appear implicitly, scattered across general claims, design principles or policy documentation. The EdTech Scan is therefore less suitable for supporting unambiguous classifications or comparisons between tools, but is valuable as an instrument for revealing patterns, gaps and shifts in responsibility.

The strength of the scan therefore lies not in classification, but in clarification. By asking for each criterion *what* is publicly transparent and *what is not*, the scan reveals where transparency is lacking, where assumptions are made and where context or additional information is needed. This makes the scan suitable as a reflection and discussion tool within selection, procurement and evaluation processes, rather than as a checklist or assessment framework with a final score.

5.2 Limits and possibilities of public- e assessment

In this exploration, the EdTech Scan has been deliberately limited to what can be ascertained from publicly available information about tools. In contrast to broader frameworks around public values, the scan does not focus on implementation, usage practices or institutional preconditions, but on characteristics that are visible in the design, documentation and communication of the tool itself. This also means that environmental factors such as teacher skills, implementation strategy or digital infrastructure have been left out of consideration. This choice makes the instrument manageable and reproducible but also sets clear limits on what can be determined with it.

As the results in chapter 4 show, many themes extend beyond what can be publicly assessed within the tool itself. Equity is not only related to technical accessibility, but also to language use, cultural recognisability and guidance. Effectiveness is highly context-dependent and is often legitimised in public sources through plausibility or general didactic assumptions, without traceable evidence at the functional level. Even with AI use, insight into underlying logic, bias monitoring and supervision often remains limited to general descriptions.

In this exploratory study, the assessment is limited to characteristics that are visible in the design, documentation and public communication of the tool, and not to those that are exclusively determined by use, design or institutional policy. This does not mean that these environmental factors are unimportant, on the contrary, but that they fall outside the direct scope of the instrument.

The findings also suggest that a significant portion of evidence and documentation circulates in non-public contexts (e.g. pilots or procurement processes), creating a structural gap between what is publicly assessable and what is known or used in practice.

This demarcation reveals where public assessment ends and where additional reflection, dialogue or research is needed. This underlines that responsible use of EdTech cannot be based on tool selection alone, but requires coherence between design, transparency, implementation and professional conduct.

5.3 Cross-thematic observations

Although the scan approaches the themes of equity, AI and effectiveness separately, the analysis shows that in practice they are closely intertwined. Patterns that become apparent in chapter 4 show that choices about automation, transparency and substantiation are not separate from questions about inclusion and equity.

For example, the use of AI has direct implications for equity. When algorithmic functionalities are not made explicit or are insufficiently explainable, it becomes difficult to keep track of possible bias or unequal effects between user groups. This requires systematic monitoring, including design and attention to diversity (Bakker, 2024; Smeets et al., 2024; Vesna et al., 2025). At the same time, the analysis shows that public information about bias monitoring and fairness measures is limited or absent in many tools. This shifts the responsibility for identifying and correcting undesirable effects largely to institutions and users.

There is also a close correlation between effectiveness and inclusion. Public claims about effectiveness are often based on plausibility or general didactic assumptions, without explicit attention to differences between students. As a result, it often remains unclear for whom a tool is effective, under what circumstances, and who may benefit less. In such cases, technology that is well suited to independent, linguistically skilled or digitally literate students may unintentionally reinforce existing inequalities.

Transparency is the connecting factor here. Insight into how it works, data use and substantiation is a prerequisite for understanding AI applications, interpreting claims of effectiveness and making inclusive choices. When that transparency is lacking or remains too general, it becomes difficult for teachers and institutions to make adjustments, consider alternatives or take responsibility for the use of technology in education.

5.4 Implications for practice and policy

The scan provides a practical basis for systematically exploring public information about EdTech tools, but also shows that responsible use cannot be deduced from tool characteristics alone. The patterns identified in chapter 0 show that transparency and substantiation are fragmentary and that much of the responsibility lies outside the tool itself.

This calls for institutional safeguards for transparency and reflection. Initiatives such as the SURF algorithm register show how insight into the use of algorithms can be structurally embedded in policy, procurement and accountability. A shared format in which goals, data use and the influence of tools are explicitly described, such as SPEA, can support institutions in making substantiated choices and conducting discussions with suppliers.

It should be noted that themes such as equity and responsible AI use have only recently been explicitly articulated within the EdTech domain. Both suppliers and educational institutions are still in the process of exploring this: which questions are relevant, which forms of accountability are appropriate, and what information is needed to actually weigh public values in decision-making. The analysis shows that public communication from suppliers on this subject is often still fragmentary and exploratory. This indicates not only reluctance, but also a lack of shared expectations and standards in the field. In many cases, it is still unclear what institutions want to know exactly, what degree of transparency is considered feasible or desirable, and what investments this requires from both suppliers and users.
This mutual search underlines that transparency and responsible digitisation cannot be approached exclusively as characteristics of individual tools. They require coordination, dialogue and joint standard development between educational institutions, suppliers and sector organisations.

In addition, the analysis underlines the importance of continuous evaluation. Effectiveness is not a static characteristic, but develops in conjunction with use, context and didactic choices. Working with a so-called *evidence portfolio* (in which various forms of evidence, practical experience and evaluation come together) with s can help to make this dynamic visible and communicate it transparently.

Finally, the exploratory study shows that there is no single dominant form of evidence or assessment within the EdTech landscape. Scientific evidence, practical experience, technical standards and social values each play a role, depending on the type of tool and its intended use. An instrument such as the EdTech Scan can, in line with the 3E Framework (Garg & Bakker, 2025), help to explicitly identify these different forms of substantiation without reducing them to a single final assessment.

6. Conclusion

This exploratory study shows that EdTech tools deal with public values such as equity, transparency around AI and effectiveness in different ways. The analysis makes it clear that these values are rarely explicitly and coherently elaborated at the functional level, and that public information about them is often fragmentary, implicit or context-dependent.

A first insight is that EdTech is not a homogeneous domain. Tools vary greatly in function, design and intended use, which has direct consequences for the extent to which criteria are publicly verifiable. Not every criterion is equally relevant or visible for every tool. The absence of information does not automatically mean a lack of attention, but often points to implicit assumptions, limited transparency or an implicit positioning of responsibilities with users and institutions.

A second insight concerns the central role of transparency. Across all themes, it appears that insight into functioning, data use and substantiation is a necessary condition for being able to assess effectiveness, critically evaluate AI applications and make inclusive choices. Without this transparency, it is difficult to interpret claims, recognise risks or make adjustments in educational practice.

Thirdly, the exploratory study shows that the effectiveness of EdTech tools in public sources is rarely substantiated by traceable evidence at the functional level. Instead, effectiveness is often legitimised through plausibility, alignment with existing pedagogical literature, and references to preconditions such as didactic design and guidance. This shifts the assessment from 'does it work?' to questions about appropriate use, context, and responsibility.

In this light, the EdTech Scan does not offer a checklist or final score, but a structured way to explore public information, make assumptions explicit, and engage in conversation about values, risks, and substantiation. The added value of the tool lies not in classification, but in revealing patterns, gaps, and connections between themes.

Public values are therefore not automatically guaranteed in EdTech. Conscious choices in design, selection, implementation and use remain necessary. Because individual institutions cannot bear this responsibility alone, responsible digitisation requires cooperation between educational institutions, suppliers and sector organisations. Initiatives around transparency, shared evaluation frameworks and continuous knowledge development (such as evidence portfolios and joint registers) are important building blocks in this regard.

This exploratory study is deliberately limited to what is visible and verifiable based on publicly available information about EdTech tools. Aspects related to use, implementation, institutional preconditions and regulations are therefore outside the scope of this report. These topics are logical starting points for follow-up publications or practical elaboration, but are not further elaborated here.

Technology does not work by itself. It is the choices surrounding it that determine what EdTech means for students, teachers and education, and to what extent public values are actually realised in this context.

Bibliography

Baker, R. S., & Hawn, A. (2022). Algorithmic Bias in Education. *International Journal of Artificial Intelligence in Education*, *32*(4), 1052-1092. https://doi.org/10.1007/s40593-021-00285-9

Bakker, T. C. (2024). *No Fairness without Awareness. Toegepast onderzoek naar kansengelijkheid in het hoger onderwijs*. Intreerede lectoraat Learning Technology & Analytics. The Hague University of Applied Sciences. https://doi.org/10.5281/zenodo.14204674

Bakker, T. C., Kraker, C. C., Eegdeman, I. M., Saçan, E., & Leeuwen, A. (2024). *AI en kansengelijkheid: Visie op de impact van AI op kansengelijkheid in het vervolgonderwijs*. Npuls.

Bauer, K., & Gill, A. (2024). Mirror, Mirror on the Wall: Algorithmic Assessments, Transparency, and Self-Fulfilling Prophecies. *Information Systems Research*, *35*(1), 226-248. https://doi.org/10.1287/isre.2023.1217

Belkina, M., Daniel, S., Nikolic, S., Haque, R., Lyden, S., Neal, P., Grundy, S., & Hassan, G. M. (2025). Implementing generative AI (GenAI) in higher education: A systematic review of case studies. *Computers and Education: Artificial Intelligence*, *8*, 100407. https://doi.org/10.1016/j.caeai.2025.100407

Bie, P. de & Pilothub EdTech (2024). *EdTech in de praktijk: 6 praktijkvoorbeelden* (pp. 1-12). Npuls.

Boateng, O., & Boateng, B. (2025). Algorithmic bias in educational systems: Examining the impact of AI-driven decision making in modern education. *World Journal of Advanced Research and Reviews*, *25*(1), 2012-2017. https://doi.org/10.30574/wjarr.2025.25.1.0253

Cermakova, A. L., Prado, Y., & Kucirkova, N. I. (2024). *Equity in EdTech by design*.

Cobbe, J., Veale, M., & Singh, J. (2023). Understanding accountability in algorithmic supply chains. *2023 ACM Conference on Fairness Accountability and Transparency*, 1186-1197. https://doi.org/10.1145/3593013.3594073

Collaborative Trust Framework (z.d.). *Collaborative Trust Framework*. TrustFramework.Eu 2.0. https://www.trustframework.eu

Dickson, R. (2022). *14 Equity considerations for EdTech*. Campus Technology. https://campustechnology.com/articles/2022/05/12/14-equity-considerations-for-ed-tech.aspx?p=1

Dommett, E. J., Dinu, L. M., & Tilburg, W. (2022). Effects of captions, transcripts and reminders on learning and perceptions of lecture capture. *Int J Educ Technol High Educ*, *19*, 20. https://doi.org/10.1186/s41239-022-00327-9

Du Plooy, E., Casteleijn, D., & Franzsen, D. (2024). Personalized adaptive learning in higher education: A scoping review of key characteristics and impact on academic performance and engagement. *Heliyon*, *10*, 39630. https://doi.org/10.1016/j.heliyon.2024.e39630

Dumont, H., & Ready, D. D. (2023). On the promise of personalized learning for educational equity. Npj Sci. *Learn*, *8*, 26. https://doi.org/10.1038/s41539-023-00174-x

ECIO. (2021). *Handreiking Universal Design for Learning: Flexibel en inclusief onderwijs met diversiteit als norm*. Expertisecentrum inclusief onderwijs. https://ecio.nl/publicaties/handreiking-universal-design-for-learning/

Garg, M., & Bakker, T. (2025). *Evidence-informed Evaluation of EdTech (3E): A Dutch Framework for Continuous Assessment of EdTech Effectiveness* (Versie 1.0, pp. 1-15). Npuls. https://doi.org/10.5281/ZENODO.15070789

Gay, G. (2010). *Culturally responsive teaching: Theory, research, and practice* (2nd dr.). Teachers College Press.

Hammond, Z. (2015). *Culturally responsive teaching and the brain: Promoting authentic engagement and rigor among culturally and linguistically diverse students*. Corwin.

Hattie, J., & Timperley, H. (2007). The Power of Feedback. *Review of Educational Research*, *77*, 81-112. https://doi.org/10.3102/003465430298487

Hill, F., Fulcher, D., Sie, R., & de Laat, M. (2018). Balancing Accuracy and Transparency in Early Alert Identification of Students at Risk. *2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE)*, 1125-1128. https://doi.org/10.1109/TALE.2018.8615370

Holstein, K., McLaren, B. M., & Aleven, V. (2018). Student learning benefits of a mixed-reality teacher awareness tool in AI-enhanced classrooms. *Proceedings of the 19th International Conference on Artificial Intelligence in Education (AIED*, 154-168.

Holstein, K., Wortman Vaughan, J., Daumé, H., Dudik, M., & Wallach, H. (2019). Improving Fairness in Machine Learning Systems: What Do Industry Practitioners Need? *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1-16. https://doi.org/10.1145/3290605.3300830

Idowu, J. A., Koshiyama, A. S., & Treleaven, P. (2024). Investigating algorithmic bias in student progress monitoring. *Computers and Education: Artificial Intelligence*, *7*, 100267. https://doi.org/10.1016/j.caeai.2024.100267

International Centre for EdTech Impact. (2025). *International Centre for EdTech Impact*. International Centre for EdTech Impact. https://www.foreduimpact.org

Kahn, L., Probasco, E. S., & Kinoshita, R. (2024). *CSET - AI Safety and Automation Bias*. CSET. https://cset.georgetown.edu/wp-content/uploads/CSET-AI-Safety-and-Automation-Bias.pdf

Kennisnet. (2020). *Waarden wegen—Een ethisch perspectief*. Kennisnet. https://www.kennisnet.nl/app/uploads/Kennisnet-Ethiekkompas-Waardenwegen.pdf

Kucirkova, N. I. (2022). *What Counts as Evidence in EdTech? A Review of EdTech Evidence Frameworks and a Proposed New Model*. WiKIT and University of Stavanger.

Kucirkova, N. I. (2025). Academia–industry partnerships in edtech: Bridging the gaps in engaged research. *Research for All*, *9*(1). https://doi.org/10.14324/RFA.09.1.07

Lindroos Cermakova, A., Pilaete, L., & Rusman, E. (2024). *Evaluation Mechanisms: A Way to Increase Trust in EdTech?* EADTU EdTech Strategy Lab.

McAlvage, K., & Rice, M. (2018). *Access and Accessibility in Online Learning* (OLC Outlook: An Environmental Scan of the Digital Learning Landscape".). Online Learning Consortium.

Molenaar, I. (2022). Towards hybrid human-AI learning technologies. *European Journal of Education*, *57*(4), 632-645. https://doi.org/10.1111/ejed.12527

Mullin, C., Gould, R., & Parker Harris, S. (2021). *ADA Research Brief: Digital Access for Students in Higher Education and the ADA*. ADA National Network Knowledge Translation Center.

Nazaretsky, T., Cukurova, M., & Alexandron, G. (2022). An Instrument for Measuring Teachers' Trust in AI-Based Educational Technology. *LAK22: 12th International Learning Analytics and Knowledge Conference*, 56-66. https://doi.org/10.1145/3506860.3506866

Onderwijsraad (2022). *Digitalisering in het onderwijs: Kansen en risico's*. https://www.onderwijsraad.nl/publicaties/adviezen/2022/06/01/digitalisering-in-het-onderwijs

Pijpers, R. (2022). *Krassen op het Dashboard: De invloed van adaptieve leersystemen op deprofessionele ruimte van de leerkracht*. Kennisnet.

Prinsloo, P., & Slade, S. (2017). Ethics and learning analytics: Charting the (un)charted. *British Journal of Educational Technology*, *48*(6), 1241-1254. https://doi.org/10.1111/bjet.12163

Seale, J. (2013). *E-learning and disability in higher education: Accessibility research and practice* (2nd dr.). Routledge.

Selwyn, N., & Pangrazio, L. (2022). Artificial intelligence in education: Critical perspectives and future directions. *Learning, Media and Technology*, *47*(1), 1-14. https://doi.org/10.1080/17439884.2022.2027120

Shen, J., Han, Y., Hou, H., Ai, B., & Zhao, L. (2023). Integrating Explainable AI Into Educational Intelligence. In M. Bhatt, K. Verma, & S. K. Pal (Red.), *Innovations in Education: Artificial Intelligence and the Future of Teaching and Learning* (pp. 231-249). Springer. https://doi.org/10.1007/978-3-031-36707-1_12

Smeets, E., Geurts, R., Helvoirt, D., & Zuijdam, B. (2024). *Algoritmen in het onderwijs: Een onderzoek in opdracht van het College voor de Rechten van de Mens*. KBA / ResearchNed.

Stephens, N. M., Hamedani, M. G., & Destin, M. (2014). *Closing the Social-Class Achievement Gap: A Difference-Education Intervention Improves First-Generation Students' Academic Performance and All Students' College Transition*.

SURF. (2023). *Responsible Tech: On Public Values and Emerging Technologies*. SURF. https://doi.org/10.5281/zenodo.10054653

Vermaas, K. (2023, oktober). *We zijn nu niet bewust van en niet transparant over algoritmes in het onderwijs. Dat moet anders. _ SURF Communities*. https://communities.surf.nl/artificial-intelligence/artikel/we-zijn-nu-niet-bewust-van-en-niet-transparant-over-algoritmes-in

Vesna, J., Andjelkovic, M., & Rodríguez, C. (2025). *Digital Divide in AI-Powered Education: Risks and Policy Responses*. UNESCO Inclusive AI Series.

Vorm, E. S., & Combs, D. J. Y. (2022). Integrating Transparency, Trust, and Acceptance: The Intelligent Systems Technology Acceptance Model (ISTAM. *International Journal of Human–Computer Interaction*, *38*(18-20), 1828-1845, https://doi.org/10.1080/10447318.2022.2070107

W3C. (2024, 12). *Web Content Accessibility Guidelines (WCAG) 2.2*. W3C. https://www.w3.org/TR/WCAG22/

Weissburg, I., Anand, S., Levy, S., & Jeong, H. (2025). *LLMs are Biased Teachers: Evaluating LLM Bias in Personalized Education* (No. arXiv:2410.14012). arXiv. https://doi.org/10.48550/arXiv.2410.14012

Appendices

Appendix 1: Tools studied in this exploratory study

Tool	**Global function type**
ANS	Didactic (testing and assessment)
Brightspace	Teaching (digital learning platform)
FeedbackFruits	Didactic (feedback and active teaching methods)
Grasple	Didactic (practice and learning)
Mentimeter	Facilitating (interaction and feedback)
Microsoft Forms	Facilitation (data collection and evaluation)
Qualtrics XM	Facilitating (survey and experience management)
Amberscript	Facilitating (accessibility and support)
Atlas.ti	Facilitating (qualitative data analysis)
Microsoft Teams	Generic (collaboration and communication)
Adobe Premiere Pro	Generic (creative production tool)

Appendix 2: Results per theme – Equity

Tool	Accessibility	Differentiation & personalisation	Inclusivity & cultural sensitivity	Support & guidance
Adobe Premiere Pro	Accessibility features (captions, transcription) · No product VPAT	Workflow personalisation · No learning adaptability	Inclusive terminology · No didactic positioning	Tutorials and product documentation
Amberscript	Strong functional contribution (captioning/transcription) · No WCAG accountability for own interface	Differentiation focused on content accessibility	Implicit inclusivity through lowering barriers	Transparent workflow · Human correction built in
ANS	WCAG 2.1 compliance report available · Test settings (including time extension) support accessibility · Dependent on test design	Differentiation via settings and templates · No adaptive/data-driven personalisation	Content-neutral test platform · No explicit inclusivity positioning	Extensive support for administrators, teachers and students · Focus on test administration
Atlas.ti	VPAT 2.4 and accessibility statement available	Personalisation via workflows · No adaptive learning logic	Method-agnostic · No cultural positioning	Comprehensive manuals and documentation
Brightspace	Explicit WCAG 2.1 AA commitment · VPAT/ACR available · Broad assistive technology support	Configurable learning paths and conditions · Adaptivity primarily teacher-driven	Platform without fixed content · No explicit cultural positioning	Built-in feedback and guidance functionality · Dependent on configuration
FeedbackFruits	WCAG compliance described per tool · Limitations explicitly stated	Configurable pedagogical working methods · No adaptive personalisation	Inclusivity explicitly addressed via UDL/experiential learning (normative)	Feedback and peer review mechanisms integrated into working methods, various options for help and support during use.

Tool	Accessibility	Differentiation & personalisation	Inclusivity & cultural sensitivity	Support & guidance
Grasple	WCAG 2.2 AA claim publicly stated · Accessibility updates reported	Adaptive learning system based on progress and performance	Domain-specific (mathematics) content · No explicit cultural positioning	Built-in feedback and progress insights · Academy and help environment
Mentimeter	Public accessibility guidelines · Screen reader/contrast/keyboard support	Differentiation through choice of working method · No adaptive logic	Inclusion mentioned in usage guidelines · No cultural positioning in design	Academy and help documentation · Focus on presentation practice
Microsoft Forms	Commitment to inclusive design · Accessibility via Microsoft standards	Limited differentiation (branches) · No learning-oriented personalisation	Inclusive design as a starting point · No explicit cultural focus	General Microsoft help · Tool use
Microsoft Teams	Extensive WCAG/VPAT documentation · Captions/transcription	No learning or level differentiation	Inclusive design organisation-wide · Not didactically specified	Comprehensive help and support
Qualtrics	Public WCAG commitment · VPATs available for selected products	Differentiation via survey logic · No learning-oriented personalisation	General inclusive positioning · No tool-specific cultural focus	Extensive support and knowledge base

Appendix 3 Results per theme – AI and algorithms

Tool	Transparency & explainability	Bias & fairness	Privacy & data use	Human oversight
ANS	Automation described at function level · No explicit AI positioning	No public bias evaluations	General privacy frameworks · No AI-specific data flows	Teacher can assess and overrule
Brightspace	Responsible AI principles · AI features explained separately	Bias/inclusion addressed at policy level	Comprehensive privacy centre · AI data use per feature	AI supportive · Teacher retains control
FeedbackFruits	AI objectives publicly described · No detailed model-level explanation; feature-level transparency documentation available	Bias/discrimination explicitly addressed (ethical)	General privacy documentation supplemented with feature-level data descriptions	Teacher decides on use and interpretation
Grasple	AI vision (LLMs) publicly described · No decision explanation at individual level	No tool-specific bias evaluations	General privacy frameworks	Teacher control, no autonomous decisions
Mentimeter	Limited automation · AI not explicitly positioned	No public bias reflection	General privacy documentation	Full human control
Microsoft Forms	AI not explicitly mentioned at tool level	No Forms-specific bias information	Microsoft 365 privacy frameworks	Full human oversight
Qualtrics	AI applications publicly described · No model details	Ethical AI principles · No product-specific bias studies	Comprehensive security & privacy governance	User retains control
Amberscript	AI deployment explicitly stated · Distinction between automatic and manual	No bias analyses · Quality assurance by humans	Privacy described · AI data flows limited	Structural human correction
Atlas.ti	AI Lab use cases publicly mentioned	No public fairness evaluations	Extensive AI privacy and GDPR documentation	AI supporting analysis

Tool	Transparency & explainability	Bias & fairness	Privacy & data use	Human oversight
Microsoft Teams	AI features publicly named · Responsible AI framework	No Teams-specific bias studies	Platform-wide privacy & security	AI support, no autonomy
Adobe Premiere Pro	AI features named at function level	No product-specific bias information	Creative Cloud privacy frameworks	User can customise AI output

Appendix 4: Results by theme – Effectiveness

Tool	3E (dominant public evidence)	Focus of evidence	Explanation
ANS	Bronze	Design or practical rationale	Test workflow, assessment logic, no impact studies
Brightspace	Bronze	Scale of use/infrastructure	Platform prerequisite, effect via design
FeedbackFruits	Silver	Didactic framework explicit	UDL, active working methods, empirical and peer-reviewed studies exist, No long-term impact studies
Grasple	Bronze	Didactic framework explicit	Adaptive practice, plausibility instead of proof
Mentimeter	Bronze	Supporting precondition	Facilitating engagement, context-dependent
Microsoft Forms	Bronze	Usage scale / infrastructure	Measurement/survey, no learning intervention
Qualtrics XM	Bronze	Usage scale / infrastructure	Evaluation tool, effect through design
Amberscript	Bronze	Supporting precondition	Lowering barriers, no direct learning claim
Atlas.ti	Bronze	Supporting precondition	Research process, no learning outcome
Microsoft Teams	Bronze	Scale of use/infrastructure	Communication, didactics decisive
Adobe Premiere Pro	Bronze	Supporting precondition	Creative tools, effect via assignment