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#3

Npuls

Learning analytics

Supporting teachers with learning analytics.

Practitioner stories, benefits, process, and external factors

‘Learning analytics enables targeted interventions based on reliable data.’

Karianne Vermaas

Dit magazine is ook **beschikbaar in het Nederlands**

Supporting teachers with learning analytics.

Practitioner stories, benefits, process, and external factors

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In this magazine

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Introduction

As Learning Analytics (LA) continues to gain traction in educational institutions, it is becoming a vital tool for improving teaching and learning practices. Learning Analytics is broadly defined as the "measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens, 2013). This expansive definition encompasses various applications, from administrative decision-making to personalized learning support for students.

Teacher-Facing Learning Analytics (TFLA) is a specific branch of LA that focuses on providing actionable insights to teachers, enabling them to adapt their instructional practices in response to real-time data on student engagement, performance and learning behaviours. This magazine dives into how TFLA can help teachers make data-informed decisions and optimize their teaching strategies for better student outcomes. If you would like to know about a different branch of LA, in our second magazine, we focused on Student-Facing Learning Analytics (SFLA), on how it has gained importance and on several projects implementing it. If you are new to LA, our first magazine provided an overview of the barriers and facilitators for its adoption, which serves as a foundation for understanding how TFLA can be effectively implemented.

Contents

In this magazine, we cover the following content:
In part 1, we dive into the literature concerning TFLA. What does LA have to offer for teachers? How can teachers integrate TFLA into their practice? What are the external factors — like policy, privacy, and technical infrastructure — that affect the success of TFLA?
In part 2, we present practitioner stories concerning TFLA. Through interviews, we provide insights from the developers and leaders of TFLA pilots in the MBO, HBO and WO sectors, offering real-world perspectives on implementation challenges and successes.
We close the magazine with a **conclusion** about common themes and suggestions for further reading.

If you have any questions or comments, we'd love to hear from you.

For our **contact details** and more information, visit the project website.

Teacher-Facing Learning Analytics: The what, why and how

Teacher-Facing Learning Analytics (TFLA) refers to using data and analytics tools designed to support educators in understanding and improving student learning outcomes. TFLA often focuses teachers' attention on those who need help the most. This is achieved by providing insights into student behaviour, engagement and performance. LA enables teachers to make informed decisions about their instructional practices. These systems help identify trends, patterns and potential issues within the learning environment, allowing for timely interventions and more targeted support.

This section explores the benefits of Learning Analytics (LA) for teachers, how they can integrate it into their practice and the external factors they need to consider when utilizing these tools.

Why should I care about Learning Analytics? What does it have to offer?

How do I prepare for it and how do I use it?

What are the external factors and other things that I should consider?

Learning Analytics

Why Should Teachers Care about LA?

When we talk about Learning Analytics (LA), it is natural that teachers would be one of the technology's most critical stakeholders and users. Teachers are expected to examine their own and their students' actions and performance to improve the teaching and learning process. Traditionally, this examination was based on the teachers' observations, on feedback from their peers or their students, or on their students' performance. However, with the advent of LA, more quantitative data can be made available for teachers to monitor and improve their teaching and students' learning.

Teacher-Facing Learning Analytics (TFLA) refers to the LA systems used by teachers. These systems usually involve a dashboard that presents teachers with insight into what is happening in their courses and possibly goes further to assist teachers with optimizing the teaching-learning process.

But how does a TFLA system provide these benefits?

The first step is the collection of student-related and teacher-related data. A wide variety of data can be collected, including but not limited to interaction with learning materials in a Learning Management System (LMS) or interactions between instructors and students in a discussion forum. Multimodal data can also be collected, for example, students' eye-tracking data in a learning environment, student conversations during an interactive tutorial session, or physical location of teacher and students in a lab session. Another example is assessment data, from simple quizzes after a video lecture to full records of grades over an education programme.

Once the data is collected, it can be processed to produce four levels of analytics: Descriptive, Diagnostic, Predictive and Prescriptive.

- **Descriptive** analytics refers to *what has happened* in the past. It examines the information available and determines and describes what happened.
- **Diagnostic** analytics focuses on discovering *why something happened*. This type of analysis looks at the relationships in the data and then attempts to provide possible reasons for why something happened.
- **Predictive** analytics estimates *what will happen and when*. This type of analysis involves analyzing the trends in the data and forecasting what is likely to happen.
- **Prescriptive** analytics determines *how to take action*. This type of analysis goes one step further and produces data-driven recommendations for solving potential problems.

While each type generally builds on the previous one, it does not mean that prescriptive is "better" than diagnostic, as they fulfil different needs.

The different levels represent different levels of maturity within organizations. As you step up the ladder from descriptive to prescriptive, you make more demands on the support staff and teachers' data literacy and the organisation's data governance, engineering and all-round IT savviness.

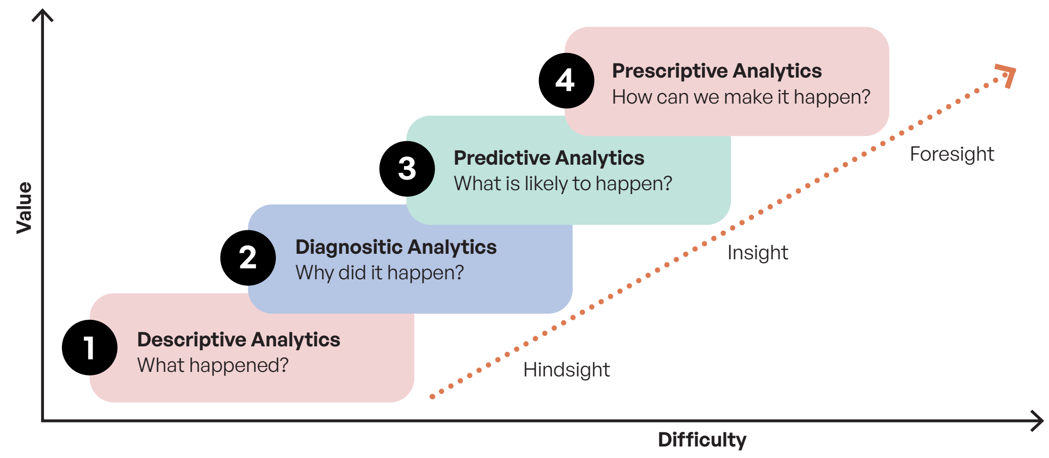


Figure 1.1 Analytics maturity levels.

In terms of literacy, the different levels of analytics can be produced using techniques such as statistics, data mining, machine learning and artificial intelligence, each offering unique capabilities, while often overlapping in their application. Statistics provides the foundation, focusing on methods to collect, organize and interpret data to uncover patterns or relationships. For example, statistical analysis can reveal trends in student engagement or help assess the impact of specific teaching interventions. Building on this, *Data Mining (DM)* applies computational techniques to process large datasets, uncovering hidden patterns, anomalies or clusters of behaviour. These insights can be used to identify at-risk students or categorize learning behaviours, often visualized in dashboards to support decision-making.

Machine Learning (ML), a more advanced approach, enables systems to learn from data and make predictions without explicit programming. It can adaptively classify students based on engagement metrics or forecast academic outcomes, providing a dynamic way to analyse evolving datasets. *Artificial Intelligence (AI)* furthers these capabilities by simulating human-like intelligence, offering tools to interpret natural language, support decision-making or interact with users through virtual tutors or chatbots. Finally, *Generative AI* (currently popularised by ChatGPT) focuses on creating new content, such as personalised learning materials, case studies or even detailed feedback summaries. While it can be used to analyse or categorise, the goal of Generative AI is more focused on dynamic content creation.

And what are the benefits that a TFLA system provides?

The most important benefit that a TFLA system can provide a teacher is insight into the teaching and learning process that can be used to evaluate and improve the educational design and delivery. As teachers receive information about their students' engagement with the course's activities, resources and tools, their performance throughout the course, and their motivation and satisfaction, they can evaluate whether their educational design works as intended. For example, a lack of engagement with a particular activity can indicate that the activity is not interesting to students, poses too little or too much of a challenge to students, or is not seen as important or valuable to students. However, there could also be other reasons for the lack of engagement. It is important to note that TFLA can only go as far as the data allows. Therefore, while the teacher can see what is happening, understanding why may not always be possible, especially if the relevant data has not been collected and processed. In such cases, follow-up surveys, interviews or focus groups with the students can help to shed some light on the reasons. In any case, TFLA can indicate whether or not the educational design is working as intended. If a teacher finds that the class shows an overall low performance, the teacher can take measures to improve the course design. However, it may be that only some students show low performance and that the TFLA indicates that they are from a particular demographic. Then, the teacher may need to take more targeted measures, for example, changes to the course design to make it more appropriate for that demographic or personalised attention for the at-risk students.

Aside from retroactive insight into what happened, TFLA can also provide real-time insight into what is happening. Teachers can receive feedback on their students' location, movement and area of focus in the class or in an online learning environment. This can help them understand where students spend the most time, indicating where they need the most attention and support. It can also help teachers know whether students are where they should be (physically or online) and redirect them if needed.

Teachers can also receive feedback on their own location, movement and area of focus. This can allow them to monitor their own performance, in terms of the distribution of attention over the class. For instance, if the TFLA system also tracks students' requests for help or support from the teacher (by using an indicator, such as a light bulb, connected to the system), the teacher can also be informed of how many students are waiting and how long each of them has been waiting.

There has been considerable research on classroom analytics. The trick is to capture the activity of students' digital streams in the classroom and convert the class-level grouping of activity into trigger points for intervention by the teacher, such as sequencing learning material, deciding when to change classroom activity, or assigning membership to groups of students to work together. The tools used for classroom monitoring are varied and include monitoring by cameras, inputs to physical simulations, virtual reality (VR), access to online dashboards, and smart devices such as tables or whiteboards. Therefore, a significant intersection exists between multimodal research and the deployment barriers associated with legal, ethical and data maturity. We will discuss these barriers briefly in section 1.3.

For more details, consider reading the following OECD report: "Classroom analytics: Zooming out from a pupil to a classroom".

A risk for the effectiveness of analytics for teachers and learners alike is the lack of context and the often increased level of literacy needed to understand the visualisations and workflows in dashboards. One approach to improve the design is to provide a contextualised story and journey around the visualisations, mostly through descriptive text driven by automated analysis of significant quantities of data and visual design. An example at the research stage is the data story telling editor, which is a teacher-centred tool for customising Learning Analytics Dashboard narratives.The story design dashboard supports teachers in creating their own data stories. The datasets available for the stories were aimed primarily at nurses. A web interface allowed the design of the stories by adding sequences of rules and writing descriptions. The workflow included defining assessment criteria and data sources, followed by modelling. The result of the teacher-designed narrative is a dashboard containing the story, which is then seen by the student.

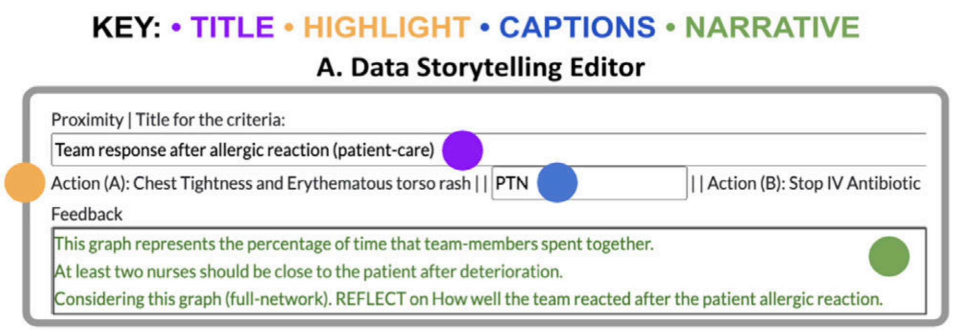


Figure 1.2 A screen from the data storytelling editor. Image from Fernandez-Nieto et al. (2024).

Because TFLA systems help teachers track their students' engagement and progress, they also allow teachers either to provide timely prompts to their students to impact their motivation and potentially reduce procrastination or to follow up with their students to identify any potential problems that may be causing a lack of engagement and progress.
Overall, TFLA systems facilitate improved student behaviour, learning process, learning outcome and academic performance as well as optimise the teaching process and teacher performance. As the data collection, analysis and sensemaking are automated, TFLA systems save teachers time and effort. In the interviews included in this magazine, we will look at examples from Dutch educational institutions.

How do Teachers Prepare For and Use LA?

After considering the benefits of Learning Analytics (LA), the next step is understanding how teachers can prepare for and make the most of these tools in their everyday practice.

Often, institutions opt for educational technology tools that offer in-built Teacher-Facing Learning Analytics (TFLA). In contrast, other institutions may export data and build their own LA system. Whichever choice is made, TFLA is not a passive tool — it requires active involvement from teachers in the preparation of their learning design, their continuous monitoring, and the interpretation of data insights, ensuring that it aligns with pedagogical goals and classroom realities. Ultimately, LA's success depends on teachers' willingness and ability to engage deeply with the data, interpret it within the context of their classroom, and act on it to enhance student learning.

Figure 1.3 shows that the TFLA process of using LA is not only **cyclical**, but also inherently **iterative**. As teachers progress through each step, they often return to previous phases with new insights.

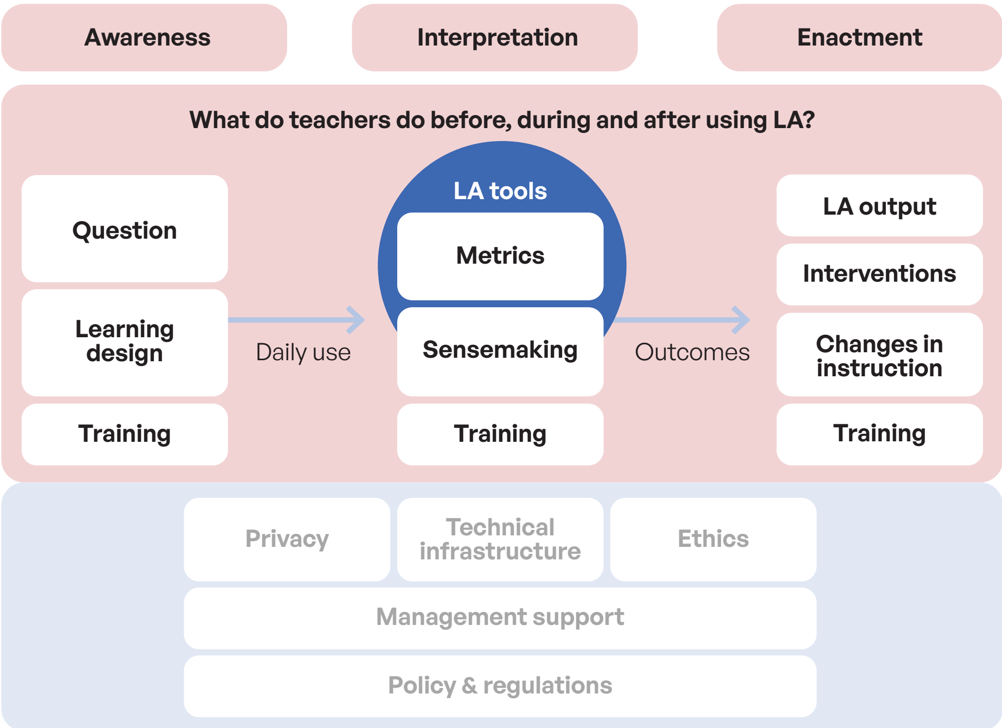


Figure 1.3 The TFLA process.

In this section, we outline three key steps through which teachers can actively prepare for and involve themselves with TFLA, where each step has both a preparation and a usage phase. In some cases, such as when a new tool is being developed, teachers may first complete the preparation for all phases before the launch of the system and then focus on usage once the LA is in place. In other cases, the boundaries between preparation and usage may blur — teachers may engage with existing data to inform future questions and then design or refine their approach as new insights emerge. Additionally, to leverage the full potential of LA, it is important that teachers develop specific skills, including data literacy and reflective practice. For each of these areas, we discuss the necessary skill sets that support the effective use of LA.

Step 1

Determining what you are looking for

Preparation

The first step in preparing to use LA is generating straightforward, meaningful questions. For teachers, this means thinking about what they want to learn from the data — whether it's about reflecting on their own teaching, understanding student engagement with materials, or identifying those who need additional support. Effective **question generation** ensures that the data collected as input for LA is relevant and actionable. Without a well-defined question, LA can become overwhelming or lack direction. For other stakeholders, such as developers and management, these questions also provide a common understanding of the teachers' needs, ensuring that LA tools are aligned with the overall instructional goals.

For example, a teacher might ask, *"How is my feedback affecting student motivation?"*, *"Are my students engaging with specific course materials as intended?"* or *"What student behaviours indicate a need for intervention?"*.

Usage

Once the LA system is in use, we move into the **awareness** phase, where teachers begin engaging with the data provided by the system, typically through dashboards or reports. Teachers might open a dashboard to check specific metrics they planned for during the preparation stage or they may be prompted to investigate when the system flags certain behaviours or trends, such as a student falling behind in the current course. Thus, systems can be built to be available whenever the teachers need them or to take a more proactive role. In both cases, this stage aims to bring relevant data to the teachers' attention, ensuring that they are aware of student performance or engagement trends.

Skills

Teachers need strong **inquiry and question-generation skills** to effectively prepare for and engage in this step. They should be able to identify the needs of their course and frame questions that the analytics can answer, whether these questions pertain to student behaviour, learning outcomes or their own teaching practices. This will likely be an iterative process, starting from a general problem that needs refining and ending with a question.

Furthermore, **learning design** plays a crucial role at this stage. Teachers can start by considering the potential interventions based on future LA insights, so that their course structure can accommodate them. This could involve modifying learning activities mid-course, preparing resources to provide targeted support for students who need it, or adapting assessment methods in response to patterns that emerge from the data.

A helpful method for honing these skills is the FoLA method (Fellowship of Learning Activities and Analytics). This game-based approach provides structure and inspiration for incorporating LA into learning design. It prompts teachers to consider both their journey and that of their students, helping generate relevant questions about the learning process.

Considering that investing time in crafting the right questions before a course starts will maximize the value of LA and ensure that it aligns with the course's goals, it should be noted that specialists, such as educational consultants and learning designers, should be available to support teachers and share the load.

Step 2

Determining what the data means

Preparation

After defining the questions to be addressed with LA, the next step is the **planning of the metrics and data points** that will provide the most relevant insights. This involves determining what kind of data needs to be collected and how it will support answering the teachers' questions. In this phase, collaboration with educational scientists or system developers is always beneficial, as they can help ensure that the chosen metrics align with both the *pedagogical goals and the technical capabilities* of the LA system. The teacher may identify key moments when data should be collected to give meaningful insights. For instance, a teacher tracking student engagement might decide to measure the frequency of interactions with course materials alongside quiz performance.

Usage

Once the relevant data is collected, the process enters the **interpretation** phase. Here, teachers start to make sense of the analytics and extract meaningful conclusions. They can review the data shown on the dashboard, aiming to understand what it tells them about student performance or engagement. For example, if the data shows that students who engage with specific course resources perform better on assessments, teachers could encourage other students to use those materials more frequently. This phase requires the teachers to go beyond simply viewing data — they must critically analyse it in the context of their class and reflect on its implications for teaching and learning.

In many cases, it is helpful to combine data from multiple sources, such as engagement metrics, assessment results or grades, and participation records, to form a more comprehensive understanding of student behaviour and learning patterns. Some LA systems can also provide alerts when attention is needed, helping teachers focus on specific areas of concern, such as students at risk of falling behind.

Skills

The ability to interpret data effectively in this step requires a combination of **data literacy** and **critical thinking**. Teachers must understand the data they are working with, so they can recognise patterns and draw meaningful conclusions. This includes becoming familiar with data visualisations, such as graphs or heat maps, and recognising patterns and trends over time. However, interpretation can have a more substantial impact when it does not happen in isolation, for example, when teachers can contextualise these insights within the broader scope of their course and students' learning journeys.

Consequently, knowledge of **learning design** is essential, as teachers connect their interpretations to the overarching instructional goals of their course. It's not enough to simply understand the data — teachers need to critically evaluate how the insights fit into the full scope of their student's learning experience and identify what changes, if any, are needed to improve learning outcomes.

Finally, teachers can participate in workshops on data interpretation and analytics, in order to improve their data literacy. Institutions should provide structured data analysis **training** and support collaboration with learning analytics **experts**. Teachers can enhance their critical thinking by engaging in peer review and collaborative reflection, with institutions fostering this through **discussion groups** or **reflection sessions**. Support from educational consultants or learning analytics specialists can further enhance teachers' data interpretation skills.

Step 3

Determining what to do with the LA

Preparation

Once the questions and metrics are determined, the next step is deciding how the data will be visualised and how it will inform teachers' actions. In cases where an LA tool does not already exist, teachers should be able to participate in the creation of prototypes to ensure the data is presented in a usable and useful way. Prototyping can range from low-fidelity sketches to high-fidelity interactive designs, with each iteration bringing the tool closer to a fully functional system. Teachers' involvement in this design process ensures that the data presentation is aligned with their needs, making it easier to translate insights into actions.

On the other hand, if the LA system is already established, this final preparation step involves **designing of potential pedagogical interventions**. Teachers must consider their initial questions and how they can act on them, for example: *What if I identify that a student is at risk? What if my course materials are not being used as expected?* Their course should be structured to **accept changes** that result from LA insights and implement any necessary changes. These considerations usually relate to the questions posed during the awareness preparation, for instance: *Can I change my feedback approach during the course, or will adjustments be made in future iterations? Is there an opportunity to modify learning materials on-the-go or change how students are instructed to engage with them?* or *Once students' needs for support are identified, what is the most effective way to provide that support?* These considerations ensure that the insights from LA can lead to practical, actionable outcomes in the classroom.

Usage

The **enactment** phase involves turning insights from the interpretation phase into pedagogical action. In short, this is acting on the questions posed in the preparation phase above. Based on their understanding of the data, teachers may adjust their teaching practices or provide targeted interventions to support students. For example, if the data suggests that students struggle with a particular concept, the teacher may decide to revisit that content in class or provide additional resources. On the other hand, if the data shows that a group of students is showing signs of being at risk of failing or dropping the course, the teacher can determine whether a targeted intervention is required.

In some cases, enacting changes may not happen immediately but could inform future course planning. Teachers may take note of recurring patterns and adjust learning activities or course structure for the next cohort of students. Additionally, LA insights can help teachers reflect on their teaching strategies and consider long-term improvements to their instructional design.

Skills

To effectively act on the insights from LA, teachers need a solid **understanding of instructional strategies** and **learning design**. They must be able to take the insights gained from data interpretation and implement changes to improve student outcomes, whether through adjustments to lesson plans, pacing or the introduction of new learning activities. The learning design skills used in Step 1 are brought full circle here — teachers must assess whether the course structure and interventions they've implemented are producing the desired outcomes and whether their LA-informed decisions have positively impacted students.

Additionally, teachers need **reflective skills** to critically evaluate their practices and the effectiveness of the LA approach. Sometimes, the data may indicate that certain methods need to be adjusted or that the LA interventions themselves require refinement. Teachers should be able to assess whether the use of LA has led to measurable improvements in student learning or their own teaching effectiveness and then plan for further iterations, if necessary.

Teachers can refine their pedagogical knowledge through ongoing **professional development and communities of practice**, while institutions should offer **evaluation-focused training and structured reflection opportunities**. Instructional coaching can support learning design evaluation, and reflective practice should be encouraged by both teachers and institutions through regular feedback and self-assessment frameworks.

Reflections

The process of using LA is not only **cyclical**, but also inherently **iterative**. As teachers progress through each step — from asking meaningful questions to interpreting data to taking action — they often return to previous phases with new insights. For example, data from the **enactment** phase might raise new questions that lead back to the preparation of the **awareness** phase, prompting teachers to refine their course design or adjust their instructional strategies. This continuous feedback loop fosters ongoing improvement, both in how teachers use analytics and in how they approach their teaching.

Moreover, the **boundaries between the phases** within a single step (preparation versus use) and **across the different steps** are often **fluid**. Teachers may find themselves moving back and forth between them or even revisiting the preparation of metrics as they engage with the system. This **constant back-and-forth and overlap** is a natural part of the process, reflecting the complexity of teaching and learning environments. Rather than viewing LA as a rigid, step-by-step process, it is more helpful to see it as a **dynamic and evolving practice**, where preparation can greatly impact the use and adoption of a system, but reflection, action and adjustment occur continuously.

To sum up, teachers are the driving force behind TFLA's success. However, implementing LA in their courses does not have to be perfect; it is a **continuously improving process**. Furthermore, several factors outside teachers' direct control influence how effectively LA is implemented. In the following section, we explore these external factors, such as institutional support, data privacy and technological infrastructure, that teachers must consider to ensure a responsible and impactful use of LA.

What are the External Factors that Teachers Should Consider when Using LA?

In the previous section, we discussed how teachers use Learning Analytics (LA) and how they can prepare to use LA in their daily practice. We considered factors related to teacher skills and the design of a course. These factors are (for the most part) under the teachers' control, but there are also factors at an institutional level that are harder for an individual to influence. These include legal policies, the institution's vision for LA and the institution's technical infrastructure.

Nonetheless, it is important to discuss these factors for several reasons. First, it is worthwhile for teachers to be aware of these issues, because they may encounter questions from students or colleagues about them. Second, it is worthwhile to know about these issues, because teachers may influence them indirectly. Third, it is important to discuss these factors, as they will play a role in determining if the LA implementation and adoption will be successful.

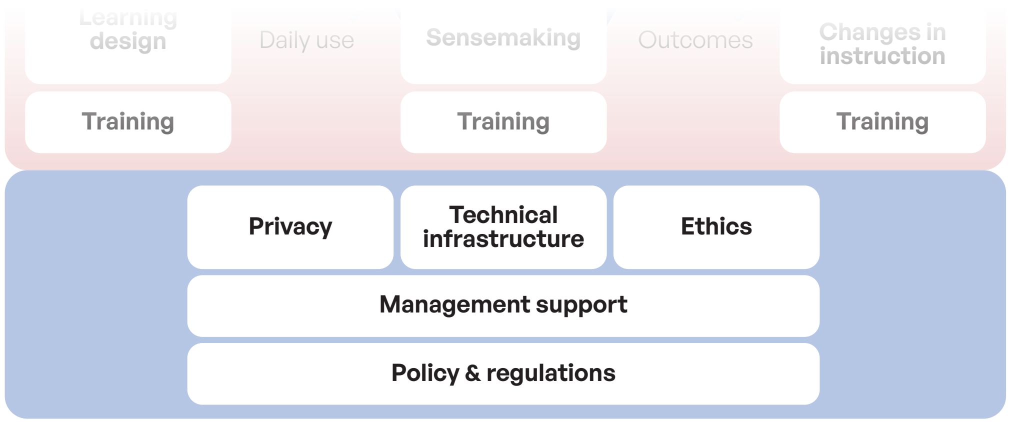


Figure 1.4 The TFLA process.

In general, and as explained in our first magazine, LA projects are interdisciplinary in nature, requiring input concerning, for example, pedagogy, IT and ethics. For LA projects to succeed, several facilities or arrangements should be available to make the project possible. When initiating LA projects, institutions typically follow one of two approaches (or a combination of both): **top-down** or **bottom-up**. In top-down approaches, institutional managers lead large-scale projects focusing on technology, but often face challenges with staff adoption. In contrast, bottom-up approaches are driven by teachers or researchers at the ground level, leading to strong engagement but with challenges in scaling the innovation across the institution.

While institutional leadership typically drives the more prominent initiatives, teachers can indirectly influence institutional policies through successful small-scale pilots. Several case studies have shown that teachers piloting LA and sharing their results with colleagues and administrators can lead to institutional change. This bottom-up approach can snowball into broader, top-down support for LA projects, as seen in multiple examples across educational institutions. In fact, international experts from our previous issue recommended starting with small, focused pilots that can gradually grow into more substantial projects with management backing. Therefore, teachers may indirectly impact external factors in the long run.

This section explores the key external factors influencing teachers' ability to use LA effectively: ethics and transparency, technical infrastructure and regulations, and management support and policy.

Ethics and transparency

Institutions increasingly recognise the importance of robust privacy and ethical frameworks for using LA. In the Netherlands, the **Versnellingsplan** project developed a **national framework for privacy and ethics** related to the use of student data, providing clear guidelines on how institutions should handle this sensitive information. Similarly, institutions like **Eindhoven University of Technology** have adopted and published their **Code of Practice for Learning Analytics**, emphasising student welfare and transparency. In an **LA policy document**, institutions like **Utrecht University** publish their ethical values for handling student data.

The Versnellingsplan Reference Framework emphasizes the responsible use of student data that aligns with the educational sector's core values. This framework is a guideline to ensure transparency and accountability, creating trust among students and staff that data will be handled carefully. A key principle of this framework is the "human-in-the-loop" requirement, which mandates that automated systems should not make decisions about students without human oversight.

As the primary users of Teacher-Facing Learning Analytics (TFLA), teachers should be aware that having access to their students' data may pose ethical concerns regarding students' digital well-being and the power balance between the teachers and their students. For instance, it is good to know things such as: Does my institution allow systems that make decisions independently of the teacher, or should a human always be in the loop? Does my institution have a code of practice detailing what data you can or cannot access?

To mitigate ethical and privacy risks, it is good to communicate clearly to all involved stakeholders about the purpose of the project and the way the data is processed. Teachers are encouraged to work closely with their institution's **privacy officer** to ensure compliance with both national and institutional policies. It is also critical that teachers communicate openly with students about how their data will be used. Clear and transparent communication builds trust and helps mitigate any ethical concerns related to data usage, such as issues around student privacy, power dynamics and digital well-being.

Resources
- Versnellingsplan Reference Framework - Please note that this document is currently being revised: Update reference framework privacy and data: focus on AI and vocational education training schools - Npuls
- Code of Practice Learning Analytics from Eindhoven University of Technology
- LA policy document from Utrecht University

Technical infrastructure and regulations

Teachers who want to start with LA can benefit from being aware that LA systems rely on robust platforms to collect, process and present data. These systems need to integrate smoothly across Digital Learning Environments (DLEs), Learning Management Systems (LMSs) and other tools, in order to provide actionable insights. However, technical issues, such as platform compatibility and data exchange, can affect the accuracy and timeliness of the data. Understanding this infrastructure helps teachers set *realistic expectations* for data processing. Additionally, depending on the IT department's maturity, teachers may need to be more active in troubleshooting and supporting system integration efforts.

Regarding **Data Control and Privacy**, **institutional policies** dictate how data is managed, with **frameworks** like the General Data Protection Regulation (GDPR) and the EU AI Act ensuring compliance. While teachers may not directly shape the infrastructure, they can advocate for transparency in data collection and ensure that it aligns with their teaching goals. All education workers should also be aware of basic security practices when working with data, such as using strong passwords, properly managing session logouts, and relying on institution-approved tools to safeguard student data and maintain responsible use of analytics.

Finally, teachers can influence decisions around technical infrastructure by engaging in bottom-up initiatives. Participating in pilot projects or co-design initiatives provides opportunities to offer direct feedback and highlight areas where systems succeed or fall short. This involvement helps institutions improve platforms, communicate feedback to developers, or create environments where teachers contribute to shaping IT infrastructure improvements.

If institutions are not (yet) able to create a fully functional LA infrastructure, they can also join national initiatives. The Npuls NELA project, for example, aims to set up an experimentation environment for LA and develop standards for unlocking data from different sources in one place. The ultimate goal is to create a national infrastructure that institutions can use.

Resources
- General Data Protection Regulation (GDPR)
- EU AI Act
- Npuls NELA project

Management support and policy

The quality and priority of the management levels in an educational organization are vital to successfully deploying LA. Adoption relies on significant management support, which itself depends on management's literacy. Management needs to understand not only what the teachers understand about learning analytics, but also the organisational context and business processes needed for successful deployment.

Teachers need access to training, documentation and ongoing professional development to maximise the value of LA tools. This involves both **top-down initiatives** and **bottom-up efforts** from teachers, and even when it's top-down, teacher feedback (or lack thereof) will influence future iterations.

It's not that buy-in or support is vital, but knowing what support options are available is good, from having the **time/budget** to getting **expert training**. Institutions looking to start with LA should provide comprehensive training on its technical and pedagogical aspects. This includes how to interpret data and apply insights in classroom practices. Clear **documentation** is also crucial, particularly for teachers who may be less familiar with the technical side of these systems. Ideally, teachers should be willing and able to actively participate in training and familiarise themselves with available documentation, taking an engaged role in the process.

Successfully deploying recent data-driven approaches, such as LA, which may include AI at scale, starts with literacy. The UN and the European Commission have published competency frameworks associated with AI and data that may help form the basis for initial staff training (see resource section).

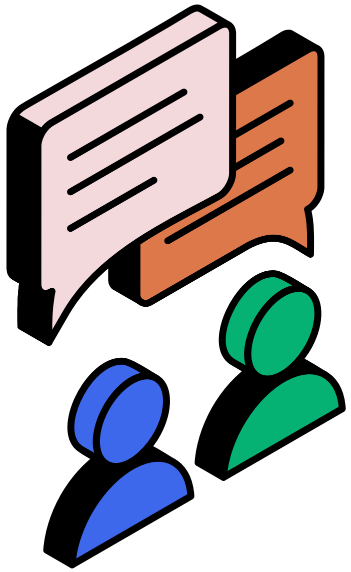
Beyond initial training, institutions should offer **ongoing professional development** to help teachers refine their use of LA tools. This could include workshops, peer mentoring or collaboration with data experts within the institution, as discussed in earlier sections.

Management should also clarify whether using LA tools is **mandatory or optional**. Some institutions may require specific course management or grading tools, while others may offer more flexibility, allowing teachers to adopt LA as it best fits their teaching style. Providing teachers with autonomy can lead to more effective use of these tools.

We encourage instructors and educators already working with LA to share their experiences and insights, fostering a collaborative approach to improving LA adoption. Npuls is one such forum.

Resources

- EC digital competency framework
- UNESCO AI competency framework - Students
- UNESCO AI competency framework - Teachers
- Making Sense of Learning Analytics Dashboards: A Technology Acceptance Perspective of 95 Teachers



Insights from the field: Interviews on Teacher-Facing Learning Analytics

Learning Analytics (LA) continues to advance both in research and in practice, with many institutions in the Dutch LA community developing applications to provide teachers with valuable insights. This section showcases some of this progress through a series of interviews with LA pioneers from several institutions in MBO, HBO and WO.

Karianne Vermaas is part of the Npuls pilot project, the Dutch Experimental Environment for Learning Analytics (NELA).

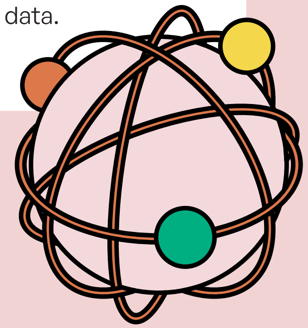
Tirza Smits, **Rynell Offerman** and **Bob Mooijenkind** work as policy advisors on blended learning at The Hague University of Applied Sciences.

Irene Eegdeman currently works for the ROC of Amsterdam-Flevoland and Windesheim University of Applied Sciences in Almere and is part of the Data Coalition.

Connection of Data between Systems on an Institution-Wide Level through NELA

Who is Karianne Vermaas?

Karianne Vermaas has been involved in Learning Analytics (LA) for a long time. Back in 2015-2016, LA emerged as a serious direction for further educational innovation, and since then, Karianne has been involved in exploring how educational institutions can be supported in realising LA. She sees the potential of LA for educational institutions, teachers and students. Although there are many technical challenges, there are also numerous organisational challenges, and applying learning analytics is not always easy. Particularly in understanding which data can provide which information and how relevant dashboards can be based on this data for education. Additionally, obtaining the necessary data, or data quality and management, is crucial. Since the pandemic, she has noticed renewed interest in LA. Developments in digitalisation, such as blended learning, generate new data that can also be utilised by teachers. Moreover, LA is advancing technically, with an increasingly comprehensive understanding of the extent of the data architecture required. LA is not an easy topic, and it demands a lot in terms of working with data from all educational institutions, but it is also the theme that inspires institutions to engage with data.



What is NELA and with what goal was the experimental environment started?

Karianne: Educational institutions experienced that connecting data between systems on an institution-wide level is necessary for LA. Data from a single system often provides little insight into the learning process, but by combining data from various systems, a more complete picture of student progress and educational implementation emerges. For this reason, SURF initiated a Proof of Concept (PoC) to demonstrate that combining data from different sources is feasible. This revealed that, while it is possible to link multiple data sources within one environment, significant effort is still required to integrate the systems and create a cohesive view from multiple applications. The data from these different systems, which come in various formats, must be translated into a standard format (xAPI) to be combined and analysed. This was achieved with simulated data, but what about real data from the Student Information System (SIS) and video systems? The PoC clearly demonstrated that combining multiple systems can make LA much more relevant, and it provided enough reason to further explore this in a pilot project.

Therefore, following the PoC, a pilot project called Dutch Experimental Environment for Learning Analytics (NELA) was established. NELA aims to help educational institutions choose a course in LA, by facilitating the integration of data from various sources based on a specific question (use-case), and by providing a part of the technical solution. By reducing conceptual and technical obstacles for institutions, the NELA environment aims to give institutions a clearer picture of how they can and want to utilise LA in secondary vocational education (MBO), higher professional education (HBO) and university education (WO).

Although NELA was founded to support those involved in LA and accelerate their development processes, the ultimate goal is also to inspire educators by showcasing what is conceptually possible and providing the initial building blocks. Through these concrete actions, we aim to make it easier for both teachers and management to highlight LA developments internally and include specific expectations in strategic agendas.

How is the NELA team composed and how was it formed?

Karianne: Starting with themes like LA within an educational institution can be challenging. It requires a lot of expertise, support and capacity in various areas such as educational science, IT, privacy, ethics and education. Even within a single institution, mobilising all the necessary effort and expertise can be difficult. Therefore, a team of experts has been assembled for NELA, from which use-cases of the institutions can be developed. Whenever the project requires additional expertise, the team is temporarily or more permanently supplemented with it. This ensures efficiency and clear goals to make targeted progress.

The team around NELA in 2024 consists of:
- **Pytrik Dijkstra** – project leader
- Jeroen de Jong – architect
- Caspar Nijhuis – developer
- Jasper Berlijn – technical product manager
- Karianne Vermaas – user research, evaluation, guidance of experiments (special mention to photographer Nienke van Denderen)

What will the headline be when NELA succeeds?

Karianne: I would be delighted if NELA no longer appears in the headlines. What should stand out, in my opinion, are statements about how it can be used in education. Some of these statements are:
- Teachers gain better insight into student progress and well-being through combined data analysis, allowing them to provide better guidance.
- Learning analytics enables targeted interventions based on reliable data.

Which educational institutions is NELA active in?

Karianne: Currently, we are experimenting with three institutions and the following use cases:

De Haagse Hogeschool
At The Hague University of Applied Sciences, the focus is on combining student progress data with well-being data. They have developed a mockup of a dashboard to integrate this information, providing teachers with insights into both academic performance and student well-being. The goal is to enable targeted interventions and better support for students. NELA is tasked with combining data from different sources to ultimately create the desired dashboard.

Universiteit Twente
The University of Twente is focusing on video analytics. They aim to develop reliable analytics across various video platforms to understand how students interact with videos, such as where they stop, rewind or linger. This information helps teachers to identify areas where students struggle and to make their videos more effective.

Graafschap College
Graafschap College is working on analysing data from various sources like the SIS (Student Information System) and LMS (Learning Management System), as well as student well-being data. The goal is to combine and analyse this data to give teachers better insights into student progress and well-being, enabling them to perform targeted interventions. Multiple vocational institutions (MBOs) are collaborating on this project to develop a solution that is useful not only for Graafschap College, but also for other institutions.

Figure 2.1 Kick-off of the Dutch Experimental Environment for Learning Analytics with MBO, HBO and WO. Image from SURF Communities.

How does NELA support the three initiatives?

Karianne explains that NELA supports the initiatives at the three institutions by creating an environment where data from different sources can be combined and analysed. The goal is to accommodate all possible use cases for LA, helping educational institutions make better use of available data and opportunities. This data can then be meaningfully fed back to students, teachers or the education system through dashboards, for example.

Karianne emphasises the importance of experimentation and of developing use-cases that genuinely address the needs of teachers, with concrete results that can engage teachers in the usage rather than just focusing on the technology. In many cases, the involvement in LA often stems from policy or ICT departments, rather than directly from the needs of teachers and academic advisors. Focusing solely on technology can sometimes lead to resistance and a lack of direct demand from the educational practice. However, it does help in ultimately realising educational ideas. Showing good examples and successful use cases that inspire and make the possibilities of LA tangible, with technology playing a facilitating role, would be beneficial. Additionally, Karianne underscores the importance of a functioning environment, where data from various sources can be combined and meaningfully analysed to bring the use-cases to life. This would help institutions, as well as teachers and administrators, take concrete steps and fully harness the potential of LA.

What are the key factors for successfully implementing Teacher-Facing Learning Analytics?

Karianne: The key factors for successfully implementing Teacher-Facing Learning Analytics (TFLA) often revolve around collaboration among various stakeholders. Internal support at the institutional level, such as from the Board of Directors (CvB), and the allocation of sufficient time and budget are crucial for the implementation of LA. Without these resources and the necessary expertise, it can be difficult to take the required steps and provide the needed support. Broad support within the organisation helps ensure smooth implementation and engagement from all stakeholders. Institutions currently participating in the pilot often struggle to gain widespread support from various organisational levels and active involvement from, for example, teachers and academic advisors. It is vital to involve these groups more and to centralise their input, now that the use-cases are becoming more concrete, to fully utilise the potential of LA.

Using LA effectively requires much more than just technology. Teachers need specific skills and support, particularly in the area of data literacy, which often involves a learning curve. Additionally, there is room for improvement in designing education with data in mind. Therefore, it is important to offer professional development opportunities, so that teachers can develop these skills and improve education. This contributes to a better understanding and use of LA, ultimately benefiting the education process.

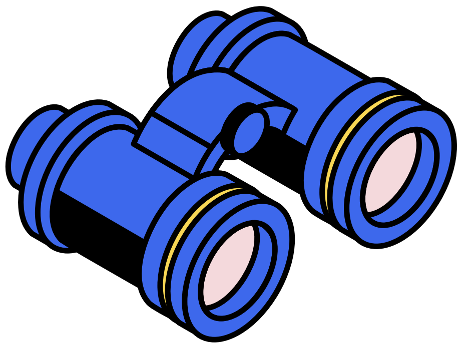
Data is, of course, crucial. LA stands or falls on the availability of data. This is easier said than done, as we have seen in the pilot. Institutions find it challenging to retrieve data from systems such as the Student Information System (SIS).

It is also important to consider how an experimental environment, developed by SURF, can integrate into an institution's IT landscape. Simply saying, "Here is the code, host it with your institution's IT department." doesn't work. Understanding each other and involving everyone in what we are doing and why is important and takes time and attention.

From NELA, we see that we must, can and want to help institutions with this. So, before we can work on a functioning experimental environment, we need to overcome hurdles together with institutions. These hurdles include "How do we get the data from the institution's systems?" and "How do we get all the necessary departments and people within the institution on board, with sufficient time and expertise? Think of IT, management, data managers, and suppliers." Only when such hurdles are overcome can we start developing the components of a national experimental environment for learning analytics.

What does the future of LA look like, now that the focus is increasingly shifting towards AI?

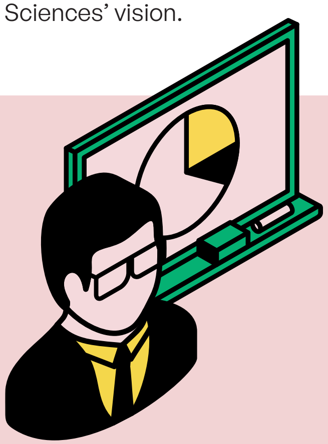
Karianne sees that developments around Artificial Intelligence (AI) are increasingly getting attention in institutional plans. While LA previously took centre stage, AI is now coming to the forefront. AI can complement LA, but it also brings new challenges. For example, extra caution is needed to prevent bias, and it can be difficult to understand exactly what is happening with the data. This may require even more control over data within institutions. The future is unpredictable, and with AI, it becomes even more uncertain. It is valuable to experiment with AI carefully now to discover how AI and LA overlap, complement or clash.



Effective Student Guidance with Insights from Study Data

Who are Tirza Smits, Rynell Offerman and Bob Mooijenkind?

Developments around Learning Analytics (LA) often involve questions around data quality, accessibility, the development of dashboards, and privacy and ethics. But LA projects can also arise differently by connecting to what is already available in current systems for individual instructors, rather than at the level of the entire educational institution. **Tirza Smits**, **Rynell Offerman** and **Bob Mooijenkind** show how this latter approach looks in practice. They work as policy advisors on blended learning at The Hague University of Applied Sciences and see a role for LA to enable effective student support, matching The Hague University of Applied Sciences' vision.



How did the learning analytics project start?

After the transition and technical implementation of a new learning management system (LMS) called Brightspace, there was an opportunity at The Hague University of Applied Sciences to plan follow-up actions. After the new LMS had gone into production, the working group decided to explore what else the new functioning environment had to offer. In this next phase, the key users, consisting of teachers and users of the new LMS, were invited to explore with the working group what possibilities there were and which ones they found interesting. One of the themes chosen was leveraging insights from data to contribute to the learning process, also called learning analytics.

Brightspace offers multiple insights into a student's learning activity or process within a course. Information around Grades, Grades Statistics, Learning Outcomes and Assignments, as well as summary views such as Class Progress, provide insight into what is happening in the online environment and how students are progressing. These insights can be viewed by the teachers involved in the tool and are summarised and visualised within the tool in a dashboard (see Figure 2.2). According to the working group, this has the advantage that little technical development is needed, and data within the tool is kept secure and always up-to-date.

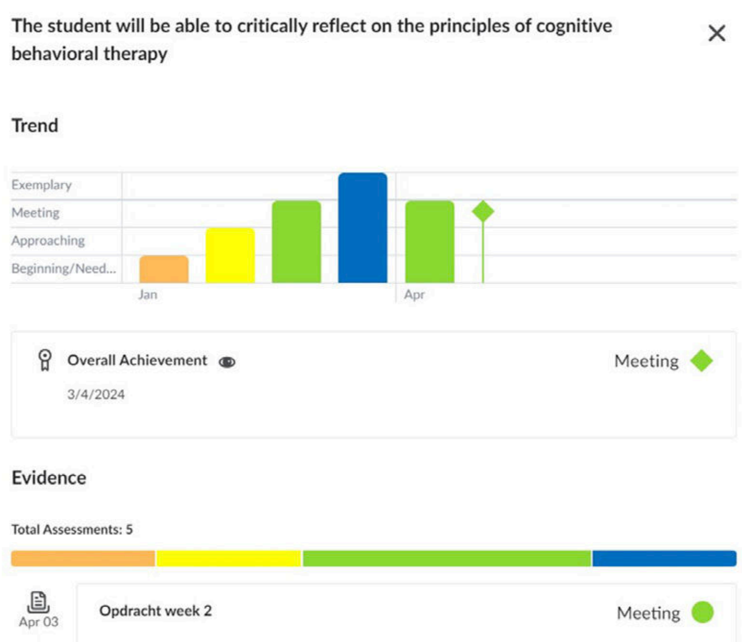


Figure 2.2
Screenshot from Brightspace, showing how information is summarised and visualised in a dashboard.

Together with the working group, Rynell, Bob and Tirza set to work to explore whether the possibilities already present within Brightspace could be used by teachers and especially study career supervisors. At the time, The Hague University of Applied Sciences was also in the midst of working on a new educational vision, which included a strong focus on guiding students. Rynell, Bob and Tirza chose to make the LA functionalities in the LMS accessible to teachers and study career supervisors, with the aim of providing more effective student guidance using insights from data.

What is Brianna Brightspace and how was it developed?

Unlike many LA projects, Tirza, Rynell and Bob did not want students and staff to have to undergo extensive training before they could use the LA tools. Instead, they wanted to show that using data within the current workflow of tutoring can be a useful addition. This raised the question of how the use of the tools available in Brightspace could be explained to teachers in an accessible way, while also focusing on achieving the goal of guiding students more effectively.

To achieve this, they developed the organisation-wide E-Learning ‘Effective student guidance with data’. In this E-Learning, student counsellors and teachers are introduced to Brianna Brightspace, a fictional avatar who interactively takes participants through cases. When participants select particular options, the avatar shows new possibilities. By going through the cases with Brianna Brightspace, participants experience what options are available in Brightspace and how to interpret the available data. Privacy and ethics are also addressed by being applied to the appropriate context of the participants. But fortunately the E-Learning does not stop there! By collaborating with different areas of expertise within The Hague University of Applied Sciences, the E-Learning focuses not only on study data, but also on conversation techniques. This deepening was created by working together with the Begeleiding & Coaching Lab of The Hague University of Applied Sciences, making study data not only more accessible, but also directly usable in educational processes after taking the E-Learning. For Rynell, Bob and Tirza, this is a great example of how, by involving multiple departments and labs, different expertise can complement each other to create a better product.

With this product, they therefore hope that insights from study data will contribute to a motivating and growth-oriented conversation with a student in educational practice, in order to make student guidance more effective for all students. They modeled this motivationally by discussing a case study with a fictitious colleague. The student coach continues to shape the conversation himself and data, instead of leading, maintains the supporting role (see Figure 2.3).

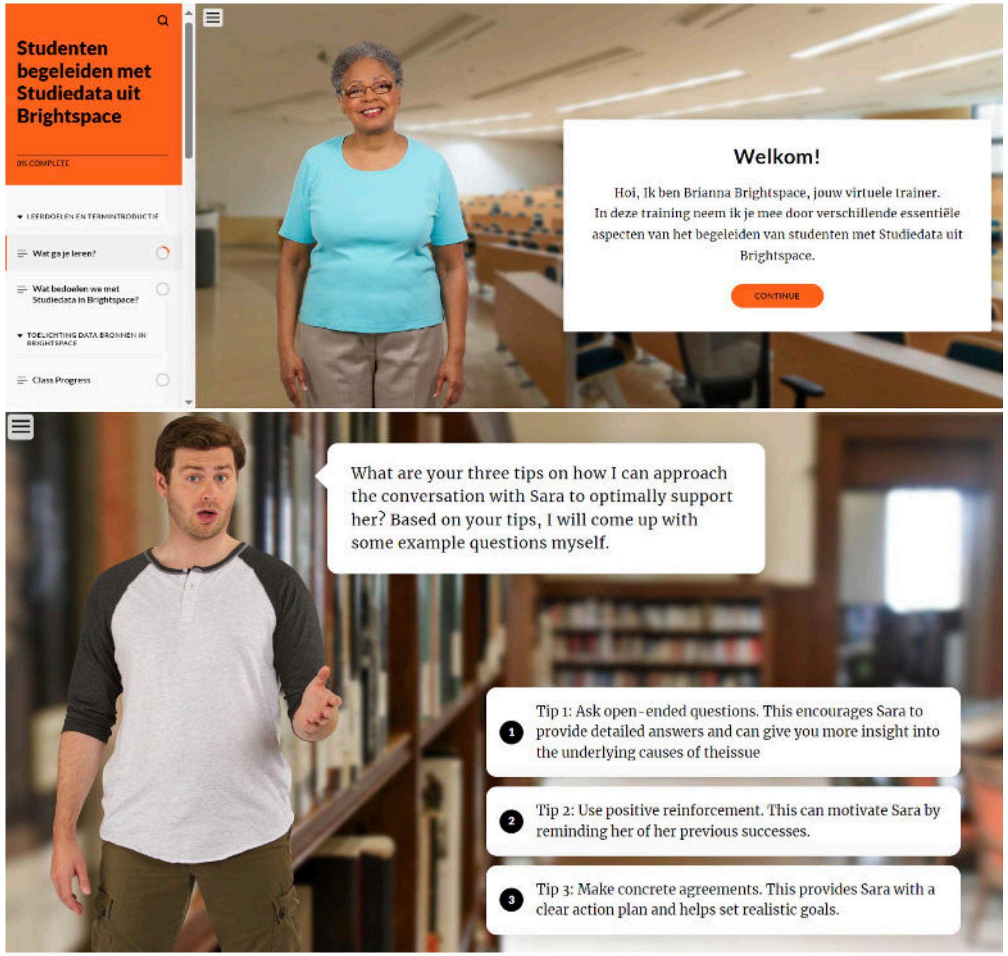


Figure 2.3 Screenshot from Brightspace, showing how the avatar, Brianna Brightspace, interactively takes participants through cases.

What are the follow-up steps?

The project by Rynell, Bob and Tirza does not start from the technology, but rather from the educational vision and the e-learning needed to accomplish that. Therefore, subsequent steps focus on the broader rollout of E-Learning, instead of on further technical development of the tools. The tools are in the LMS and will remain within it, and it is precisely their use that they can stimulate by rolling out E-Learning more widely within The Hague University of Applied Sciences, in conjunction with the new educational vision.

Prevention of Student Dropout using Historical Data

Who is Irene Eegdeman?

Irene Eegdeman currently works for the ROC of Amsterdam-Flevoland and Windesheim University of Applied Sciences in Almere and is part of the Data Coalition.

She received her PhD in June 2023 on the topic of student dropout in secondary vocational education (MBO), and she has continued this research within two institutions. The reason to start working with Learning Analytics (LA) and Artificial Intelligence (AI) arose from her earlier research into a test that measures students' abilities and personality. This test was widely used by schools in the Netherlands to guide students well, but it turned out to not have predictive value for student dropout. Therefore, the need to predict dropout remained!

What is the invitation rule and how was it developed?

During her PhD research, Irene discovered that machine learning, although not widely used in education yet, had the potential to identify students at high risk of dropping out. Her supervisor, Marijn Meeter, and co-supervisor, Chris van Klaveren, suggested using machine learning to predict who had the highest risk of dropping out, rather than explaining why it happened. This meant that LA would play a central role in collecting, analysing and interpreting data to gain insight into student behaviour and performance, including dropping out. The quality and availability of the data would be crucial in this process.

Irene looked into the use of machine learning to predict who was at risk of dropping out, which led to the development of the invitation rule, using historical data, with predictive models that were ultimately also implemented to reduce student dropout. By looking at the information generated by the models about the risk of dropout and combining it with the information they already had, study career counselors could make a better assessment of which students needed extra support. The models could also help teachers work more effectively to prevent student dropout. During a pilot, through the invitation rule, students were invited for an initial conversation in order of dropout risk. After these conversations, there could be a referral to additional support, enabling early identification of students who could benefit most from extra support. During this pilot, research was also conducted to see if working with this information indeed leads to early detection, better student guidance and reduced dropout.

Irene was often told that research was not necessary at all and that her colleagues could already predict dropout very well. Therefore, Irene put this to the test. She asked teachers to estimate the risk of dropout for first-year students at the beginning of the program. The teachers turned out to be fairly good at making this estimation. However, the teachers' estimation combined with the predicted dropout risk from Irene's models was even better. This means that it is not a matter of either the teacher or the computer, but rather of the teacher with the computer. You can read more about this here.

The methodology, in the form of the invitation rule, has meanwhile been adopted by the Data Coalition. The original research was replicated at Albeda, ROC Mondriaan, ROC of Amsterdam-Flevoland, Gilde opleidingen and Yonder. After a successful replication, the path was open for a cautious implementation.

How has the invitation rule been implemented?

At three institutions, study career counselors have now received dropout information about their students for the first time, so that the invitation rule can be used to sequence the initial conversation at the start of the year.

Before the research started at these institutions, teachers/mentors were offered several preparatory steps and support to successfully integrate the project into their education. For example, each team participating from ROC of Amsterdam-Flevoland had three in-depth sessions - an explanation of the invitation rule, an ethical discussion that provided input for rules, and finally the development of an intervention (initial conversation) and conversation guide. After the summer, there was a kick-off to summarise all the agreements and discuss the rules. Irene emphasises that this approach, with the three in-depth sessions, has strengthened the process and research and has ultimately contributed to the improvement and acceptance of the predictive models.

An initial evaluation shows that study career counselors are generally positive and feel they have a good picture of the student earlier. In addition, early detection indeed occurs more frequently, allowing students to enter a care trajectory sooner. By the end of this year, it will be possible to determine whether reports were actually made earlier (not just more frequently) and whether this has had an impact on dropout rates.

Of course, a pilot also brings to light areas for improvement. During the implementation of the project, Irene noticed that some teachers were not hesitant to apply new technology. However, sometimes, they even wanted to go further and do more with the outcomes of the models, which meant that she had to push back a bit during the ethical discussions. Also, some teachers are less comfortable working with the information from the invitation rule or they begin to doubt themselves because they find it hard to accept that they didn't notice the early signs themselves (why can a computer see it and not me?).

Irene is still in the middle of the pilot with the data coalition, and thus the process of monitoring and evaluation is ongoing.

What are the factors that have played a role in the implementation of the invitation rule?

In addition to the contact with and research on teachers, other factors have been important to ensure careful implementation and the success of Irene's project in collaboration with the Data Coalition (Figure 2.4).

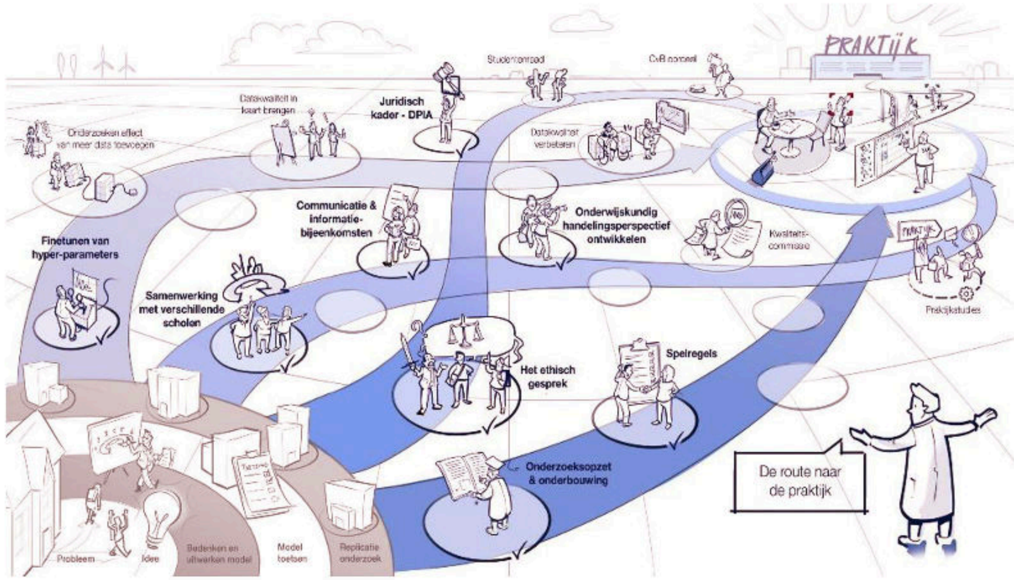


Figure 2.4 Factors playing a role in the implementation of the invitation rule. Image from Data Coalition 2024.

As previously indicated, ethical discussions were held with students, teachers, managers and care coordinators from the various programs. The outcomes of these discussions were translated into rules, to ensure that the predictive models were used responsibly. These measures ensured that, in addition to the benefits for guidance, student privacy and well-being remained central. A conscious decision was also made about who would have access to the information, to ensure the entire process was as careful as possible. Additionally, a Data Protection Impact Assessment (DPIA) was evaluated and approved by the relevant authorities within the educational institutions.

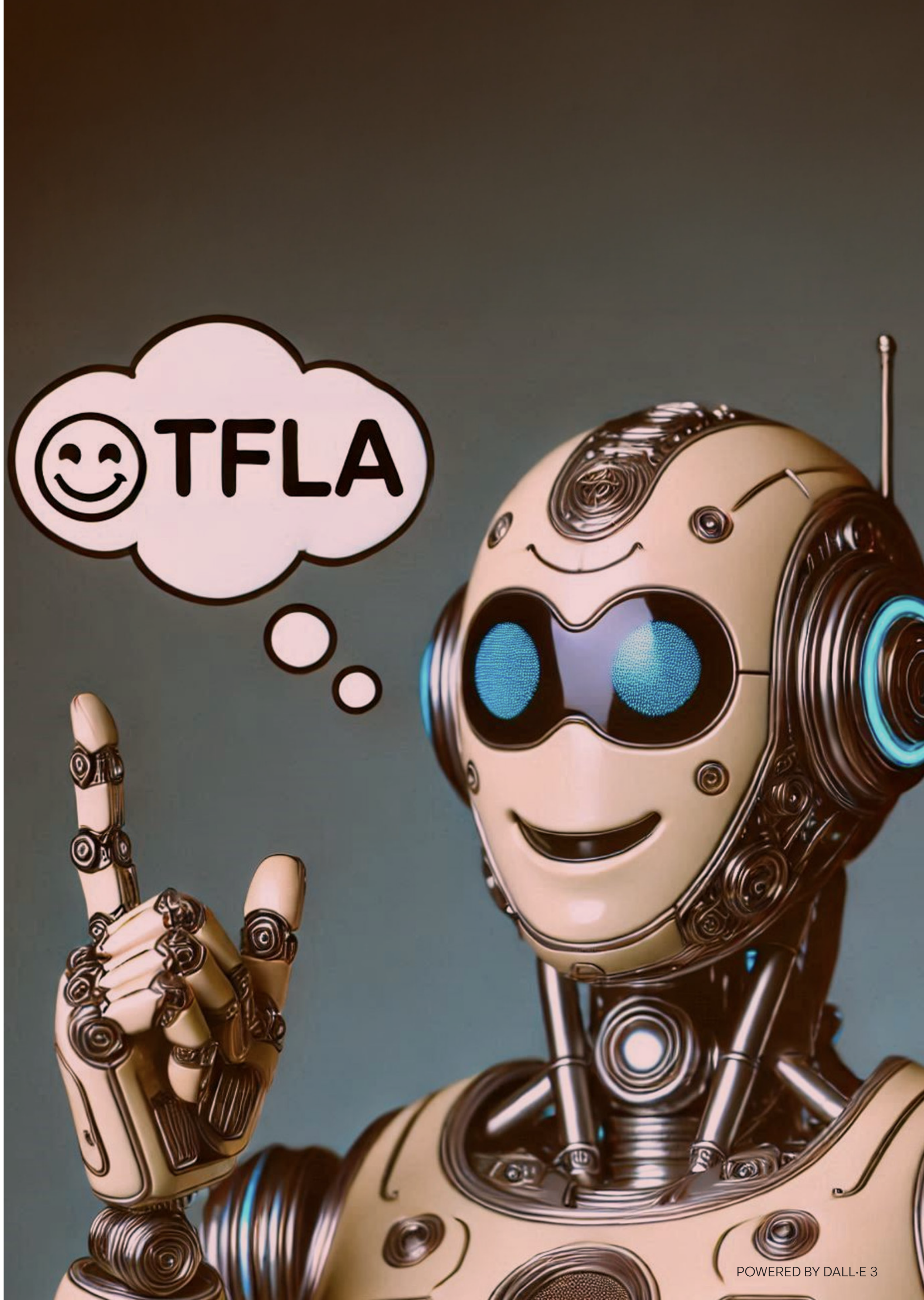
What is the status of the research?

The research is currently ongoing at the institutions, and the results are not yet known at the time of this interview. All steps taken, including the materials developed, are accessible to everyone and can be found at Regiobijeenkomsten – de uitnodigingsregel. The evaluations are expected to be published on the Data Coalition's website.

For now, we say: Stay tuned!

Wrapping up

The interviews presented in this section highlight the diverse approaches and innovative efforts undertaken by various institutions to develop Teacher-Facing Learning Analytics (TFLA). From connecting data between systems on an institution-wide level to effectively guiding students and preventing student dropout, these pioneering projects showcase the potential of LA to transform education. While they show an inspiring process, widespread adoption remains a challenge. As we continue to explore and implement TFLA, we look forward to seeing even greater advancements and their positive impact on student learning and success.



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Conclusion

Magazine one provides examples of opportunities to improve organisations' implementation of Learning Analytics (LA) tools that can provide insights and support teaching priorities. The LA field is dynamic and quickly incorporates generative AI to help provide descriptions as part of data storytelling and content suggestions, specifically for students (as seen in Magazine two).

In this magazine, we took a look at Teacher-Facing Learning Analytics (TFLA), which refers to the application of data and analytics tools that are designed to support educators in understanding and improving student learning outcomes. TFLA makes teachers more aware of the learning context they are working within, allowing them to pay greater attention to class and individual learner dynamics, resource sequencing, and many other interventions. The process is iterative and agile. The interventions are measured, reflected upon and improved. We repeat the cycle often.

Support tools will never replace the need for digital literacy. TFLA requires a degree of digital and AI literacy from students and teachers. However, TFLA is a shared journey with the wider organisation. Managers involved in digital transformation, who wish to support the deployment of TFLA within their organisation also need data, AI and digital literacies, as well as an awareness of business processes. Examples of data and AI competency frameworks include the European Commission's Digitcomp framework and the UNESCO AI competency framework.

TFLA will prosper if we share our experiences and support each other. In this magazine, the Npuls LA team has provided examples and interviewed practitioners who have demonstrated success with TFLA.

Karianne Vermaas discussed the National LA Experimentation Environment (NELA). NELA aims to help educational institutions chart a course in LA, by showing what is possible and by providing initial technical solutions. NELA demonstrates the value of integrating multiple data sources. Teachers gain better insight into student progress and well-being through combined data and learning analytics, enabling targeted interventions based on reliable data.

Tirza Smits, Rynell Offerman and Bob Mooijenkind work as educational innovation policy advisors at The Hague University of Applied Sciences. They see a role for LA in enabling effective student guidance per the university's vision. To motivate academic advisors and teachers, they developed the organisation-wide e-learning course 'Effective Student Guidance with Data', in which they introduce the academic advisors and teachers to Brianna Brightspace, a fictional avatar who interactively guides participants through case studies.

Irene Eegdeman works for the ROC of Amsterdam-Flevoland and Windesheim University of Applied Sciences in Almere and is part of the Data Coalition. The coalition involves fifteen vocational institutions and takes concrete steps to enhance student support through pilots, experiments and research. Irene detailed her work on preventing student dropout. It is motivational to read how combining human intuition and computer models can lead to even better predictions of student dropout rates. The research highlighted the power of collaboration between educators and technology.

We would like to thank those who we interviewed for this magazine as well as those who have contributed research to the field. Through their efforts, we hope we have given you a sense of the potential that can be unlocked by implementing LA at scale.

We wish the reader success in this shared journey. The team looks forward to meeting you at our workshops and broadcasting your LA accomplishments to the largest audience possible.

Further Reading

The selection of papers and books below is for those who are interested in knowing more about Teacher-Facing Learning Analytics (TFLA).

A: General overviews that are helpful for orientation:

- Introduction of Teaching Analytics: Describes Teaching Analytics (TA), which combines teaching expertise, visual analytics and design-based research (DBR) to help teachers use data effectively and enhance their data literacy
- Teacher and Student Facing Learning Analytics: Reviews the growing use of learning analytics systems in K-12 and post-secondary education
- Learning Analytics Implementation Design: Outlines how to design learning analytics implementations
- Learning Analytics in Education: Literature Review and Case Examples From Vocational Education: Provides examples of learning analytics in vocational education

B: Resources about the Dutch context:

- Learning Analytics in Five Steps: Describes the five steps an organisation can take towards deploying learning analytics
  Note: This document was written before the EU AI Act.
- Learning Analytics In Het Onderwijs: Provides context about the questions that learning analytics can answer

C: Examples, details and hints that you can apply during the TFLA process:

- Teaching and Learning Analytics: Discusses Teaching and Learning Analytics (TLA), which supports Teacher Inquiry, where “teachers identify questions for investigation in their practice and then design a process for collecting evidence about student learning that informs their subsequent educational designs”
- The TEADASH Dashboard: Explains how a TFLA dashboard was designed
- Human-Centred Learning Analytics Design: Describes a Human-Centred Learning Analytics (HCLA) design approach for developing TFLA dashboards for K-12 classrooms that maintain both contextual relevance and scalability—two goals that are often in competition
- Learning Analytics and Teachers’ Data Visualisation Literacy Skills: Describes research on how teachers use their visualisation skills in dashboards (not surprisingly, different dashboard complexities are needed for teachers with different skill levels)

- Will, Skill, and Tool (WST) Analysis of Teachers' Use of Digital Data: Describes research on teachers' use of digital data and the related factors, such as the available technologies in schools (teachers' self-assessed data literacy and positive beliefs towards digital technologies significantly predict their use of digital data for pedagogical purposes)
- Learning Analytics to Support Teaching Skills: Reviews learning analytics and its link to the teaching skills carried out in university practice (learning analytics offers teachers feedback to change their practice and improve their skills; teachers' critical concerns include students' privacy, their skills, and integrating learning analytics systems into their practice)

D: In-depth exploration of learning analytics:

- Handbook of Learning Analytics: A thorough guide to learning analytics
- Handbook of Artificial Intelligence in Education: A comprehensive overview of AI within the educational context

E: Previous editions of this magazine:

- Magazine 1
- Magazine 2

Contact

We hope this magazine has been an inspirational read. If you have any questions or suggestions, we would be happy to hear from you. Please visit our project page for our contact details.

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