LEARNING ANALYTICS AMONG UNIVERSITY TEACHERS: PRELIMINARY FINDINGS

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This study investigates the use of learning analytics among university teachers. A survey, developed based on a literature review, was distributed to faculty members at the University of Maribor, Slovenia, and the University of Rijeka, Croatia. The preliminary findings show that university teachers primarily use learning management systems to collect data, but rarely combine data from different sources or use advanced analytics techniques such as machine learning. The study also reveals scepticism around ease of use, confidence in analytics and social impact, highlighting the importance of facilitating conditions for adoption. Despite these challenges, participants recognise the benefits of learning analytics to make informed decisions and improve teaching effectiveness. The study underscores the need for further research to develop better tools and support for widespread adoption.

Keywords:
learning analytics,
higher education,
university teachers,
acceptance,
benefits

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1 Introduction

The increasing accessibility and use of digital technology leaves behind extensive data trails that form a basis for meaningful analyses and predictions of user behaviour. In areas such as marketing, customer data is used to predict interest in future products; Netflix curates movie recommendations based on individual viewing habits and Amazon anticipates book preferences to drive engagement and sales. The vast potential of data analytics has also spread to academia, where similar methods are being used to improve learning experiences and outcomes. Studies examining learning analytics in higher education have shown promising results in identifying student needs, improving academic outcomes and supporting student retention (Cobo-Rendon et al., 2021; Denley, 2014; Gašević et al., 2016; Kaliisa et al., 2022).

Learning analytics, broadly defined, provides educators with insights into student learning behaviour through the analysis of data patterns, enabling more informed decisions about targeted interventions. At the course level, these insights can significantly improve the quality of pedagogical support by revealing barriers to learning and enabling timely feedback. The notion that learning analytics can drive meaningful improvements in educational practise has gained widespread acceptance in recent years. In this study, we adopt the widely accepted definition of the Society for Learning Analytics Research (SoLAR), established at the first International Conference on Learning Analytics and Knowledge and cited by (Siemens & Long, 2011, p. 34): "Learning analytics is the measurement, collection, analysis, and reporting of data about learners and their contexts for the purpose of understanding and optimising learning and the environments in which it takes place."

Learning analytics can generally be divided into two main categories: descriptive and diagnostic analytics, which focus on the analysis of past data, and predictive and prescriptive analytics, which aim to predict learner behaviour or outcomes and guide appropriate interventions. While descriptive and diagnostic analyses help to understand students' past performance and identify patterns, predictive and prescriptive analyses enable the development of strategies to support individual learning trajectories and predict likely educational outcomes (Bamiah et al., 2018). For educators, particularly in higher education, this ability to both understand and predict learners' needs represents a major opportunity to improve academic support and promote learning success.

However, despite this potential, the full scope of learning analytics is not yet being fully utilised, even by universities with significant investment in this area, such as The Open University UK (Olney et al., 2021). There is a growing awareness of the opportunities and limitations associated with these tools. Critics argue that learning analytics should not only be considered as a tool to promote the digital transformation of education, but must also take into account the human element, as outcomes depend on the interaction between the analytics tools and the various stakeholders, including students, lecturers and administrators (Ferguson et al., 2019; Olney et al., 2021). Considering these human factors is critical to understanding the real-world application of learning analytics and fostering a supportive, data-driven academic environment.

This study aims to broaden our understanding of the practical use of learning analytics from the perspective of university teachers and academic staff. Using a quantitative approach, we aim to investigate how teachers use learning analytics, what challenges they face and what benefits they see. By focusing on these stakeholders, we fill a critical gap in the literature that often emphasises technological capabilities over the nuanced, human-centred challenges of integrating data analytics in education. The findings of this study contribute to the ongoing discourse on optimising learning environments by providing initial insight into the factors that facilitate or hinder teachers' use of learning analytics. The findings are valuable not only for academic institutions, but also for educational technology developers who want to design and implement analytics tools that truly support teaching and learning. This paper presents the preliminary results of this research and highlights the current situation in higher education in Slovenia and Croatia.

2 Theoretical background

In the pre-digital era, educational data was rarely collected or used, and learning technologies were mainly developed based on behaviourist principles. Although behaviourism appears to be disconnected from learning analytics, Rodriguez (2013) has noted that large online education platforms such as MOOCs like Udacity, EdX and Coursera apply behaviourist principles by relying on traditional methods such as skill learning and reinforcement of concepts through interactive exercises. Clearly defined, measurable learning objectives make it possible to assess certain levels of learning outcomes even by digital technology (Ye, 2022).

In educational research, a distinction is made between assessment and evaluation in the educational context. Formative assessment aims to improve a learning product during its development, while summative assessment assesses the effectiveness of the final version. Initially, only quantitative data was collected, but later qualitative data was added, allowing researchers to observe student behaviour using rubrics and checklists. Today, both assessment and evaluation are fundamental to pedagogical practise as researchers seek to utilise all relevant data to improve both teaching and learning.

Although digital technology had already found its way into education at the beginning of the 20th century, it was not until the 1990s that online learning became widely accepted (Ye, 2022). The introduction of learning management systems (LMS) created a multi-channel platform where students could participate and share information. Lecturers were able to share lectures, assign tasks, make exams and promote online discussions that supported collaborative learning. LMSs also enabled efficient data collection and recording, creating a rich repository of information about student engagement and performance. Data from LMS platforms capture interaction traces and link key stakeholders (such as students and instructors) to course content (e.g., videos, web pages, quizzes, and discussion forums) and actions (e.g., clicks, responses, and views). This automatic data collection is a fundamental element for the development of learning analyses.

Despite the increasing use of LMS, content creation and course delivery still largely depend on the intuition of teachers. Since many LMSs still offer only basic analyses, deeper data analysis is essential to unlock the full potential of this information to improve teaching and learning practises. Advanced techniques — such as social network analysis, sentiment analysis, impact analysis and predictive modelling of learning outcomes — are particularly valuable (Siemens & Baker, 2012). Hoppe (2017) proposes a triad of methodological approaches in learning analytics: (1) social network analysis, which focuses on the relationships between actors and artefacts; (2) process-oriented analysis, which includes action pattern detection and sequence analysis; and (3) content analysis, which uses techniques such as text mining to analyse student-generated artefacts. These overlapping approaches can create valuable synergies and provide a more nuanced view of learning behaviour and outcomes.

Advanced analytics require specialised expertise, facilitating the creation of dashboards that visualise data to help educators and administrators identify and address specific learning challenges. Despite their potential, these tools remain underutilised in education, revealing a notable implementation gap. To bridge this gap, more research and practical strategies are needed to seamlessly integrate learning analytics into daily educational practices, transforming raw data into actionable insights that enhance teaching quality and support student achievement.

3 Methodology

To investigate the actual use of learning analytics among university teachers, as well as the drivers for adoption and perceived benefits, we conducted a quantitative survey drawing on established theoretical frameworks. We chose Unified Theory of Acceptance and Use of Technology (UTAUT) (Davis, 1989) as the primary framework for our study as it comprehensively covers the relevant acceptance factors identified in the literature. To elicit responses, we developed a structured questionnaire with a 5-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5). This format allowed for a standardised approach to assessing teachers' perceptions, challenges and usage patterns of learning analytics. The questionnaire was designed and distributed via the online platform 1ka, which enabled secure data collection and allowed us to efficiently manage and analyse the responses.

We started distributing the questionnaire by contacting the deans of education at each faculty of the University of Maribor and the University of Rijeka. An introductory email was sent with a link to the survey and a request for further distribution, asking the vice deans to forward the survey to all faculty members involved in teaching. This approach was intended to capture a broad and representative sample from a range of disciplines and faculties, reflecting a range of views on the use and potential of learning analytics in higher education. Despite this approach, the initial response rate was lower than expected. We therefore extended the data collection period to improve the sample size and reliability of the data.

In this article, we present an initial analysis based on the collected responses. The data has been exported and analysed using Microsoft Excel. Future analyses will extend this preliminary assessment by examining correlations between demographic factors (such as teaching experience and subject specialism) and attitudes towards learning analytics.

4 Results

As part of the study, 154 university teachers were surveyed, with 148 participants completing the questionnaire in full; only these responses were included in our analysis. The respondents came from 14 faculties of the University of Maribor and 12 faculties of the University of Rijeka. The majority of respondents held the academic title of full professor (26%), associate professor (25%) and assistant professor (24%), followed by assistant (14%), lector (8%), senior lecturer (3%) and lecturer (1%).

56% of respondents had more than 15 years of professional experience, followed by those with 11-15 years (21%), 6-10 years (13%), 1-5 years (10%), and less than one year (1%) of experience. In terms of age distribution, respondents aged 45-54 years (36%) were predominant, followed by those aged 35-44 years (35%), 55-64 years (14%), 25-34 years (11%) and 65 years or older (3%).

The participating university teachers use learning analytics, albeit to a fairly limited extent. Mostly they use the functions of LMS and collect data from platforms, such as the submission of assignments and quizzes. They use available reports in LMS tools and occasionally other web applications, but data collection through student surveys or online tools such as MS Teams is less common. The use of sensors or wearable devices for data collection is rare. Data integration is also rare, with participants occasionally merging data of the same format and rarely combining data from multiple sources with different data types. Analytical functions within LMS tools are occasionally used, while dashboard analyses using Excel or business intelligence tools and machine learning to predict learning outcomes are rarely used (Figure 1).

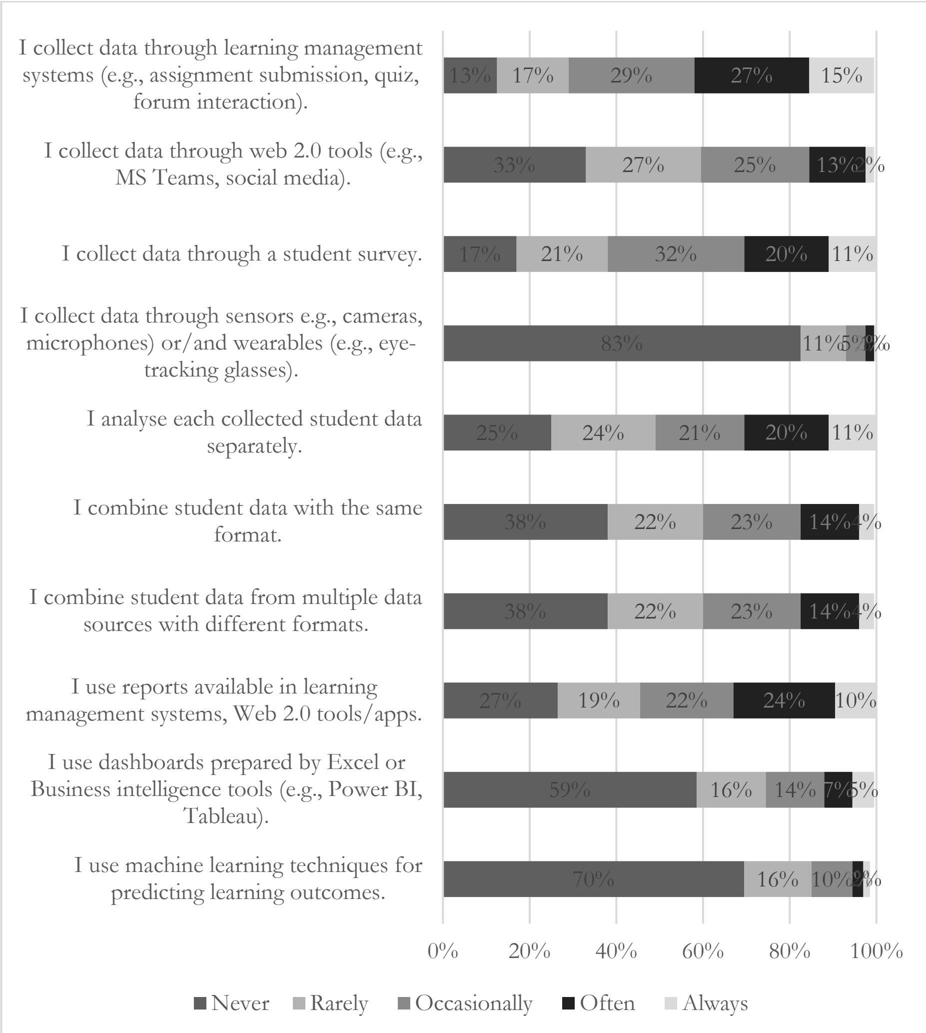

Figure 1: Use of learning analytics
Source: Own

We also analysed the most important factors mentioned in the literature: perceived effort, social influence, perceived risks and facilitating conditions.

Perceived effort: Majority of the respondents (60%) neither disagreed nor agreed with the statement that using learning analytics is easy. 17% disagreed or strongly disagreed and 23% agreed or strongly agreed. Similar trends were observed for the statements about the ease of using learning analytics and acquiring the relevant skills.

Social influence: The results showed varying levels of agreement, suggesting that social influence is not a significant factor. Respondents most agreed with the statement that learning analytics is currently popular, followed by the statement that they know others who use it, and least agreed with the statement that influential people recommend it.

Perceived risks: Most respondents were neutral on perceived risks, although a greater proportion saw learning analytics as an opportunity. 45% of respondents were neutral on whether they trust the information provided by Learning Analytics. 38% agreed or strongly agreed and 1% disagreed or strongly disagreed. Similarly, 54% were neutral on the question of whether learning analytics provides accurate information for decision making, while 41% agreed and only 5% disagreed. The highest level of agreement was for the statement that learning analytics provides information in real time.

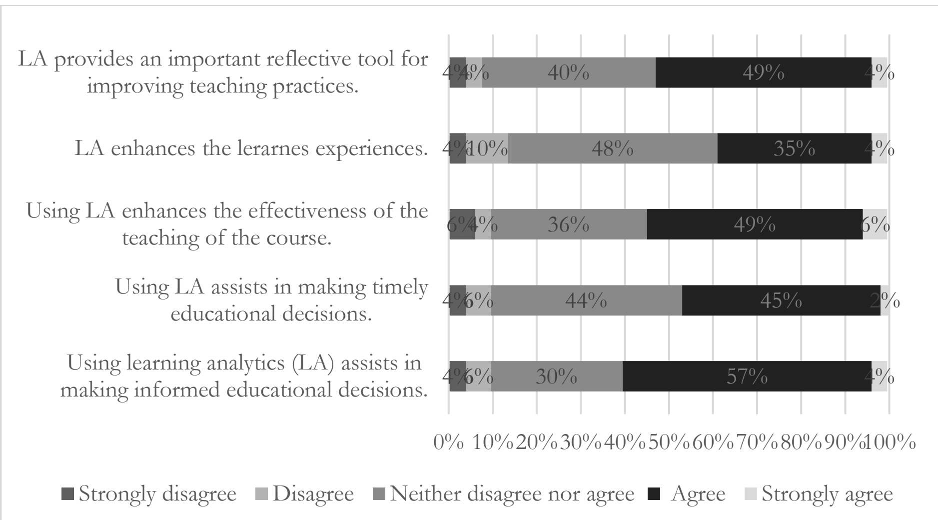

Figure 2: Benefits of using learning analytics

Source: Own

Facilitating conditions: Respondents mostly agreed that they have adequate tools to analyse data, but were less sure whether they have sufficient information and training on learning analytics. The lowest level of agreement was when asked about suitable guidelines for regulating data access.

Despite the limited use of learning analytics, respondents were largely in agreement about its benefits. Most agreed that learning analytics helps to make informed educational decisions, followed by the statement that it improves the effectiveness of the teaching of the course. They were less likely to agree that learning analytics contributes significantly to a better learner experience (Figure 2).

5 Conclusion

Learning analytics is transforming from a purely research-driven field to one with practical and widespread applications. Its growth is enhancing the educational experience by providing actionable insights and promoting a more learner-centred approach. The main contributions of this paper lie in providing a cross-national perspective on the practical implementation of learning analytics, identifying context-specific challenges and opportunities faced by university teachers in Slovenia and Croatia.

The preliminary findings of the study show that the use of learning analytics is still in its infancy at both universities. Although more and more institutions and stakeholders are recognising the potential of learning analytics to improve learning outcomes, the analysis shows that university teachers are primarily using LMS features. Data is mostly collected through assignments, quizzes and other activities, but rarely integrated with other data sources or analysed using advanced techniques such as machine learning. Despite the limited use of learning analytics, university teachers recognise the benefits. There is the strongest support for the statement that learning analytics helps to make informed pedagogical decisions, increase teaching effectiveness and serve as an important tool for improving teaching methods.

University teachers at both universities face challenges when it comes to implementing learning analytics. The analysis of factors such as perceived effort, social influence, perceived risks and conducive conditions indicates that teachers are relatively sceptical about the user-friendliness of learning analytics. Social influence does not play a major role in the introduction of these tools. In terms of perceived risks, teachers are rather cautious about the use of learning analytics. However, they generally agree that the framework conditions, such as appropriate tools and supportive environments, play a crucial role in promoting the use of learning analytics.

Although learning analytics has a positive impact on higher education, it is still only used to a limited extent by university teachers. To realise its full potential, it is important to create a supportive environment that includes advanced analytics tools, customised dashboards, access to relevant information and training, and clear guidelines for data usage. In addition, it is crucial to involve university teachers and other staff as active stakeholders in the development and implementation of learning analytics, as their direct engagement can lead to a better understanding and utilisation of these analytics tools.

As with most empirical research studies, it is necessary to point out certain limitations of this study. This study was conducted at a specific time and on a specific sample, which may limit the generalizability of the findings to other timeframes or populations. Testing on a larger sample group would contribute to a better reliability of the results and could provide more comprehensive insights into attitudes and perspectives on the practical implementation of learning analytics. It is also important to note that the study is limited as it was conducted on participants from only two universities, potentially limiting the diversity of perspectives and experiences within the sample. Additionally, the use of a rating scale (a Likert-type scale) can be seen as a limiting factor in conducting this study, as rating scales can influence the results of the study to some extent initially, potentially leading to biases in responses. Finally, the anonymity of the survey may hinder the researchers' ability to follow up or clarify responses, limiting the depth of understanding of participants' perspectives.

Future research should focus on more comprehensive and longitudinal studies that include different perspectives and stakeholders in the educational process. In addition, the development of improved methodological approaches is necessary to enable generalisable and transferable results. Learning analytics has the potential to become an important tool for improving pedagogical practise, but further research and the development of a supportive environment is needed to ensure a successful transition from theory to practise.

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