



Npuls

edition 1 | May 2024

Onwards to Success with Learning Analytics.

An Overview of Facilitators and Barriers

Inspiration and practitioner stories
on how to get started with
learning analytics

Dit magazine is ook
beschikbaar in het Nederlands



Onwards to Success with Learning Analytics.

An Overview of Facilitators and Barriers

Authors

Alan Berg, Anouschka van Leeuwen, Annie Slotboom,
Symen van der Pas, Priyanka Pereira, Manuelle Valle Torre

Editors

Ella Put, Suzanne Vink

Publication

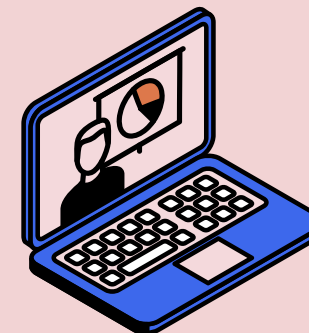
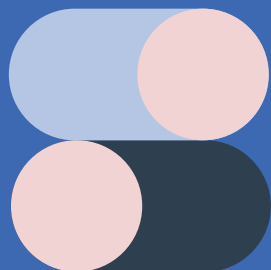
May 21, 2024



The Creative Commons Attribution-ShareAlike 4.0 license applies to this publication. When using this work, please cite the following reference: Studiedata&AI - Learning Analytics (2024). On the road to success with Learning Analytics: an overview of facilitators and barriers. Utrecht: Npuls.

Contact

info@npuls.nl



In this magazine

Introduction & Meet the Team

Results from a literature review

Interview with DPO data coalition

Interviews with international colleagues

Suggestions for further reading



Alan Berg

Alan researches the influence of artificial intelligence on education across Europe. He is also a Product Owner for a central data team at the University of Amsterdam (UvA). In his spare time he consults.



Annie Slotboom

In addition to her work at Npuls, Annie is conducting her research on the application of Learning Analytics and AI tutoring at Graafschap College in Doetinchem.



Anouschka van Leeuwen (coordinator)

Anouschka is the coordinator of the project. She also works as a researcher and learning analytics project leader at Utrecht University.



Symen van der Pas

Besides his role at Npuls, Symen is a program manager on Studydata and AI at Inholland University of applied science.



Priyanka Pereira

Along with being a member of the Npuls project team, Priyanka is a researcher and the 4TU.CEE Coordinator at the University of Twente. She is currently finalizing her PhD thesis on peer feedback in tertiary education.



Manuel Valle Torre

Besides his role at Npuls, Manuel is working on his PhD research concerning learning analytics to support students in complex learning tasks at the Technical University of Delft.



Introduction & meet the team!

Welcome to this magazine! This magazine is the first output of the project “Best and Worst Practices Learning Analytics”, which is one of the projects from the [Npuls pilothub Study Data & AI. Learning Analytics \(LA\)](#) is about trying to answer questions from educational practice by means of using student data. The goal is to analyze and report on student data with the aim of increasing the quality of education. Many Dutch educational institutions are currently investigating the potential of LA for their students and staff. In this project, we will combine insights from literature and practice into output that is easily accessible and aimed at easy translation into practice.

Our project runs in 2024, and during that time, our aim is to provide inspiration and practical information around LA concerning three “themes” or content areas. We will cover each theme by diving into relevant (international) literature, as well as talking to Dutch and international practitioners who have experience with LA in that area.

Before we dive into specific applications of LA, we first want to provide an overview of what it takes for an organization to start with LA. Experience has taught us (and the literature confirms) that a number of factors have to be considered or arranged to be ready for LA. In this magazine, we will summarize these “facilitators and barriers”, provide advice and insights from practitioners, and suggest further readings to get started!

How can you reach us?

We hope this magazine inspires you and helps organizations on their road to implementing learning analytics to support education. We would very much welcome any feedback on this magazine, whether it concerns its content or its form. If you have suggestions for future output or events, would like to exchange ideas, or collaborate in any other way, please feel free to reach out.

Visit the [project website](#) with also our **contact details**.

Facilitators and Barriers for LA: Results from a literature review

Introduction

Tertiary education institutes in The Netherlands are in different phases of LA implementation. While some are just getting started and are exploring the possibilities, others have already had some initial successful stories and are looking to scale up. No matter which phase of implementation an institute is in, there are certain factors that act as facilitators, which ease or enhance the implementation, or barriers, which impede or restrict the implementation.

We expect that, at most institutes, there is some knowledge of these factors, based on experience or what has been heard or read. However, a complete picture of the factors can be helpful – when we know what can make the implementation easier or more difficult, we can plan accordingly. Therefore, we set out to explore the literature to find and compile a list of the factors that can have an effect. Putting together the information from over 100 articles, we were able to create a comprehensive list of considerations, which we categorized into six themes for ease of understanding. The full set of papers that we reviewed are available online [link]. In the text below, references to the articles are indicated as clickable pieces of the text, which will direct you to the source article.

The six themes are presented below. We hope that they can act as a guide for both institutes that are currently using LA and institutes that are planning to do so in the near future. With good and timely planning of the implementation, measures can be taken to incorporate the facilitators in the process and mitigate the barriers to the process. Of course, the situation is different in each sector of tertiary education (vocational education, tertiary education and universities) and within each institute. Therefore, the specific ways and the extent to which the different themes can be applied will vary. However, with a team member who is familiar with learning analytics in your specific context, you can use the information to customize and optimise the implementation of learning analytics at your institute.

1 Cultural factors

Culture is crucial in successfully deploying Learning Analytics (LA) because it influences how technology is perceived and used within educational environments. This theme includes how we govern the data together, our awareness, involvement, and curiosity about what LA can do with the data and what is appropriate, and the level of buy-in at the management level.

In complex organisations with data silos such as Student Information Systems (SIS), getting the data to flow and maintaining its quality requires a significant effort. Establishing a data governance board can help. As a result, procedures can be set up at a central level, preventing different departments from having to constantly reinvent the wheel. There are also frameworks for data governance, such as [DAMA DMBOK](#), which suggest an order for prioritising efforts. Enacting a framework requires management buy-in and a sense of urgency for the whole organisation. Top-down buy-in supporting bottom-up evangelism provides the necessary focus.

[Many cultural barriers](#) exist to adopting AI/LA in Education, including overwhelming demand, budget, concerns and anxiety, lack of responsibility, data sovereignty and data understanding. Culture is unavoidably related to management literacy and curiosity as a driver for change. [Building](#) a university culture that encourages innovation and entrepreneurship, along with formal rules and policies, is essential to enhancing learning analytics awareness and increasing its impact with a student-centric approach.

Our literature review discovered over sixty pieces of advice highlighting the complexity of cultural transformation, from a gut instinct to a data-informed to a data-driven culture.

The advice includes:

1. Spend time developing [policies and procedures](#). This focused time will allow for buy-in and uncover possible issues that can be addressed early in the process.
2. Encourage the [flow of data](#): Learning analytics should be considered a data ecosystem within a more extensive data ecology. Within this ecosystem, there should be an acknowledgement and intentional nurturing of the relationships, interdependencies, and data flows between a variety of stakeholders and the varying data interests between these stakeholders
3. Establish and communicate [clear goals](#) related to using the system to meet the goals ascribed to the system.
4. Develop a [change management plan](#) to identify and address cultural issues.
5. [Students' expectations](#) towards Learning Analytics across Europe are comparable. Therefore, Learning Analytics systems can be shared across institutions rather than implemented separately as tailored solutions, where standardised or modular LA systems are reasonable.
6. Learning analytics must leverage rather than replace [human contact](#). A realistic evaluation of staff capacity and capability to deliver interventions is key.
7. Institutions need to make the [benefits](#) of learning analytics visible to students so that the 'gains' of sharing personal data are clear and relevant to individuals.
8. [Advisers at Universities](#) are sensitive to LA tools' moral and ethical considerations. Any tool that provides advice or support for advice requires the adviser to be in the loop and provide early feedback on design. This will help prevent self-fulfilling feedback cycles and accidentally treating students as numbers.
9. Be sensitive to the [perceptions of instructors](#): The implementation of LA might be hindered by instructors' resistance to change, perceived extra workload or wariness of systematic data logging if perceived as a control or surveillance mechanism rather than as a tool for greater pedagogical support.
10. [Involve students](#) in the design of LA tools, such as dashboards.
11. As long as the LA tool ensures that students are aware of their [engagement](#) in a course, complex data visualisations or dashboards may not be necessary.
12. [Allocate time](#) for teachers to participate in design feedback. Teachers have busy workloads and competing demands on their time; they may be willing to engage in participatory design if they can see the long-term benefits an LA platform may bring them and their students.
13. It is important to introduce LA systems to students in the [context](#) of their learning, i.e. in-class, to maximise buy-in.

2 Frameworks

Adopting a framework helps you avoid repeating the mistakes of others or inventing your own. An extensive set of frameworks exists, including Dutch-specific frameworks, that focus on the deployment of [Learning Analytics](#).

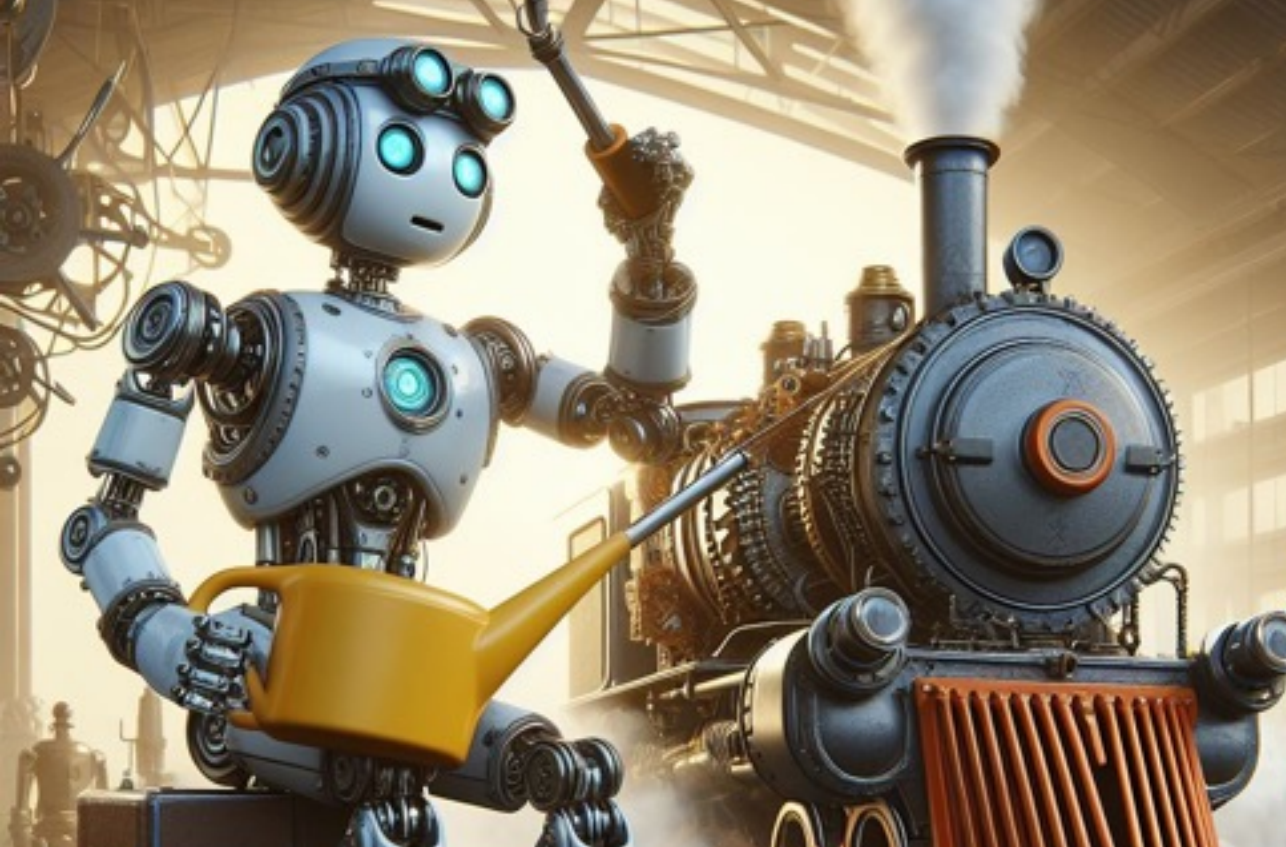
Reviewing the Frameworks provides a realistic overview of previously applied mitigation and success factors and suggests priorities. For [example](#), emphasising user support, communication with users, user training, and software standardisation are critical to adoption. If you are scaling Learning Analytics, where first to look?

1. [Capability model](#) for learning analytics is a Dutch Framework that helps practitioners such as program managers, policymakers, and senior management by providing them with a comprehensive overview of necessary capabilities and their operationalization.
2. [SHEILA](#) is a rapid policy development framework designed to create effective strategies and evidence-based policies in complex environments. It includes case studies that demonstrate its application in real-world settings, particularly for large-scale implementation in tertiary education contexts. It addresses challenges and provides action and policy prompts for systematic adoption.
3. [The dashboard checklist](#) lists 18 factors for successful dashboard deployments.
4. [The DELICATE framework](#) defines the aspects of privacy policy that need to be focused on within an educational organization.

3 Literacy and Training

No system is useful unless the people who are supposed to use it actually know how to use it. This applies to LA too. Therefore, it is key to ensure that all the stakeholders involved — technical staff, teachers, students, parents and management — know how to use the system. Each stakeholder group can be trained in using the system and interpreting the data through classes or seminars, which can be further supported via the technical staff and instruction manuals.

Technical staff are the backbone of an LA system; without them, it is difficult to implement, customise, and maintain the system. Ensuring that they are well-trained goes a long way to securing that the system functions smoothly and as intended. Teachers can make optimal use of the LA system when they know what the system can do and how they can collect, request, access and utilise the data, such that they can view and act upon their own and their students' engagement and performance. Similarly, students can benefit when they know how to view their own data, such that they receive feedback on where they are doing well and where there is room for improvement. When students can view their own data, but more importantly, when they are able to view what data is being collected, their trust in the usefulness and confidentiality of the system may increase. This also applies to parents who may want to be aware of how their children are doing, but also may have concerns about their children's privacy regarding what data is being collected and stored in the system and how it is being used. Finally, if management knows how to use the system, they can independently keep themselves abreast of what is happening in their institute and can take the necessary measures as and when needed.



4 Learning Theory

It is natural to assume that the analysis of learning should be based on learning theory: the design of learning analytics systems should be guided by learning principles. This applies not only to the selection of which data to collect and use but also to the techniques used to modify and process the data, the way the models are created and algorithms are formulated, and the adaptability and personalization of the system. The decisions based on insights from learning analytics systems should also be guided by learning principles. The way the results are interpreted and the design and implementation of interventions based on these results, for example, providing the students with a specific type of feedback or scaffolding, can have a significant impact on teaching and learning. Therefore, the decisions must have a solid foundation in evidence-informed theory and principles.

Once learning analytics systems are designed and implemented, they should be evaluated to ensure they function as intended. This evaluation should include examining the evidence to determine whether the implementation of the system was appropriate. The LA system can be assessed for its accuracy (does the analysis of the data yield the right results?), effectiveness (does the intervention based on the results bring about the desired effect?) and efficiency (does the system function in a timely manner, with minimal requirements of staff's time and effort?). If a system has been found to function as intended, the results from the analysis or the intervention based on the analysis can be applied to other settings and can be used to form generalised knowledge and contribute to the literature.

5 Ethical and Legal considerations

Learning Analytics involves the collection and use of data pertaining to humans. As such, it is subject to certain ethical and legal obligations. There exist a number of policies or regulations at the national, city or other levels that aim to put in place guidelines for the collection and use of educational data. The General Data Protection Regulation (GDPR) and the Artificial Intelligence (AI) Act are two noteworthy regulations that apply to the European Union.

Good ethical practice dictates that the way the data is collected, analysed, and used is fair to everyone who will be affected by the decisions made based on the analysis. The procedures and algorithms must be formulated with this in mind. This means the algorithms should be inclusive, considering all students, such as students with disabilities. It also means that the algorithms should be unbiased and not treat certain groups, such as at-risk students, differently. Inclusivity and a lack of bias may be difficult to achieve because different groups of students have different levels of access to the system and of willingness to consent to their data being collected and used, thus biasing the dataset on which the algorithm is run. Regular inspection of which students are contributing data to the system may help with being aware of and taking precautionary measures to mitigate any lack of inclusivity or bias in the dataset. Also, sound coding is advisable to prevent the algorithm from inadvertently developing these issues.

The legal obligations are mainly concerned with the privacy of those whose data is collected. This is one of the most important and widely talked-about issues regarding learning analytics. There is a growing concern about privacy violations and security breaches. However, this concern can be alleviated by putting the right measures in place. To address this, transparency and security are important. Transparency involves the LA system having a clear objective and the stakeholders being made aware of which data will be collected and what will be done with the data. Security involves the appropriate measures being taken to ensure that the collected data is protected and cannot be breached.

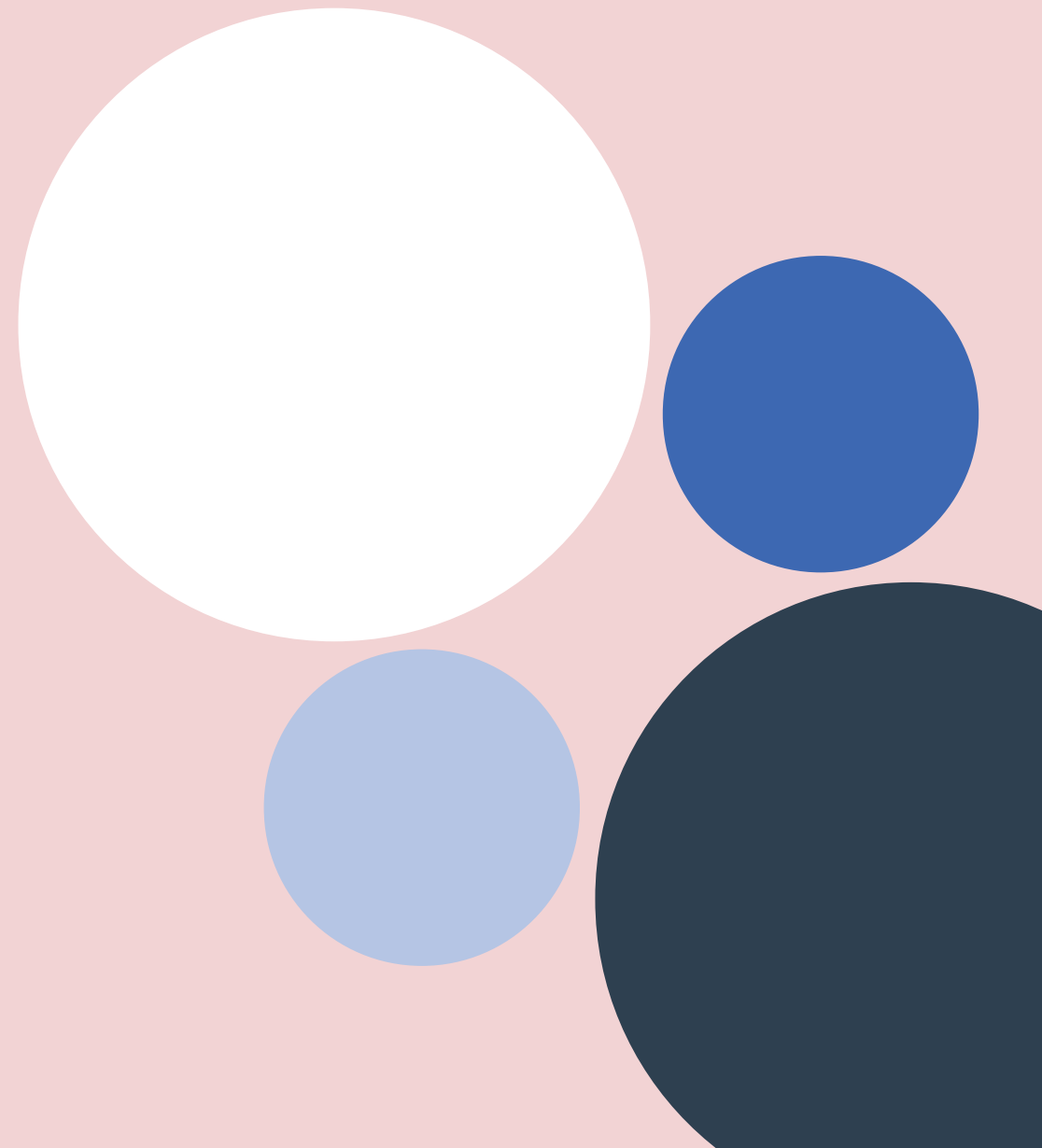
6 Technical factors

Learning Analytics harnesses the digital footprints created during educational activities to enhance learning experiences, such as prompting students with reminder emails to take action. This process depends on a robust and adaptable system to work effectively. A significant technical challenge is the commitment to successfully breaking down data walls within an organization to merge and monitor information from various sources. Frameworks such as DAMA DMBOK help in this effort. A framework helps an organization develop a shared understanding and speak the same language.

A solid cultural and policy framework primarily guides effective technology implementation. Fostering data literacy is essential to driving these elements efficiently. Enhancing relationships between stakeholders is also essential, helping them prioritize the quality of data; without quality, even the most appealing visualizations fail to deliver, turning into a case of ‘garbage in, is nicely visualized garbage out.’ Highlighting this point, it was noted that only half of the students believed that the displayed data was accurate on an investigation of an existing learning analytics tool.

To encapsulate the entire analytics life cycle, consider:

1. Learning standards could contribute to a more effective collection and platform-independent comparison of educational data. They also allow for interoperability across platforms. Learning standards include data formats such as XAPI, Caliper, and learning tool interoperability (LTI).
2. Technical details impact, such as how to deal with imbalanced datasets or (Ding et al. 2019) developing flexible dashboards that allow for customization. Therefore, the skills of the technical staff need to reflect this complexity. Upskilling and scaling of support staff is necessary (See Training and Literacy section)
3. Where possible, include multiple data sources; they may reflect the dispersed activities of learners in a more precise way than what is possible for each data source (See Learning Theory section)
4. Data Quantity & Quality: Add data quality standards to determine targets for data readiness.
5. Ensure your LA tech is compatible with your Learning Management System.





Interview with
Frank van Dijk, René Boutelje and Erik Bood
Data Platform Onderwijs (DPO)

“The trick is to get started with learning analytics inside your own institution as well.”

Getting started with learning analytics in MBO institutions

For the theme “Facilitators and Barriers for Learning Analytics”, we spoke with Frank van Dijk (ROC Tilburg), René Boutelje (Summa College) and Erik Bood (MBO Amersfoort). Together with colleagues from 16 other MBO institutions, they work in the Data Platform Onderwijs (DPO), or *educational data platform* partnership, on the use of data and dashboarding to support study career guidance. All three indicated that, although they are not yet working fully with learning analytics (LA) at the institutional level, they are exploring the possibilities, and LA is definitely on the map for them.

DPO

Instead of each MBO institution setting up its own approach to data, 16 institutions joined forces with external partner Macaw to form the DPO partnership. This partnership makes study data from different systems accessible and usable for institutions on a bronze, silver and gold layer. This allows institutions to make better choices about which data are suitable for analysis and which data are suitable for specific purposes. One result of this collaboration is that several MBO institutions within this partnership have started building dashboards for LA purposes, such as study career guidance and student guidance (see [link](#)).

Facilitators and Barriers

We sat down with Frank, René and Erik to discuss the factors that act as facilitators or barriers to working with data and using LA in MBO institutions. In doing so, we presented them with the six themes we found in our exploration of the literature (see page 6).



Interview with
the DPO coalition

MBO institutions are experiencing a rapid implementation of data utilization by visualizing operational data and management processes. However, the move from this form of data utilization to LA is not a given. For example, Frank concludes that LA requires a different level of data. Instead of overview data, as with student numbers and yield, the need now arises for much more detailed data focused on the learning process of a group of students, a program trajectory or individual students. Although many examples are mentioned, Frank emphasizes that in discussions with, for example, teachers or management, **it is difficult to get a grip on which measurement indicators are relevant for a learning process**. Often, processes are set up specifically for a particular course, but little is known about which measurement indicators are relevant for all *niveau 4* or *niveau Entree* courses as input for LA. Frank explains that this is also a challenge for LMS vendors. Namely: how can they ensure that the implementation of the application also takes into account the learning process?

René highlights the complexity of this issue, because the movement towards flexibilization will result in less standard trajectories as students can make their own choices. While this is a nice development, the implication is that multiple systems are involved, each containing a piece of the puzzle to capture the entire learning process. Unlocking data from all these systems is certainly not a done deal yet! Erik points out that data from these applications are not yet easy to unlock due to a lack of interfaces (also known as Application Programming Interfaces or APIs). Although the DPO helps by increasing the accessibility of shared data models, **connecting multiple applications remains a challenge**, and detailed knowledge of the application is needed to make sense of the data. Frank confirms this – he has experienced that, despite much fiddling with applications, there is little benefit in continuing to browse by himself, and he sees more relevance in what is now happening in the DPO and **how it allows institutions to collectively leverage data much faster**. According to him, cooperation in the DPO could be even more intense. He says that **sharing solutions** may not create 100% utilization of all data, but it will get you to 80% sooner. Frank also hopes that, in this way, masterpieces of development that he sees in his environment will not only be shared “on the fly” but also be given a permanent place for exchange.

In addition to measurement indicators and standardization, René also sees a barrier in **data availability**. In the *studieloopbaanbegeleiders* (SLB) or *study career guidance* dashboard now in use, users are enthusiastic about the fact that the data is shown as an overview. However, René thinks showing timely data is a technical challenge for LA. In particular, providing real-time data which allows you to try to prevent problems instead of just identifying them after the fact. He sees this as a new development area for the DPO – there is great potential in obtaining information that can be acted upon immediately, especially for providing guidance to students.

Besides the technical challenges, all three gentlemen also see the **importance of the culture in the institution**. According to Erik, there are conversations with the Data Protection Officer about what is and is not allowed. Frank often finds that people do not completely grasp what he is talking about during presentations about data models and standardization or that they fail to realise the amount of investment required to realise the goal. Erik says that working with data is abstract and tough, which makes it important to come up with concrete examples. Frank puts it more sharply: just put something on the table, **even if it is only a small starter**. Only then can people think of it as nothing noteworthy or discover new possibilities – at least both responses lead to a conversation. Within both René’s and Erik’s institutions, the SLB dashboard is now the most widely used reporting tool. The dashboard is viewed positively because it is not (like management information) global and static but supports SLB processes.

René points out that, in addition to the technical requirements, you must ensure **that trust grows**. Effective dashboards encourage colleagues to start using them and help management gain confidence in the development of data processes. However, in order to deploy LA to users other than management, such as teachers, there is still a step to take. According to Frank, teachers know very well what they want, and beautiful developments could take place with that collective energy. Yet more is needed because, currently, initiatives often linger on a small scale at the departmental level within teaching teams and are not elevated to solutions at the organizational level. All three gentlemen, therefore, would like to urge their Board of Directors, management and fellow DPO members to pay attention to LA at all levels.

What are the next steps?

René and his team continue to keep all the balls in the air for the delivery of management information. In addition, for him, participation in the DPO ensures more continuity, convenience, and less vulnerability when working with data and preparing for LA. Frank and Erik also experience these benefits of participating in the DPO. By working together in this partnership, they have already made great strides in data visualization with PowerBI, for example. LA remains the next step, which they will certainly continue to highlight in the near future.



Interviews with
Abelardo Pardo, Stephanie Teasley, Bart Rienties,
Simon Buckingham Shum, Mutlu Cukurova,
Alyssa Wise and Professor Xavier Ochoa

Introduction

Although we are working hard at Npuls on Learning Analytics in Dutch MBO, HBO, and WO, we are certainly not the only country where LA is a hot topic. In their role as researchers, two of our team members went to Kyoto, Japan, to participate in LAK24 (Learning Analytics and Knowledge), an international conference for researchers and those involved in learning analytics from around the world. In addition to exploring LA's latest insights and developments, there was time to engage with international colleagues to discuss their experiences with facilitators and barriers to the adoption of LA. You can read what they had to say about this in the boxes.

What are international colleagues saying about facilitators and barriers?



Professor Abelardo Pardo

University of South Australia

Author of over 200 research papers in scholarly journals and international conferences in the area of educational technology and engineering education.

“For me, the number one element that is both a facilitator and a barrier is: you need a cross-institutional working group. What we have seen in institutions when they try to implement LA is that there is usually a group – for example, instructors or IT or leadership – that understands that the use of data is probably very powerful and that it will help to support students, so they want to get something going. What is important is that you have to carefully look at the structure of your institution – and choose a very wide type of team to connect with that initiative. So this is what we have seen in institutions that manage to get LA going.”

Interviews with
**international
colleagues**





Professor Stephanie Teasley

University of Michigan

Project Lead for My Learning Analytics (MyLA):
A Student-Facing Performance Dashboard.
Past-president of SoLAR (2017-2019).

“In my experience with my university, one of the main facilitators has really been institutional support from a very high level. At my institution, our Provost is sort of the top officer for academic practices. The Provost’s blessing really allowed a number of other things then to take place. And so I think for institutions that are looking to get more deeply into it, really educating your top leadership about what it is, how it works, how it fits with the mission of the university, and really get that person or those people to be your champions.

One of the things that wasn’t a barrier for us, that is still a barrier for many institutions, is an interpretation of the legal standard in the US called FERPA [in Europe: GDPR], which is a legislation that protects student data and legislates how it can and can’t be used. Many institutions interpret this to mean that you can’t access certain aspects of student data. However, my university understands FERPA to be fair use of student data when there are business reasons to know. That’s a FERPA exemption. And my university said, well, it is our business to educate students. And so using our own institutional data to help our students is not a violation of FERPA. So I think a barrier can be a misunderstanding of the rules that apply. And I know that different countries have different standards and different uses. And I think that one can respect those and the intent of those because I very much value student privacy. But when those laws maybe are not clearly understood or clearly implemented, they can prevent the use of the data in a way that really is beneficial to the students and to the academic institution.”



Professor Bart Rienties

Open University (UK)

Professor in Learning Analytics.
Current president of SoLAR.

“The most important facilitator is to have strategic buy-in for whatever you’re implementing. Learning analytics is really important, but it has to start from the work floor, from the bottom up. So try to find one or two or three really engaged teachers or educators or students. Start with them! So start small, learn from that experience and then gradually build that momentum. That’s at least what we’ve done at the Open University. Don’t go big full scale but start small.

So oftentimes what I’ve seen with other organizations also within my own organization: If you start small with your little hobby project, but no one is actually supporting you from senior management, eventually when the money runs out, the project dies. They really have to buy into the idea of why this is important and this links to: What is the key problem that you’re trying to solve as an organization. If you’re identifying that, and if you find a reason why learning analytics might help, then I think you’re halfway.

The main facilitator, the people, are also the main barriers, so there will always be people, after you initially have reached these early adopters, how do you reach that critical mass of other people? People, for valid reasons, are often very resistant to change. So how can you convince the majority of people to do something which probably is a little bit outside their comfort zone? Well, if I had the secret of success, I would not be standing here! But it’s all about empowering people, finding champions and seeing that, ‘hey, my colleague is using it, maybe I should use this as well.’ And ‘my colleagues are really enthusiastic about it. I don’t really believe him, but maybe I should try.’”



Professor Simon Buckingham Shum

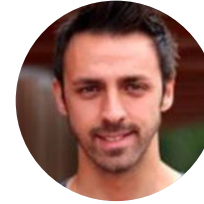
University of Technology Sydney

His applied research sits at the intersection of the multidisciplinary fields of Human-Computer Interaction, Educational Technology, Hypertext, Collective Intelligence, Computer-Supported Collaboration, Learning Analytics, and AI in Education.

“In our experience, the key thing is to align the learning analytics - whatever form that takes - to make it a meaningful activity. If we’re going to ask students to use a tool. You know, we have to get that aligned with the curriculum, with the assessment criteria. It must be embedded in a student activity. If you simply ask students to use a tool as an optional extra that has no apparent relevance for what they are doing for the grades, then you will only get very early adopters, curious students. So that alignment of tools, learning design, assessment and outcomes, is important.

Of course, before we can deploy a tool with any students, we have to have the trust of the academics. They are putting their reputation at risk by deploying a tool with students. If it blows up, students will be unhappy, their time has been wasted. They have a loss of reputation, so it’s all about building trust with the academics. Building trust with the academics, however, also involves having solid software. How do you get solid research software at scale? So now we have to talk to the IT people, the IT people say “ohh well, where’s our budget?” So it becomes a complex ecosystem of conversations which has to go all the way up to alignment with the university strategy as well. So I talk about having the right conversations in the boardroom, the staff room, the server room and the classroom. And the 4 rooms are symbolic of the multi levels in the system that need to align to have successful deployments. But it can be done, it’s not impossible. But otherwise, we will never deploy at scale.

As for barriers - Many universities think that before we can do any analytics or dashboards or feedback we need to sort out all our data. We need to basically straighten out all the plumbing, clean the data, get all that right and then we can do something. But that is a massive undertaking and the horizon is always receding, so our approach has been that we focus on a very specific kind of data, like writing data or dispositional analytics survey or a skills analytics web application. So much smaller data in some senses, but data that we have access to and can control. So you do not have to sort out all your enterprise data before you can do interesting productive things. Otherwise, it’s just a huge, massive, massive undertaking and it’s a never ending task.”



Professor Mutlu Cukurova

University College London

Professor of Learning and Artificial Intelligence
Director of the UCL Analytics & AI for Learning Team

“When you think about this next step of real-world adoption of LA, I think you need to start thinking about the whole ecosystem-level factors that actually influence the effectiveness. So, adoption factors, in my mind, that relate to ecosystem-level can certainly be categorized into four aspects: the technological infrastructure, the existing pedagogical culture of the institution, the human-to-human interactions (like practitioners sharing their experiences and interacting with support teams), and leadership and governance. Another significant factor that predicts real-world adoption is to what extent teachers have the ownership of the tool in the sense that: to what extent when they are using this tool do they consider the success or failure of the tool as their own success or failure. Similarly, to what extent a practitioner thinks that the tool that they are using could challenge their own ethical principles, would have a very significant impact on the adoption.

It goes without saying that perhaps the most important factor that we have identified and wanted to keep as last because it’s relatively straightforward is: in almost all the adoption work that we have done, the feedback with regards to adoption was related to the extent to which these tools are adding to the existing workload of the practitioners. So, if a practitioner thinks that the tool will add to their workload, the existing workload, rather than making things easier for them. And this is not always a very explicit workload add-on - it’s sometimes very implicit in the sense that: “now do I have to collect this type of data instead of that type of data to fill in the content into the analytics?”, or: “do I need to shift from my pedagogical practice of starting with a lecture and then doing the collaborative work and then finishing with the rehearsal to something different in the sequence of act, because I need to use these analytics tools?”. These transitional workloads itself would have an impact, a negative impact on the adoption. If they have to change their practice then it’s this change itself that is a huge threshold for them to add to their workload. So that’s a very challenging problem that we have come across in our work.



**Professor Alyssa Wise
and Professor Xavier Ochoa**

Vanderbilt University & New York University
Collaborated on NYU's Learning Analytics
Research Network (LEARN).

Xavier: “Ik”Xavier: I would say engaging the right stakeholders is the main facilitator. At the right level, sometimes it's higher manager, sometimes it's middle management that you need to engage. Having the right people that take the decisions and also the people that actually use the tool.

Alyssa: When you say adoption I think well, what do you mean by adoption? Do you mean getting licenses and technology available to everybody or do you mean getting people to actually use the thing? And so one thing that I've seen to be very effective is - and it's hard to get people to have the time for this - but the peer-to-peer. So faculty learning from other faculty. I'm thinking of this one guy who was an early adopter and was just so enthusiastic about how it informed his practice and how it helped him, and he was just this natural advocate. And it was very authentic because he didn't have skin in the game. He was just someone who had enjoyed using it and found it really helpful. So those kinds of sort of evangelists can be really helpful.

Xavier: Well, maybe one barrier that I have seen and also have heard before is: “Don't make us look bad”. This attitude of: maybe we don't want to know what you will find. This fear of what will happen if we have opened the box and seen what's inside.

Alyssa: Because once something is made visible, it can have life outside of you and you don't quite have that same level of control over it. If universities know something, they may have a duty to act on it, which can be hard. I think the example at that time was if a predictive model tells you all these students need help - then you need to help all the students. So basically those kinds of things, what are the entailments.

The other systemic factor is, I think, too often we start thinking about the tool and then we kind of push out. But where is this going to fit into the teaching and learning routines? For example, there was a model that was supposed to help figure out which students were going to need extra support in a math course. So who's the person who's going to initiate the process of doing the analytics? Who's the person who's going to connect with the students? Who's the person who's going to offer support? And so there was a triangulation between the data team, the course instructor, and the advising function, and that had to line up in order for it to happen.

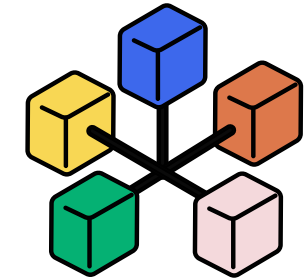
Xavier: And from experience from a previous implementation, I designed two tools, one for advice and one for analyzing courses. And the one was designed for advisors and it was designed to fit on what they exactly need to do. That was adopted immediately. It was one of the tools that you didn't have to ask people to use. They were using them - “We want this tool” - because it facilitated their work. On the other side, we created this tool to analyze courses and presented it to program directors. Like: “Nice to see. Yeah. I can see it.” But they never use it again. So I agree that fitting it inside the process, whatever process that is, is important.”

Closing

There is an international association dedicated to LA: the Society for Learning Analytics Research ([SoLAR](#)). Part of SoLAR's activities includes organizing the annual international LAK conference. The conference is a meeting place for all LA researchers and practitioners worldwide and an excellent opportunity to learn about the research and projects conducted by all our colleagues. In 2025, the conference will take place in Dublin.

Further reading?

We hope to have provided inspiration and tips in this magazine the enablers and possible barriers to Learning Analytics. In this final section we provide tips for further resources, networks and articles to explore.



Networks

- [SoLAR](#) and the yearly LAK conference
- [SURF SIG LA](#)
- [AI Watch](#) - They monitor the development, uptake and impact of Artificial Intelligence for Europe

Getting started with LA

- [Quickscan Study data](#), to find out the data maturity level of your institution
- [Handbook of Learning Analytics](#)
- [Learning Analytics Explained](#) by Niall Sclater

Resources on ethics and privacy

- [Reference frame study data](#)
- [DEDA](#), the ethics data assistant

Journal articles

Below we provide - for the enthusiast - some tips for scholarly articles on LA that we find relevant and accessible.

Real world priorities

The paper titled “Learning analytics: state of the art” explores the field of Learning Analytics (LA) and its application in educational institutions. It presents practical experiences from 16 institutions, analyzing their results, challenges, and expectations. Many LA initiatives aim to improve student retention, with fewer focused on enhancing the teaching/learning process. The paper discusses how institutions invest in LA software, with many developing their technology, allowing for proactive interventions for students at risk of failing. The study also considers the impact of the COVID-19 pandemic on education and how LA can help adapt to new forms of educational delivery. The authors hope the paper will serve as a useful reference for researchers and faculty to exploit LA in education.

Why read this paper?

You will get an idea of others’ priorities, see various definitions of Learning Analytics and obtain an overview of data integration issues.

Dashboards

The paper “A checklist to guide the planning, designing, implementation, and evaluation of learning analytics dashboards” discusses the design and implementation of teacher-facing learning analytics dashboards in tertiary education. It emphasizes that while these dashboards aim to provide insights for teachers to improve their teaching methods, they often lack actionable insights for intervention. Through a systematic literature review, the study found that most dashboards are not customizable and lack theoretical grounding. It also notes that teacher involvement in the design process is limited, and privacy considerations are often overlooked. To address these issues, the authors propose a checklist for planning, designing, implementing, and evaluating learning analytics dashboards, ensuring they are more effective and ethically designed.

Why read this paper?

It provides a checklist for creating dashboards.

Adoption Framework - SHEILA

The paper titled “SHEILA policy framework: Informing institutional strategies and policy processes of learning analytics” presents a framework to guide tertiary education institutions in integrating learning analytics. Based on interviews with 78 senior managers from 51 institutions across 16 countries, the framework utilizes the RAPID Outcome Mapping Approach (ROMA) for creating effective strategies and evidence-based policies in complex environments. It includes three case studies demonstrating its application in strategic planning and policy processes, particularly for large-scale implementation in tertiary education contexts.

Why read this paper?

It provides a checklist for creating dashboards.

Student Expectations across Europe

The paper “Students’ Expectations of Learning Analytics across Europe” explores the expectations of European tertiary education students regarding Learning Analytics (LA). The study uses the ‘Student Expectations of Learning Analytics Questionnaire’ (SELAQ) to compare expectations among students from Germany, Spain, the United Kingdom, and the Netherlands. The findings reveal a homogeneous expectation concerning LA ethics, privacy, and service features. It suggests that European Higher Education Institutions (HEIs) face similar challenges in implementing LA, indicating the possibility of adopting standardized LA solutions rather than creating tailor-made ones from scratch.

Why read this paper?

Consider reviewing existing solutions and stakeholders’ expectations before implementing LA at scale.

Student Wellbeing

The paper “Making a #Stepchange? Investigating the Alignment of Learning Analytics and Student Wellbeing in United Kingdom Higher Education Institutions” describes how learning analytics is used to identify wellbeing-related behaviour changes among students and staff. It puts forth the idea that learning analytics applications can pose a risk to well-being since students may respond inappropriately to dashboards, and staff may be burdened with the additional work involved with using learning analytics. Load.

Why read this paper?

The paper provides insight into the alignment of learning analytics and student and staff wellbeing.

Co-design of Learning Analytics Systems

The paper “Being more human: Rooting learning analytics through resistance and reconnection with the values of tertiary education” recommends that learning analytics systems be co-designed in collaboration with students to ensure that it is not punitive but pedagogically focused, supportive, and compassionate. Students should not be consulted merely as a token gesture, but instead should be brought into the picture right at the start and maintained throughout the process.

Why read this paper?

This paper emphasises an important point to be kept in mind when designing learning analytics systems – the human factor.

Standardization - XAPI

The paper titled “Dutch Cooking with xAPI Recipes: The Good, the Bad, and the Consistent” discusses the experiences of Dutch projects in applying the xAPI standard and various design patterns, including the deployment of Learning Record Stores (LRS). The paper provides an overview of the advantages and disadvantages of implementing the xAPI standard by presenting projects that applied xAPI in different ways, followed by the lessons learned. The authors aim to improve the consistency and effectiveness of xAPI implementations in educational technology.

Why read this paper?

Collecting learner activity streams creates a need for data standardization. One example is xAPI, which has its benefits and drawbacks.



**Moving
education.**