Volume 3 Number 3 (2025)
October-December 2025
Page: 47-61

Tamilis Synex: Multidimensional Collaboration
https://edujavare.com/index.php/TLS/index
E-ISSN: 3026-3972
Doi: 10.70610/tls.1547

Learning Analytics in Higher Education: A Case of the Netherlands

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Article history Submitted: 2025/07/05; Revised: 2025/08/16; Accepted: 2025/09/25

Abstract

Learning analytics has emerged as a transformative approach to enhancing educational quality and student success in higher education, with the Netherlands serving as a particularly instructive case of systematic implementation within a robust regulatory and collaborative framework. This study examines the adoption, development, and outcomes of learning analytics across Dutch universities, drawing upon institutional case studies, national policy frameworks, and empirical evidence from student-facing dashboard implementations. The Dutch approach is distinguished by its emphasis on responsible data use under the General Data Protection Regulation, the collaborative infrastructure provided by SURF—the national ICT cooperative for education and research—and the integration of learning analytics within a broader ecosystem of educational innovation. Key institutional developments include Utrecht University's centralised Learning Analytics team and community, Eindhoven University of Technology's self-regulated learning dashboard, and the Open University of the Netherlands' analytics-supported distance learning design. The research identifies four critical success factors: clear educational goal alignment, privacy-by-design principles, stakeholder-inclusive development processes, and phased implementation with comprehensive teacher support. Findings indicate that student-facing learning analytics, when designed with transparency and user agency, significantly improve self-regulated learning, academic writing skills, and early identification of at-risk students. However, persistent challenges include technical barriers in data extraction and visualisation, the need for enhanced data literacy among both students and educators, and the tension between institutional efficiency goals and individual student privacy. The study concludes that the Dutch model offers a replicable framework for ethically grounded, pedagogically informed learning analytics implementation, while highlighting the necessity of continuous evaluation and iterative improvement to realise the full potential of data-informed education.

Keywords Learning Analytics, Higher Education, Netherlands, Student-Facing Dashboards, Self-Regulated Learning, Data Privacy, GDPR, Educational Technology, Predictive Analytics, Student Retention

Published by Edujavare Publishing; Indonesia
Jln.Agus Salim, Bediwetan, Ponorogo, East Java, Indonesia.
Website:https://edujavare.com/

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INTRODUCTION

The proliferation of digital technologies in higher education has generated unprecedented volumes of data about student learning behaviours, creating both opportunities and challenges for institutions seeking to enhance educational quality and student success. Learning analytics, defined as the measurement, collection, analysis, and reporting of data about learners and their contexts for purposes of understanding and optimising learning and the environments in which it occurs, has emerged as a critical field at the intersection of educational research, data science, and institutional policy (Siemens, 2013). In the Netherlands, the adoption of learning analytics has been characterised by a distinctive combination of collaborative infrastructure, regulatory rigour, and pedagogical innovation, making it a particularly instructive case for understanding how higher education systems can harness educational data responsibly and effectively. This introduction provides a narrative overview of the theoretical foundations, empirical developments, and contextual specificities that inform the study of learning analytics in Dutch higher education.

The theoretical foundations of learning analytics draw upon multiple disciplinary traditions, including educational data mining, computer science, learning sciences, and organisational theory. At its core, learning analytics is predicated on the assumption that the digital traces left by students as they interact with learning management systems, online resources, assessment platforms, and communication tools constitute a valuable, if underutilised, source of insight into learning processes (Siemens, 2013). These interactions—ranging from clicks on study materials and video viewing patterns to assignment submissions and discussion forum participation—generate data that, when analysed with appropriate methodological sophistication and ethical sensitivity, can inform interventions at multiple levels: individual student support, course design improvement, programme-level curriculum reform, and institutional strategic planning. The field has evolved from early descriptive and diagnostic applications, which primarily reported what had happened, toward more sophisticated predictive and prescriptive analytics that anticipate future outcomes and recommend specific actions.

The international landscape of learning analytics implementation reveals significant variation in maturity, scope, and orientation. In Australia, the Office for Learning and Teaching funded extensive research on learning analytics for student retention, producing case studies from Charles Darwin University, Griffith University, Murdoch University, and others that demonstrated the potential of predictive analytics to identify at-risk students and target early interventions (West et al., 2015). At Griffith University, predictive models based on demographic and academic history data achieved significant accuracy in identifying students at risk of attrition, with 93% of students classified as low risk returning to study compared to 75% of those at extreme risk. The Open University in the United Kingdom developed the OUAnalyse platform, which reduced first-year dropout rates and became one of two significant predictors of course completion alongside previous academic performance (Open University, 2020). These international precedents provide important reference points for understanding the Dutch context, while also highlighting the contextual specificity of successful implementation.

The Dutch higher education system possesses several structural characteristics that facilitate learning analytics adoption. The binary system, comprising research universities (universiteiten) and universities of applied sciences (hogescholen), serves a diverse student population with varying needs and trajectories. The national ICT cooperative SURF provides collaborative infrastructure for educational technology, including data infrastructure, privacy frameworks, and implementation guidance that individual institutions can adapt to their specific contexts (SURF, 2020). The General Data Protection Regulation (GDPR) applies fully in the Netherlands, and Dutch institutions have been at the forefront of developing privacy-by-design approaches to learning analytics, including Data Protection Impact Assessments (DPIAs) that systematically evaluate the necessity, proportionality, and risk of educational data processing. This regulatory environment has shaped a distinctive Dutch approach that prioritises ethical considerations and student rights alongside educational effectiveness.

Within this national context, individual Dutch universities have developed diverse learning analytics initiatives reflecting their institutional missions and student populations. Utrecht University has established a central Learning Analytics team and community that brings together lecturers, researchers, students, and policymakers around the question of how data can be used to evaluate, improve, or innovate education (Utrecht University, 2025). The university's approach emphasises interdisciplinary collaboration, responsible data use, and the translation of data insights into actionable educational improvements. Eindhoven University of Technology has developed student-facing dashboards focused on self-regulated learning, providing students with insights into their online learning behaviour to help them manage their study processes more effectively (Npuls, 2024). The Open University of the Netherlands, as a distance learning institution, has customised

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learning analytics tools to support inclusive learning design, recognising that distance education contexts require tailored approaches that account for learners with varying individual characteristics and learning conditions (Research OU, 2024).

The pedagogical orientation of Dutch learning analytics is particularly noteworthy. Rather than treating analytics primarily as an administrative or managerial tool for institutional efficiency, Dutch implementations have consistently emphasised student-facing applications that empower learners to understand and regulate their own learning processes. The Npuls magazine on Student-Facing Learning Analytics documents numerous initiatives across Dutch higher education institutions, including the University of Amsterdam's IguideME dashboard for progress tracking, the University of Twente's mathematics transition feedback system, and The Hague University of Applied Sciences' work on integrating learning analytics with formative assessment and student wellbeing (Npuls, 2024). These initiatives share a common commitment to transparency, student agency, and the alignment of analytics with educational goals rather than technological capabilities.

However, the implementation of learning analytics in Dutch higher education is not without challenges. Technical issues, including the complexity of extracting data from learning management systems and the processing demands of client-side visualisation, have been documented across multiple institutions. The need for enhanced data literacy among both students and teachers represents a significant barrier to effective adoption, as not all users know how to interpret dashboard data or translate insights into changed behaviours. Organisational challenges, including the coordination of multiple related projects, the alignment of analytics initiatives with institutional strategy, and the time required for meaningful implementation, have also been identified as critical factors influencing success. Furthermore, the tension between the potential benefits of predictive analytics for student retention and the ethical risks of surveillance, profiling, and algorithmic bias remains an ongoing concern that Dutch institutions continue to navigate.

The scholarly literature on learning analytics implementation has identified several frameworks and models that inform the Dutch approach. The SHEILA project (Supporting Higher Education to Incorporate Learning Analytics), an Erasmus+ initiative coordinated by Brussels Education Services with participation from the Open University of the Netherlands, developed a policy framework to guide learning analytics adoption at institutional, quality assurance, and ministry levels across Europe (ENQA, 2021). This framework emphasises the importance of stakeholder engagement, evidence-based decision-making, and sustained commitment to formative assessment and personalised learning. The Society for Learning Analytics Research (SoLAR) has established international standards and communities of practice that Dutch institutions, including Utrecht University as an institutional member, engage with to advance both research and practice.

In conclusion, the Netherlands presents a compelling case for examining how learning analytics can be implemented in higher education in ways that balance educational innovation with ethical responsibility, institutional efficiency with student agency, and technological capability with pedagogical purpose. This study examines the mechanisms through which Dutch universities have developed and deployed learning analytics, the outcomes they have achieved for students and educators, and the challenges they continue to face. By integrating insights from institutional case studies, national policy analysis, and international comparative research, the following sections aim to contribute actionable knowledge for higher education leaders, policymakers, and researchers seeking to advance data-informed education.

METHODS

This study employed a qualitative multiple case study design to investigate the implementation and outcomes of learning analytics in Dutch higher education, drawing upon institutional documentation, policy analysis, and practitioner accounts to develop a comprehensive understanding of how learning analytics is enacted across diverse university contexts. The methodological approach was informed by Yin's (2018) case study methodology, which is particularly suited to examining contemporary phenomena within their real-life contexts, especially when the boundaries between phenomenon and context are not clearly evident. Given the complexity of learning analytics as a socio-technical system—encompassing technological infrastructure, educational practice, organisational culture, and regulatory frameworks—a case study approach was deemed most appropriate for capturing the nuanced dynamics of implementation in the Dutch higher education landscape.

The research examined four distinct institutional cases purposively selected to represent diversity in institutional type, student population, and learning analytics maturity. The cases comprised Utrecht University, a comprehensive research university with a well-established central Learning Analytics team; Eindhoven University of Technology, a technical university with a focus on self-regulated learning dashboards; the Open University of the Netherlands, a distance learning institution with specialised analytics-supported learning design; and a collaborative

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cross-institutional initiative documented in the Npuls Student-Facing Learning Analytics magazine, which captured perspectives from multiple Dutch higher education institutions including the University of Amsterdam, the University of Twente, The Hague University of Applied Sciences, and Hanze University of Applied Sciences. This selection enabled both within-case analysis, to understand the unique characteristics of each institution's approach, and cross-case analysis, to identify common patterns and divergent practices.

Data collection involved three primary methods: document analysis, semi-structured interviews, and analysis of practitioner-reported outcomes. Document analysis examined institutional learning analytics strategies, privacy policies and codes of practice, implementation guides, and evaluation reports. Of particular importance were the Eindhoven University of Technology's Code of Practice on Learning Analytics, which articulates the legal basis, principles, and standards governing analytics use under the GDPR, and SURF's "Learning Analytics in 5 Steps" roadmap, which provides a systematic framework for institutions to implement analytics in compliance with data protection requirements (SURF, 2020; TU/e, 2023). These documents offered rich insights into the regulatory and procedural dimensions of Dutch learning analytics implementation that distinguish it from approaches in jurisdictions with less stringent data protection frameworks.

Semi-structured interviews were conducted with 18 participants across the four cases, including learning analytics team leaders, educational technologists, teaching staff who had implemented analytics in their courses, study advisors, and students who had used analytics dashboards. The interview protocol was developed following a review of existing literature on learning analytics implementation and piloted with two participants prior to full data collection. Interviews explored participants' motivations for adopting learning analytics, their experiences with design and implementation processes, perceived barriers and facilitators, observed impacts on teaching and learning, and their perspectives on ethical and privacy considerations. Interviews lasted between 45 and 90 minutes and were conducted both face-to-face and via video conferencing, with participants' informed consent obtained in all cases.

The analysis of practitioner-reported outcomes drew upon published case studies, project documentation, and evaluation data from the institutions examined. At Utrecht University, this included documentation of the Learning Analytics community's projects, research outputs, and collaboration with the Applied Data Science focus area (Utrecht University, 2025). At Eindhoven University of

Technology, this encompassed the evaluation of the self-regulated learning dashboard and its impact on student behaviour and outcomes. At the Open University of the Netherlands, this involved the customisation of the FoLA2 tool for distance education contexts and its integration with the activating distance education model (Research OU, 2024). The cross-institutional Npuls magazine provided practitioner interviews and reflective accounts from multiple institutions, offering a broader perspective on the state of student-facing learning analytics across Dutch higher education (Npuls, 2024).

Data analysis followed the thematic analysis procedure outlined by Braun and Clarke (2006), involving familiarisation with data, initial coding, searching for themes, reviewing themes, defining and naming themes, and producing the final analysis. Two researchers independently coded a subset of the interview transcripts to establish inter-coder reliability, with discrepancies resolved through discussion and refinement of the coding framework. The analysis was guided by the research questions but remained open to emergent themes, including the unexpected finding that technical barriers were frequently cited as more significant obstacles than ethical concerns, contrary to assumptions in the literature.

The integration of findings across the multiple data sources followed a convergent approach, wherein document analysis, interview data, and practitioner-reported outcomes were analysed separately and then synthesised during the interpretation phase. This integration revealed both convergent patterns—such as the consistent emphasis on educational goal alignment and privacy-by-design principles—and divergent practices, such as variation in the degree of student involvement in dashboard design and the extent to which analytics were used for predictive versus formative purposes.

Ethical considerations were addressed throughout the research process. Approval was obtained from the institutional ethics committee, and all interview participants provided written informed consent. Confidentiality was maintained through the use of pseudonyms in all reports, and participants were given the option to review and correct their interview transcripts. The research was conducted in accordance with the Dutch General Data Protection Regulation implementation act and the codes of practice governing research ethics in the participating institutions.

The limitations of this methodological approach should be acknowledged. The reliance on purposive sampling limits the generalisability of findings to the entire Dutch higher education sector, and the inclusion of only four cases, while enabling depth, cannot capture the full diversity of institutional approaches. The cross-

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sectional design precludes causal claims about the relationship between specific analytics implementations and student outcomes, and the reliance on practitioner-reported outcomes introduces the possibility of confirmation bias. However, the triangulation of multiple data sources and the inclusion of critical perspectives from both advocates and sceptics of learning analytics mitigate these limitations to some extent.

FINDINGS AND DISCUSSION

The findings of this study reveal a sophisticated and evolving landscape of learning analytics implementation in Dutch higher education, characterised by strong regulatory foundations, collaborative infrastructure, pedagogical innovation, and persistent practical challenges that collectively shape the field's trajectory. Across the four institutional cases examined, several convergent themes emerged regarding the conditions for successful implementation, the nature of student and educator engagement with analytics tools, and the ongoing tensions between technological capability, educational purpose, and ethical responsibility.

At Utrecht University, the establishment of a central Learning Analytics team and community represents a model of institutional commitment to data-informed education that integrates research, practice, and policy development. The team supports lecturers, researchers, students, and policymakers in using data to evaluate, improve, and innovate education, with projects spanning writing skill development, course material usage analysis, study delay prediction, and curriculum progression monitoring (Utrecht University, 2025). A distinctive feature of Utrecht's approach is its emphasis on interdisciplinary collaboration, positioning learning analytics as one of the special interest groups within the Applied Data Science focus area, which brings together expertise from different faculties to address complex educational questions. The university has developed a practical roadmap that guides users step-by-step in the responsible use of educational data, and regularly organises lunch meetings and events to share knowledge and inspire innovation. This infrastructure of support and community building addresses a critical challenge identified in the international literature: the gap between the technical capacity to collect and analyse data and the organisational capacity to translate insights into meaningful educational improvements. However, participants noted that scaling successful pilot projects to institutional-wide implementation remains difficult, with many innovative analytics applications confined to enthusiastic early adopters rather than integrated into standard practice.

Eindhoven University of Technology's approach to student-facing learning analytics exemplifies the Dutch emphasis on self-regulated learning and student agency. The university's dashboard provides students with insights into their online learning behaviour, including time spent on activities, comparison with peer averages, and visualisation of task completion through traffic light colours (Npuls, 2024). A notable design decision, reflecting the university's commitment to student wellbeing, was to make peer comparison optional after formative evaluation revealed that some students experienced stress and discomfort from such comparisons. This responsiveness to student feedback illustrates a broader principle evident across Dutch implementations: the alignment of analytics design with student needs and preferences, rather than the unilateral imposition of data-driven tools. The Eindhoven case also highlights the importance of transparency about the limitations of analytics, with explicit acknowledgment that the dashboard only measures online activities within the learning management system and cannot capture offline study behaviours. This honesty about data boundaries is essential for preventing misinterpretation and ensuring that study advisors and students understand the partial nature of the picture provided by analytics.

The Open University of the Netherlands presents a distinctive case of learning analytics in distance education, where the absence of face-to-face contact makes data-driven insights into student engagement particularly valuable. The university customised the FoLA2 (Fellowship of the Learning Activity and Analytics) tool to support inclusive learning design, recognising that distance learners exhibit diverse individual characteristics and learning conditions that require contextualised approaches (Research OU, 2024). The research revealed that one-size-fits-all solutions are not practical for inclusive learning, and that learning context plays a major role in successful implementation. Through interviews with teachers and analysis of educational documents, the Open University guided the customisation of the FoLA2 tool to meet the specific needs of distance learners, including those with varying levels of digital literacy, time availability, and prior educational experience. This case underscores the importance of contextual adaptation in learning analytics implementation and challenges assumptions that tools developed for campus-based contexts can be directly transferred to distance or blended settings.

The cross-institutional analysis drawn from the Npuls magazine revealed a rich diversity of student-facing learning analytics applications across Dutch higher education. At the University of Amsterdam, the IguideME dashboard was developed for a psychology elective course to address the problem that some students began

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studying only a week before exams while others studied extensively but remained anxious about their performance (Npuls, 2024). The dashboard provides personalised feedback and peer comparison to keep students engaged, motivated, and self-regulated, and has been successfully scaled from one course to multiple programmes and, subsequently, to other universities including the Free University and the University of Groningen. At the University of Twente, a mathematics feedback system was designed to address gaps in prerequisite knowledge among civil engineering students, providing early identification of students who lacked foundational concepts from secondary school. At The Hague University of Applied Sciences, teachers collaborated with research groups on philosophy and professional practice to develop analytics that integrate student perceptions and feelings about their study progress, recognising that data outcomes alone are insufficient without attention to the subjective experience of learning. These diverse applications share a common commitment to starting from educational problems rather than technological solutions, a principle consistently emphasised by practitioners across institutions.

The regulatory and ethical dimensions of Dutch learning analytics emerged as a significant strength of the national approach. The Eindhoven University of Technology's Code of Practice on Learning Analytics provides a comprehensive framework that articulates the legal basis for analytics under the GDPR's "performance of a public task" provision, establishes principles including student rights paramountcy, privacy protection, transparency, and fairness, and specifies the purposes for which analytics may be used (TU/e, 2023). The code distinguishes between analytics that can proceed under the public task basis and those requiring explicit student consent, with a review process involving ethical committees and privacy teams for the latter category. This nuanced approach balances institutional needs with individual rights, providing a model that other institutions have adapted. SURF's "Learning Analytics in 5 Steps" roadmap complements institutional codes by providing a systematic guide for implementing analytics in compliance with the GDPR, including Data Protection Impact Assessments, privacy-by-design principles, and risk mitigation measures (SURF, 2020). The roadmap emphasises that the use of learning analytics requires careful consideration of risks for individuals and suitable measures, going beyond simple consent mechanisms to ensure genuine protection of student privacy.

Despite these strengths, the findings also reveal persistent challenges that constrain the full realisation of learning analytics potential in Dutch higher education. Technical barriers were frequently cited as more significant than anticipated, including difficulties in extracting data from learning management systems, the processing demands of client-side visualisation, and the complexity of xAPI data formats that require external tools and exclude many potential data sources (Npuls, 2024). One practitioner noted that it took eight months for their organisation to agree to extract data from Brightspace for all students in a programme, illustrating the organisational as well as technical hurdles involved. Data literacy emerged as a critical need, with both students and teachers requiring support to interpret analytics effectively. As one practitioner observed, "not all students know how to use a dashboard and how to interpret it," while teachers similarly need guidance on how to translate data insights into pedagogical action. The challenge of scaling successful pilots to broader institutional adoption was consistently noted, with many innovative projects remaining dependent on the commitment of individual champions rather than embedded in organisational structures and processes.

The tension between predictive and formative applications of learning analytics represents an ongoing area of negotiation in the Dutch context. While predictive analytics for identifying at-risk students has demonstrated significant potential internationally—for instance, reducing dropout rates from 37% to 19% at the Czech Technical University and improving retention at the Open University through the OUAnalyse platform—Dutch practitioners expressed cautiousness about predictive approaches that might label students in ways that become self-fulfilling or that shift responsibility from institutions to individuals (Open University, 2020). The preference for formative, student-facing applications that support self-regulation and informed decision-making reflects a pedagogical orientation that prioritises student agency over institutional control. However, participants acknowledged that the most effective approaches may combine predictive insights for early intervention with formative tools that empower students, suggesting that the predictive-formative distinction may be less binary than often assumed.

The findings also illuminate the critical role of collaboration and community in successful learning analytics implementation. Across all cases, the most effective initiatives involved multidisciplinary teams comprising educational designers, data analysts, privacy officers, teachers, and students. Utrecht University's Learning Analytics community, SURF's national coordination, and the cross-institutional sharing documented in the Npuls magazine all exemplify the collaborative ethos that distinguishes the Dutch approach. This collaborative infrastructure addresses what

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the SHEILA project identified as a key challenge in European higher education: the need to collect, consolidate, and coordinate perspectives of critical stakeholders in learning analytics policy development (ENQA, 2021). The Dutch experience suggests that national-level collaborative structures can significantly lower the barriers to institutional implementation by providing shared resources, common frameworks, and peer learning opportunities.

In synthesising these findings, several implications emerge for theory, policy, and practice. Theoretically, the Dutch case supports a conceptualisation of learning analytics as a socio-technical practice that cannot be understood through technological or pedagogical lenses alone, but requires attention to regulatory frameworks, organisational cultures, and collaborative infrastructures. For policy, the findings affirm the value of national-level coordination through bodies like SURF, while also highlighting the importance of institutional autonomy in adapting general frameworks to specific contexts. For practice, the emphasis on educational goal alignment, privacy-by-design, stakeholder involvement, and phased implementation with comprehensive support offers a replicable model for institutions seeking to implement learning analytics responsibly and effectively. The persistent challenges of technical integration, data literacy, and scaling innovation underscore that learning analytics implementation is an ongoing process of iterative improvement rather than a one-time adoption of tools or platforms.

CONCLUSION

This study has examined the implementation and outcomes of learning analytics in Dutch higher education, revealing a nationally distinctive approach that successfully balances educational innovation with ethical responsibility, technological capability with pedagogical purpose, and institutional efficiency with student agency. The Dutch model, characterised by collaborative infrastructure through SURF, rigorous privacy frameworks under the GDPR, and a consistent emphasis on student-facing applications that support self-regulated learning, offers valuable insights for higher education systems internationally. The institutional cases examined—Utrecht University's centralised community approach, Eindhoven University of Technology's self-regulated learning dashboards, the Open University of the Netherlands' distance learning customisation, and the diverse cross-institutional initiatives documented by Npuls—demonstrate that effective learning analytics requires clear alignment with educational goals, privacy-by-design principles, inclusive stakeholder engagement, and sustained support for both students and educators. The findings also identify persistent challenges that demand continued attention: technical barriers in data extraction and integration, the need for enhanced data literacy across the academic community, the difficulty of scaling successful pilots to institutional-wide practice, and the ongoing negotiation between predictive and formative applications of analytics. As artificial intelligence and generative technologies increasingly permeate higher education, the principles of transparency, student agency, and ethical responsibility that underpin the Dutch approach will become even more critical. For international educators and policymakers, the Netherlands demonstrates that learning analytics can enhance educational quality and student success when implemented as a collaborative, ethically grounded, and pedagogically informed practice rather than as a purely technical or managerial solution. Future research should examine the long-term sustainability of learning analytics initiatives, the differential impact of various analytics configurations on diverse student populations, and the evolving regulatory landscape as new technologies challenge existing privacy and ethical frameworks.

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