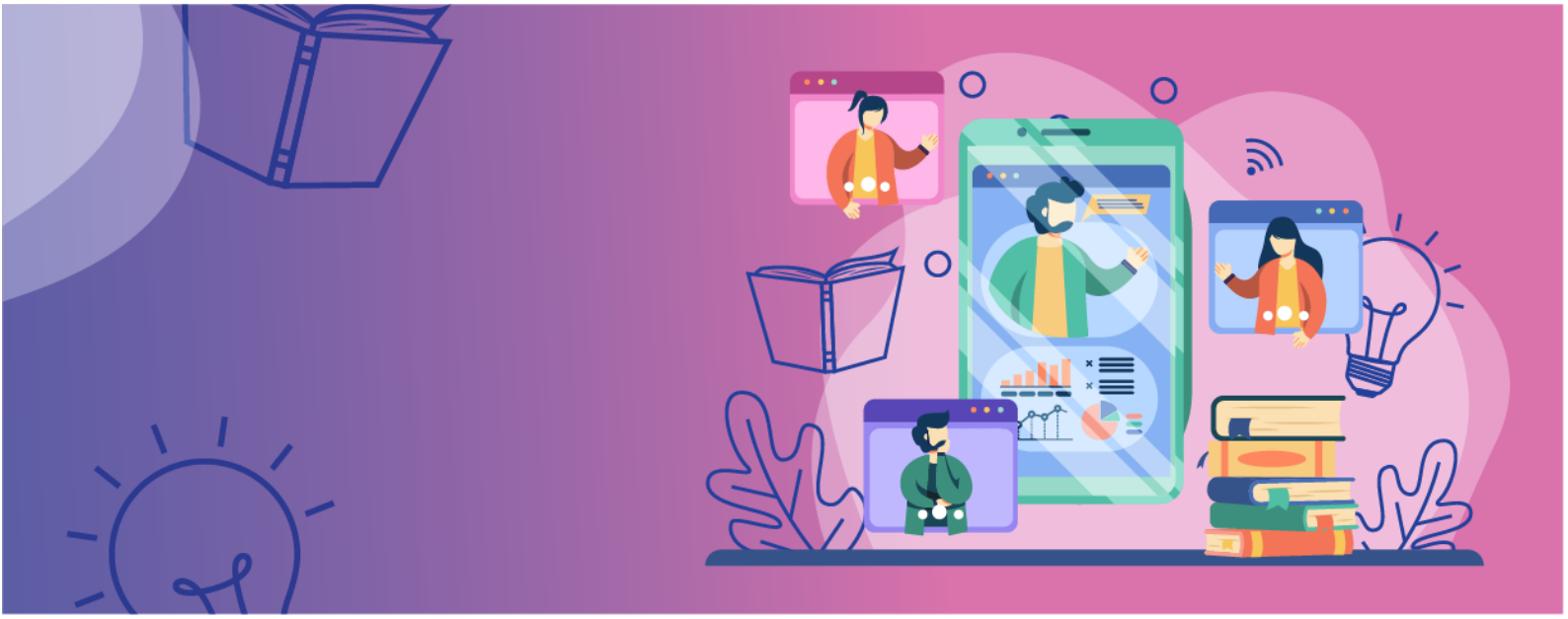
DIGITAL FIRST

Digital Tech as the First Language:

Informatics for Digital Natives

D7.3 Data modelling, data visualisation and data interpretation in learning analytics for informatics



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PREFACE

Welcome to the second installment of our guidebook series on learning analytics (LA) in informatics education. In this volume, we build upon foundational concepts introduced in Guidebook Part 1 and explore how data can be modeled, visualized, and interpreted to empower both teachers and students in the digital age.

Who Is This Guidebook For?

This guidebook is designed for educators, informatics specialists, researchers, administrators, and decision-makers, and anyone interested in learning how to use data to inform teaching, learning, and educational planning. Whether you are new to LA or seeking to deepen your understanding, this resource offers practical explanations, real-world examples, and clear guidance in accessible language. While focused on informatics, much of the content is applicable to other educational contexts.

Developed under the Digital First Project, this guidebook results from collaboration between the Turku Research Institute for Learning Analytics (TRILA), University of Turku, Finland; Vilnius University; and other project partners. Content draws on a literature review, TRILA expertise, and group discussions with experts and practitioners from partner countries (Bulgaria, Croatia, Cyprus, Finland, Greece, Italy, Lithuania, Portugal, Slovenia, Spain).

Guidebook Part 2 comprises three chapters:

1. **Introduction to LA, *A brief recap and contextual overview*:** This chapter provides a concise summary of LA—what it is, why it matters, and how it supports teaching, learning, educational planning. (For a more detailed introduction, readers are encouraged to consult Guidebook Part 1).
2. **Defining the most appropriate models for learning analytics in informatics teaching, *Selecting effective models*:** Here we introduce various data models used LA. We discuss how to choose models that best fit specific education scenarios.
3. **Visualization and interpretation of data for learning analytics in informatics, *Turning numbers into insights*:** This chapter focuses on how to represent data visually (using charts, graphs, dashboards, and more) and how to interpret these visualizations to derive meaningful conclusions that can enhance teaching practices and student outcomes.

How to Use This Guidebook

Feel free to read this guidebook from cover to cover or to consult individual chapters as needed. Each section contains practical explanations, simplified examples, and key takeaways. Technical terms are introduced gradually and always explained in plain language.

Our deepest gratitude goes to all contributors, particularly Prof. Jari Metsämuuronen, for guidance, and to the Algebra University team for reviewing and producing the manuscript.

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TABLE OF CONTENTS

PREFACE 1

1 INTRODUCTION TO LEARNING ANALYTICS 5

1.1 What is Learning Analytics? 5

1.2 Distinction Between Learning Analytics and Traditional Educational Assessments 6

1.3 Learning Analytics in K–12 Education 7

1.4 Learning Analytics in Informatics Education 9

References 9

2 DEFINING THE MOST APPROPRIATE MODELS FOR LEARNING ANALYTICS IN INFORMATICS TEACHING AND THEIR AUTOMATIZATION 12

2.1 Analytical Goal-Oriented Learning Analytics Models 12

2.1.1 Descriptive analytics model *12*

2.1.2 Diagnostic analytics model *13*

2.1.3 Predictive analytics model *14*

2.1.4 Prescriptive analytics model *15*

2.1.5 Profiling and Automated Decision-Making in Learning Analytics *15*

2.2 **Function-Oriented Learning Analytics Models** 16

2.2.1 Performance model *16*

2.2.2 Meta-cognitive model *17*

2.2.3 Interactivity model *17*

2.2.4 Communication model *18*

2.2.5 Data model *18*

2.3 Process-Oriented Learning Analytics Models 19

2.3.1 5-steps Oblinger Model *19*

2.3.2 LA Cycle Model *19*

2.3.3 4-dimensions LA Model *20*

2.3.4 7-steps LA Model *21*

2.3.5 Dynamic LA Model *22*

Summary: 23

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References 23

3 VISUALIZATION AND INTERPRETATION OF DATA FOR LEARNING ANALYTICS IN INFORMATICS 25

3.1 The Role of Data Visualization in Learning Analytics 25

3.2 Best Practices for Data Visualization 33

3.3 Interpreting Learning Analytics Data 34

3.4 Challenges and Considerations 35

Summary 36

References 36

LIST OF TABLES

Table 1: Common visualization techniques in learning analytics *25*

Table 2: Visualization methods for teaching and learning evaluation (TRILA, 2021, p. 14) *30*

LIST OF FIGURES

Figure 1: Automatic analytics in ViLLE platform detecting students' learning misconceptions in mathematics based on submission data 12

Figure 2: Predictive modeling of student learning outcomes based on course achievements during the first two weeks of an eight-week course 13

Figure 3: The 5-steps Oblinger Model (Image from Sciarrone & Temperini, 2019, p. 289) 18

Figure 4: The LA Cycle Model (image from Sciarrone & Temperini, 2019, p. 289) 19

Figure 5: 4-dimensions LA Model (image from Sciarrone & Temperini, 2019, p. 289) 20

Figure 6: 7-steps LA Model (image from Sciarrone & Temperini, 2019, p. 289) 20

Figure 7: Dynamic LA Model (image from Sciarrone & Temperini, 2019, p. 290) 21

Figure 8: Column chart from a teacher's view in the Moodle learning platform, showing statistics for a quiz with 6 questions. The "Facility Index" indicates how easy each question is—higher values mean more students answered correctly. "Discriminative efficiency" shows how well each question distinguishes between students who know the material well and those who do not 26

Figure 9: Administrator dashboard view in Moodle learning platform, displaying actions taken by users for courses flagged as "at risk of not starting" by the insight model 26

Figure 10: Heatmap from a teacher's view in the ViLLE learning platform, showing how many tasks each student has completed in different math content areas. Green indicates more completed tasks, while red indicates fewer completed tasks 27

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Figure 11: Histogram from a teacher's view in the Moodle learning platform, showing the number of students in each grade range (0–100) for a graded activity, such as a quiz or lesson.....27

Figure 12: Histogram from a teacher's view in the ViLLE learning platform, showing how many students earned each type of trophy—none, bronze, silver, gold, or diamond—based on the number of tasks.....28

Figure 13: Scatterplot from the teacher's view in the ViLLE learning platform, showing each student's diligence in a lesson by plotting their time spent and scores received.they completed in each math lesson.....28

Figure 14: Time series from a teacher's view in the Moodle learning platform, showing user activity in a course over one week. Each line indicates a different user role, and the vertical axis shows how many actions were performed by users, based on log entries.....29

Figure 15: Combined column and line charts from a teacher's view in the Moodle learning platform, showing the number of students who submitted exercises in a lesson, their accuracy, and the average time spent on the task.....29

Figure 16: Administrator dashboard in the ViLLE learning platform, showing whole-class data over an academic year: accuracy percentage, average number of submissions, average time spent, score per minute, and the number of active student accounts.....31

1 Introduction to Learning Analytics

A brief recap and contextual overview

Learning Analytics (LA) is transforming education by providing powerful tools to monitor, understand, and improve teaching and learning. In simple terms, LA refers to the process of measuring, collecting, analyzing, and reporting data about learners and their environments, all with the aim of optimizing educational outcomes (Ferguson & Buckingham Shum, 2011; Shum & Ferguson, 2012; Nistor & Hernández-García, 2018). For a more detailed introduction to LA, please see Guidebook Part 1.

1.1 What is Learning Analytics?

LA uses the "digital traces" left by students interacting with educational technology—such as online platforms, learning management systems, and digital assessments—to track and analyze aspects of their learning. Because LA relies on digital data, it describes only those parts of the learning process that are recorded electronically.

At its core, LA turns raw data into usable knowledge. This enables educators to make informed, evidence-based decisions that boost teaching effectiveness and support student learning.

Why Does Learning Analytics Matter?

LA helps both learners and educators in several ways:

- **For Learners:** Students benefit from real-time feedback and receive tasks tailored to their current abilities and learning needs. This allows for personalized learning experiences and helps keep students motivated and engaged.
- **For Educators:** Teachers can use LA to monitor individual student progress, spot difficulties and misconceptions, identify early signs of disengagement, and adjust their teaching methods to better support each learner. With these insights, educators become more responsive and effective in addressing diverse classroom challenges.
- **For Educational Institutions:** LA assists schools and universities in curriculum planning, professional development, and quality assurance. By analyzing data, institutions can adapt their strategies to better align with students' needs and drive continuous improvement.

Beyond the Classroom

LA is not just a practical classroom tool—it is also valuable in educational research. By examining large sets of data, researchers can gain a deeper understanding of how students learn, which teaching methods work best, and what factors influence educational outcomes.

A Socio-technical Approach

LA brings together education, data science, and pedagogy. It uses statistical methods, machine learning, and data visualization—all supported by learning theories and sound instructional design. The real value of LA lies in transforming data into actionable insights: predicting student behaviors, evaluating learning outcomes, suggesting interventions, and enhancing overall educational quality (Yu, 2025; Awad et al., 2024).

However, success in LA depends not only on technical analysis, but also on how well the results are interpreted, communicated to learners and educators, and incorporated into everyday teaching and decision-making.

The Role of Artificial Intelligence

Recent advances in artificial intelligence (AI) have made LA even more powerful. AI can quickly analyze enormous amounts of educational data—helping teachers and institutions gain valuable insights into student performance and engagement. Research shows that when LA is applied well, it can lead to improved student achievement (Awad et al., 2024).

Ethical Considerations

It is crucial to address ethical issues such as data privacy, transparency, and fairness. Responsible use of LA fosters trust among students, teachers, and other stakeholders, and ensures accountability.

Key Takeaway:

LA is a blend of technology and educational practice. It offers the promise of more responsive teaching, more personalized learning, and ongoing improvement in education—so long as technical, ethical, and practical aspects are thoughtfully balanced.

1.2 Distinction Between Learning Analytics and Traditional Educational Assessments

Rapid technological progress and evolving teaching strategies have changed the way we assess student learning. The differences between traditional educational assessments and LA are important to understand, as they help educators deliver more effective and individualized education.

Traditional Educational Assessments

Traditional assessments usually measure student achievement using standardized tests or teachers' observations. These familiar formats—like multiple-choice tests, essays, and practical exams—have long been the backbone of education systems. However, they typically offer only limited snapshots of student performance at particular points in time, focusing mainly on what students know or can do at the end of a lesson or unit.

This approach often misses the complexity of the learning process itself. It tells us the final result, but not how the student got there. Feedback is usually delayed until after grading, making it harder for teachers to adjust their instruction in response to student needs.

How Learning Analytics Differs

LA takes a fundamentally different approach by focusing on the *process* of learning, not just the *outcome*. Here are some key differences:

- **Process-Oriented Data:** LA tracks how students learn over time—monitoring patterns of engagement, the steps they take, time spent on tasks, and their problem-solving strategies (Raković et al., 2023). This helps teachers see not just what was learned, but how it was learned.
- **Timely Feedback:** Unlike traditional methods that may take weeks to return results, LA can deliver feedback almost instantly. This allows teachers to intervene immediately if students face challenges, and supports formative assessment practices that encourage ongoing improvement (Khajuria et al., 2025; Janardhana et al., 2025).
- **Holistic View of Learning:** LA looks beyond test scores. It can also measure student engagement, motivation, collaboration, persistence, and self-regulation. These insights support modern educational goals—such as student independence, lifelong learning, and continuous personal development—not just academic achievement (Knight, 2020; Russell & Wallis, 2019).

- **Predictive Insights:** LA uses predictive analytics to identify students who may struggle in the future. This enables educators to intervene early, offering help before problems escalate—a proactive step that traditional assessments rarely provide (Kumar et al., 2025).
- **Personalized and Adaptive Support:** With AI and big data, LA can create customized learning pathways and personalized feedback for each student. This represents a shift from "one-size-fits-all" assessments to adaptive approaches that recognize and respond to individual strengths and needs (Silva et al., 2024).

Key Distinction

The main difference between traditional educational assessments and LA lies in their approach to data and feedback (Kanth et al., 2018):

- **Traditional assessments** offer standardized methods and mostly static, delayed results.
- **Learning analytics** provides dynamic, data-driven insights with timely, personalized feedback and predictive recommendations.

This transformation supports educators in personalizing learning experiences, monitoring progress as it happens, and focusing on the ongoing development of every student. Ultimately, LA aligns better with modern educational goals of fostering continuous growth and learner agency.

Summary:

LA moves beyond traditional assessment by making the learning process visible, enabling immediate intervention, and supporting individual student needs—all of which are crucial for today's education systems.

1.3 Learning Analytics in K–12 Education

Global Context

Over the past decade, interest in LA has skyrocketed—with more than a thousand scholarly articles published between 2014 and 2024 (Kılıç & İzmirli, 2024). While LA initially gained traction in universities and corporate training settings, recent research is increasingly focused on primary and secondary schools (K–12). This reflects a growing commitment to using data to inform teaching and learning across all levels of education.

Despite this progress, the use of LA in K–12 schools is still relatively limited and inconsistent compared to its more widespread application in higher education. To unlock the full benefits of LA for younger learners, schools need greater involvement from teachers, closer alignment with curriculum standards and educational goals, and adaptations that fit the realities of each school environment (Kılıç & İzmirli, 2024; Sousa et al., 2021; Zamecnik et al., 2022).

Potential and Challenges: Research indicates that LA holds significant promise for improving student engagement, personalizing learning, and supporting school decision-making. Tools like dashboards can visualize student progress, deliver real-time feedback, and raise awareness about learning processes—helping educators act quickly and effectively (Valtonen et al., 2025). However, actual use of LA in K–12 classrooms is still in its early stages and not yet widespread (Sousa et al., 2021).

Global Perspectives: Cross-national studies involving countries like Finland, China, South Africa, Uruguay, and the USA show that, while collecting data is relatively straightforward, making sense of analytics and applying insights in schools can be quite complex. Cultural differences, technology access, and diverse teaching practices all influence

how LA is interpreted and used. These variations make large-scale, consistent implementation a challenge (Aguerrebere et al., 2022).

Practical Barriers: Practical issues such as limited teacher time and workload also present obstacles. For example, teachers may not have enough time to use formative assessment tools effectively, even when LA systems are in place (Karademir et al., 2024).

European Context

Our review of documents from ten EU countries provides insights into how LA is understood and implemented within European schools. Across Europe, the main aim of LA is to use data-driven methods to improve teaching, learning, and educational management, catering to the varied needs of K–12 schools.

In project partner countries, LA is primarily designed to support teachers in their daily practice. Key objectives include:

- Facilitating formative assessment
- Identifying students at risk of falling behind
- Enabling personalized and timely instruction
- Enhancing course and curriculum design
- Understanding student performance in depth

These goals equip teachers with tools to apply data-informed strategies, better meeting individual student needs.

LA also directly benefits students by personalizing learning paths, supporting timely interventions, and improving outcomes. By providing individualized feedback and recommendations, LA encourages students to reflect on their progress and grow into self-regulated learners—thus boosting motivation and academic success.

At the school and institutional level, LA supplies actionable data for decision-making. This helps prevent dropouts, aligns resources with school goals, informs curriculum changes, and supports ongoing quality assurance. These insights assist educational leaders in making strategic choices that lead to system-wide improvements.

Another important development is using LA to strengthen transparency and collaboration between home and school. By giving parents real-time access to their child's progress, LA allows families to play a more supportive role in their children's education.

The document review shows broad stakeholder engagement across Europe. Policymakers, education authorities, school leaders, teachers, students, technical teams, and researchers all participate in LA implementation. International organizations, including EU institutions and the World Bank, also help advance these initiatives.

Global vs. European Context: Summary

Globally, Learning Analytics is growing but faces challenges—including cultural, technological, and practical barriers in K–12 environments. Europe's approach mirrors these global trends but is characterized by coordinated stakeholder involvement, strong emphasis on teacher support, and efforts to foster home–school collaboration. While the core goals—personalized learning, formative assessment, and improved outcomes—are shared worldwide, European initiatives often focus on transparency and strategic alignment at both the classroom and institutional levels.

1.4 Learning Analytics in Informatics Education

LA has the potential to transform education across many fields—and informatics education is a prime example. Because informatics (including computer science and programming) is taught through digital platforms, simulations, and interactive tools, it generates exceptionally rich data on how students learn.

Each time a student writes code, solves a computational problem, or interacts with a simulation, digital systems record detailed traces of their actions. These traces provide teachers and researchers with in-depth information about the learning process—not just the final outcomes.

Insights Beyond Code

LA allows educators to see how students develop problem-solving strategies, work through coding errors, and apply computational concepts in real time. For example:

- Teachers can use analytics to pinpoint where students struggle with debugging and help them correct errors more effectively.
- Common error patterns and misconceptions in programming tasks are revealed, enabling educators to address these issues proactively, instead of waiting for mistakes to show up in final projects.

Beyond tracking coding performance, LA also supports the assessment of advanced thinking skills—including abstraction, decomposition, and algorithmic reasoning. By analyzing students' behaviors and decisions as they work through tasks, teachers gain insight into cognitive skills that traditional assessments might miss.

Impact on Engagement and Performance

Research shows that integrating LA into technology-rich informatics classrooms improves student engagement and performance, especially when used alongside strong teaching strategies (Awad et al., 2024). Students receive timely, targeted feedback, which helps them stay motivated and learn more efficiently.

Connecting Analytics with Practice

Projects like CT&MathABLE (**https://www.fsf.vu.lt/ct-math-able**) demonstrate the power of LA in informatics education. By connecting analytic insights to assessment and classroom practice, these initiatives help teachers create more meaningful and impactful learning experiences.

Summary:

LA gives informatics educators a deeper window into how students learn, where they struggle, and how they think. By leveraging detailed digital traces, LA enables more responsive teaching, effective intervention, and better support for developing the complex skills crucial in informatics.

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2 Defining the Most appropriate Models for Learning Analytics in Informatics Teaching and Their Automatization

Selecting effective models

Selecting and automating effective LA models is essential for harnessing the full potential of data-driven approaches in. LA models can be classified in various ways—such as by their goals, purposes, or processes—each offering a unique lens for addressing educational challenges. As Quadir et al. (2021) note, an LA model is made up of components and techniques that work together to carry out cognitive tasks and achieve targeted educational outcomes. The success of any LA model depends on how well its components are aligned with the objectives of the specific educational context (Chatti et al., 2012; Pinnell et al., 2017). This chapter explores three major ways to categorize LA models: analytical goal-oriented, function-oriented, and process-oriented classification.

2.1 Analytical Goal-Oriented Learning Analytics Models

LA models can be categorized according to the analytical goals they support within educational environments. The most common approaches are descriptive (What happened?), diagnostic (Why did it happen?), predictive (What could happen?), and prescriptive (What should be done?) models (OKM, 2024). This purposeful categorization enables educators and researchers to select models that match their objectives, allowing for focused analysis and effective intervention to improve the educational experience.

2.1.1 Descriptive analytics model

The descriptive analytics model is designed to summarize and interpret existing data about the learning process and outcomes. By examining information from past and current activities, it identifies trends, patterns, and distributions that provide educators with a foundational understanding of learner behaviors and performance. Descriptive analytics often organizes data using visual tools such as histograms, pie charts, or statistical indicators, making complex data easier to grasp and interpret.

Typical examples of descriptive metrics include the number of assignments completed, time spent on tasks, perceived difficulty levels, grade changes, absence, and course or program completion rates. These insights allow educators and training specialists to observe individual or group progress, monitor engagement levels, and evaluate instructional practices, all of which inform ongoing teaching adjustments. Descriptive analytics model is an integral part of every LA system, such as Moodle or ViLLE—a digital learning platform developed by the Turku Research Institute for Learning Analytics (TRILA).

A core element of descriptive analytics involves statistical summaries—such as calculating means, medians, and variance—to highlight central tendencies and variability in student performance. Clustering techniques, including k-means and hierarchical clustering, can group students according to similar behavior patterns or performance profiles, providing deeper insight into the diversity of learning approaches within a class. Automation is also a key feature of modern descriptive analytics. Batch data processing pipelines, using programming languages like Python or R, can be set up to automatically analyze raw data and generate summary reports after each class or term (For example, see Figure 1).

In informatics education, descriptive analytics might track how many coding exercises students finish, how much time they spend debugging code, or the frequency with which they use online resources. Visual dashboards can show how student grades evolve across programming modules or highlight participation rates in collaborative projects. By presenting clear summaries of student activity and outcomes, descriptive analytics forms the backbone of LA,

enabling teachers to quickly assess what has happened in their classrooms and providing the essential groundwork for more advanced analysis and targeted intervention.

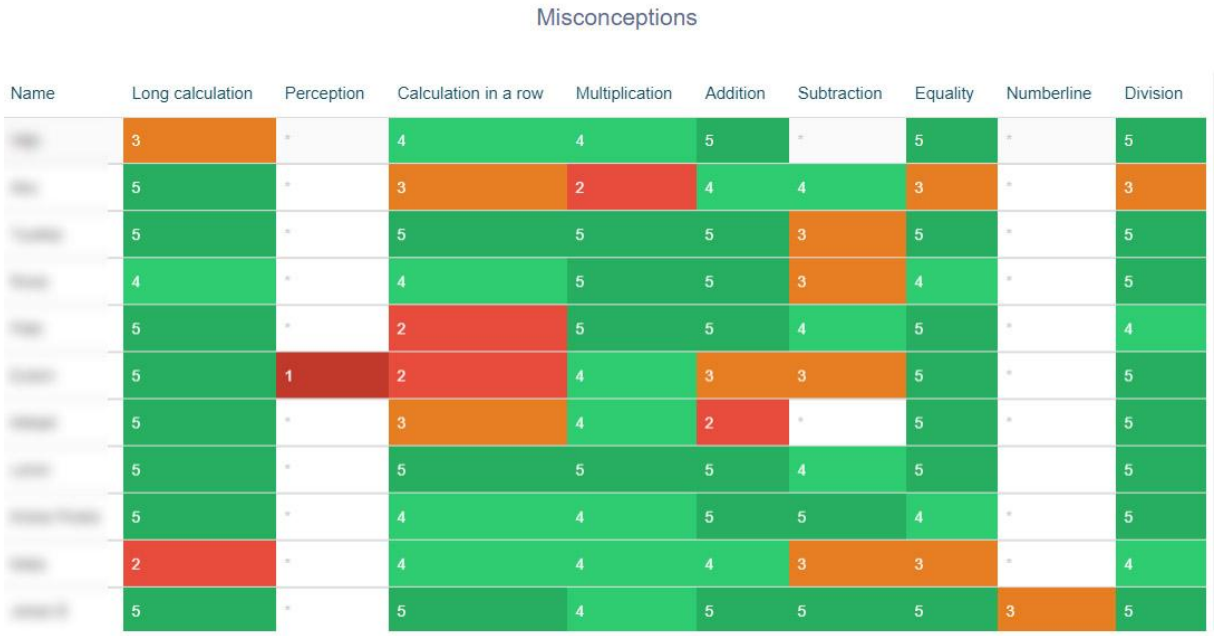


Figure 1: Automatic analytics in ViLLE platform detecting students' learning misconceptions in mathematics based on submission data.

2.1.2 Diagnostic analytics model

The diagnostic analytics model focuses on uncovering the underlying causes of specific learning behaviors or outcomes identified through descriptive analytics. It addresses questions such as why certain students struggle with particular concepts, why engagement levels drop at specific points in a course, which background factors precede lower or higher scores, and whether concurrent capabilities—such as reading fluency—influence math performance. By analyzing patterns, profiles, and anomalies in student data, diagnostic analytics helps educators move beyond simply observing what happened, toward understanding the reasons behind those outcomes.

Diagnostic analytics often involves comparing student performance across different tasks, identifying trends in error rates, or analyzing the influence of instructional methods and interventions. It can generate profiles from continuous data streams to highlight common challenges or learning bottlenecks within a group. In practice, digital assessment tools such as FUNA (Functional Numeracy Assessment; www.trila.fi/en/assessments/funa/), MUREA (Multilingual Reading Assessment; www.trila.fi/hankkeet/murea/), and DigiArvi/DigiEva (a digital tool supporting teachers' year-level assessment ; www.trila.fi/en/assessments/digiarvi/) are examples of diagnostic tools used within the Finnish education system to investigate learning achievement and difficulties and inform educational decisions.

Advanced diagnostic analytics techniques, such as association rule mining (using algorithms like Apriori) and Bayesian networks, help uncover relationships and dependencies within student data. These methods can reveal patterns—for example, which errors frequently co-occur or how mastery of one concept affects others. Automation plays a key role, with data pipelines and dashboards updating analyses as new data is added. This allows for real-time identification of related mistakes or conceptual gaps, enabling instructors to respond quickly with targeted support.

In informatics education, diagnostic analytics might examine why a group of students consistently fails certain programming exercises, pinpoint which coding concepts most often precede students' misunderstanding, or highlight anomalies in engagement—such as sudden drops in participation or recurring difficulties with debugging tasks. Educators can use these insights to tailor support, redesign course content, or provide targeted feedback that addresses the root causes of learning obstacles. Diagnostic analytics empowers teachers to make informed decisions, ultimately enhancing student learning experiences in computer science and programming classrooms.

2.1.3 Predictive analytics model

The predictive analytics model builds upon descriptive and diagnostic approaches by applying statistical modeling and machine learning algorithms to forecast future learning outcomes. This model uses historical and real-time data to anticipate trends, estimate grades, assess dropout risks, and predict academic performance (For example, see Figure 2). By recognizing early patterns associated with underperformance or disengagement, predictive analytics allows educators to intervene proactively and support students before problems escalate. DigiArvi/DigiEva (a digital tool supporting teachers' year-level assessment; www.trila.fi/en/assessments/digiarvi/) also incorporates predictive analytics models to help educators forecast student performance and identify those who may require targeted support. Beyond student support, predictive analytics also informs professional development by forecasting how effectively educators or employees will apply newly acquired skills.

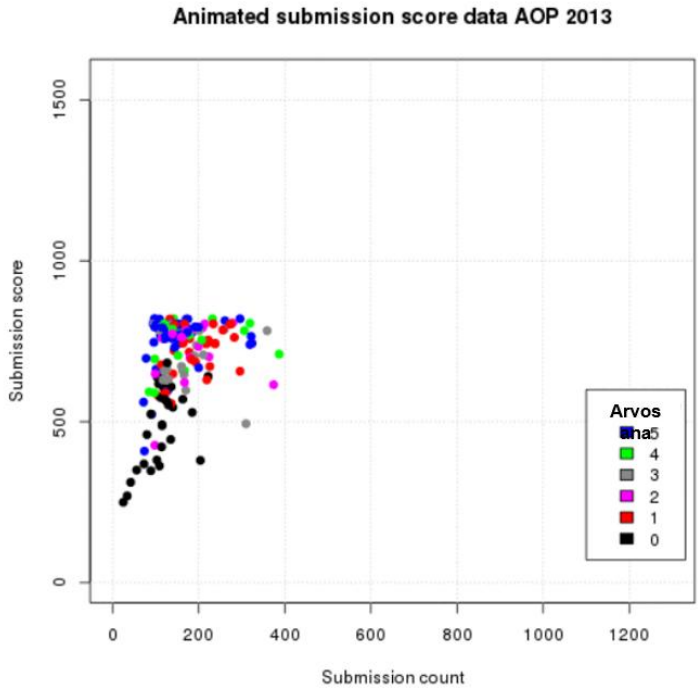


Figure 2: Predictive modeling of student learning outcomes based on course achievements during the first two weeks of an eight-week course.

Predictive analytics relies on techniques such as regression analysis (both linear and logistic), decision trees, random forests, and neural networks to analyze data and generate forecasts. Automation is integral: systems can be set up to continuously collect data from sources like learning management systems (LMS), train and update models regularly, and trigger alerts when risk factors are detected—such as signs that a student may struggle or disengage.

In informatics education, predictive models might forecast which students are likely to need help with upcoming programming assignments, predict success rates for coding challenges, or identify learners at risk of dropping out

from a course. For example, a predictive model can analyze patterns in coding submissions, quiz performance, and participation in online discussions to highlight students who may disengage or require additional support. Automatic alerts can notify instructors to provide timely mentorship or tailored resources, improving retention and student outcomes. Additionally, these models can inform curriculum planning by predicting task difficulty in programming modules, estimating future classroom participation rates, or forecasting the effectiveness of new instructional approaches in computer science courses.

2.1.4 Prescriptive analytics model

The prescriptive analytics model advances beyond description and prediction by offering concrete recommendations to optimize the learning experience, processes, and outcomes. It synthesizes insights from descriptive and predictive analyses to determine the best possible actions for achieving educational goals. Rather than simply asking what has happened or what might occur, prescriptive analytics addresses the question: "What should be done next?" This approach ensures that interventions are not just timely, but specifically tailored to individual learners or target groups.

Prescriptive analytics can guide educators in selecting the most effective teaching strategies, personalizing feedback, allocating resources efficiently, and recommending learning materials or activities based on projected student needs. Common applications include suggesting adaptive learning pathways for students, providing individualized automated feedback, and recommending instructional adjustments for teachers. For example, digital tools like BOSS (Briefcases of Special Support for basic education; www.trila.fi/en/ville-2/briefcases-of-special-support/) and TOMA (A second chance to learn numeracy for Grades 8–9 and vocational education; www.trila.fi/hankkeet/toma/) use prescriptive analytics to generate personalized and support learning pathways.

Techniques such as recommendation systems (using collaborative or content-based filtering) and reinforcement learning help optimize these suggestions, while automation ensures real-time responses through digital dashboards or bots.

In informatics education, prescriptive analytics models might recommend specific coding exercises to reinforce struggling concepts, suggest personalized practice tasks based on real-time student performance, or automate feedback to guide students toward improved programming habits. In programming courses, prescriptive analytics can be integrated into learning platforms to help instructors automatically assign remediation tasks, remind students about deadlines, or tailor coding challenges that adapt to individual skill levels—ultimately enhancing both student engagement and learning outcomes.

2.1.5 Profiling and Automated Decision-Making in Learning Analytics

This section summarizes key considerations described by the Ministry of Education and Culture, Finland (OKM, 2024, pp. 38–39) regarding profiling and automated decision-making in LA. Profiling and automated decision-making are important considerations when implementing LA, especially regarding data protection and privacy regulations. According to the General Data Protection Regulation (GDPR), profiling refers to any automated processing of personal data used to evaluate certain personal aspects of an individual—such as performance at work, financial status, health, preferences, interests, reliability, behavior, location, or movements. Automated decision-making, in turn, involves decisions made entirely by machines without human intervention, which can significantly affect the individual involved.

When using LA for profiling or automated decisions, it is essential to ensure that all the requirements of data protection laws are met. The processing of personal data must always be lawful, and compliance with data

protection regulations must be maintained even if automated decision-making is allowed in certain situations. Analytical models described in LA, including descriptive, diagnostic, predictive, and prescriptive analytics, can be analyzed from the perspective of profiling and automated decision-making.

Descriptive analytics, such as creating summaries and visual reports, generally does not require special actions related to profiling or automated decision-making, provided no individual-specific conclusions are drawn. **Diagnostic analytics**, which aims to identify the reasons behind certain outcomes (often using multiple data sources), may involve profiling if individual-specific conclusions are made. Such processing is considered normal as long as conclusions are not tied directly to individuals—or, if the data is anonymized, specific data protection rules may not need to be applied.

Predictive analytics, which uses models to forecast future events, often involves profiling if predictions are tied to individuals. **Prescriptive analytics**, using prediction models to guide decisions or actions, can be divided into categories based on the degree of automation in guidance. Fully automated decision-making that directly impacts a learner's legal status or significantly affects them is prohibited; however, automation can be used to support decisions, as long as it does not have such direct effects. For example, automated prompts, scoring, or recommendations are permitted, so long as they cannot result in failing a course or losing a study place without human oversight. It is permitted to use profiling as a tool for supporting decisions, as long as final decisions are made by a human and the criteria for assessment can be clearly explained.

There are no barriers to using LA as an aid for teacher or learner decision-making. However, if LA guides a learner's behavior or actions in a way that has legal ramifications, this is considered automated decision-making under GDPR and must be handled accordingly. The guiding principle is that LA should be regarded as a valuable assistant in decision-making—not the sole authority.

Importantly, student grades should not be determined solely by automated decision-making. Information generated by LA can serve as one demonstration of competence, but grades or official student records should always involve human review. Machine-generated grade recommendations can be used as evidence of ability, but cannot be directly transferred into student records without additional verification. The use of profiling and automated decision-making across all analytics models raises important concerns about fairness, accountability, transparency, and ethics (FATE), making it essential to address these issues thoughtfully in educational practice.

2.2 Function-Oriented Learning Analytics Models

LA models can be categorized according to their functions, with each model offering information such as students' performance and progress, modes of communication, or patterns of interactivity. This functional categorization enables educators and researchers to choose models that directly address the specific tasks or aspects of learning they wish to analyze. Quadir et al. (2021) identified five categories of function-oriented LA models in articles published in international journals between 2011 and 2019: Performance model, Meta-cognitive model, Interactivity model, Communication model, and Data model. Each of these categories represents a distinct functional focus within learning analytics and will be further explained in the following paragraphs.

2.2.1 Performance model

Performance models are designed to provide detailed insights into learning outcomes and patterns over time. These models track a learner's progress, academic achievement, development of skills, and overall competence—whether in formal assessments, informal activities, or long-term learning trajectories (Pinnell et al., 2017). Performance

models may also encompass additional aspects such as teacher effectiveness, instant response system outcomes, and even institutional measures like university rankings.

In informatics education, practical examples of performance models include analytics systems that monitor students' ability to write functional code, complete programming assignments, or meet specific computational learning goals. For instance, a performance model might analyze student achievement in coding challenges, difficulties faced by students in programming, or track skill acquisition in algorithm design. Similarly, these models can assess teacher performance by evaluating how well instructors facilitate learning in programming environments or how effectively automated feedback systems support student computational thinking.

2.2.2 Meta-cognitive model

Meta-cognition refers to the awareness and understanding of one's own thinking and learning processes. In the context of Learning Analytics, meta-cognitive models aim to capture and analyze the mental strategies, attitudes, and self-regulation behaviors that learners use while engaging with educational tasks (Petty et al., 2007; Pinnell et al., 2017). These models go beyond tracking simple outcomes, instead focusing on, for instance, how learners approach challenges, reflect on their progress, and make decisions during learning.

Advanced LA platforms can infer cognitive states by observing patterns in student behavior—such as problem-solving approaches, revision strategies, or response times (Petty et al., 2007). By identifying factors that influence incorrect answers or gaps in understanding, meta-cognitive models help teachers pinpoint not just what went wrong, but why it happened. This allows for targeted feedback and supports the development of critical thinking and learning habits.

For example, in informatics education, a meta-cognitive model might observe how students debug their code, monitor their responses to errors, or track their use of hints and help resources. If a new programming tool or learning environment is introduced, the model can analyze students' behavioral intentions and previous experiences to predict their acceptance and adaptability. Insights from these models empower educators to design instructional activities that foster reflective practices and improve student learning outcomes.

2.2.3 Interactivity model

The interactivity model focuses on the dynamic relationships and exchanges that occur during the learning process. Interactivity encompasses both social interactions, such as learner-to-learner and learner-to-teacher engagements (Pinnell et al., 2017) as well as human-computer interactions, where students interact with digital platforms and tools (Fischer, 2000). These models examine how the quality and frequency of these interactions influence student learning, engagement, and achievement.

By tracking and analyzing patterns of communication, collaboration, and participation, interactivity models help educators understand how learners connect with one another and with instructional resources. For example, these models can monitor contributions to online discussions, group project activities, peer feedback, and whole-class debates. The role of the teacher is also examined, particularly how instructors facilitate interaction and affect student engagement. Furthermore, interactivity models consider the influence of learning environments and stakeholders—including teachers, learning platforms, and interactive resources. They assess factors such as access to social learning tools, engagement with digital practice materials, and opportunities for collaborative learning.

In informatics education, interactivity models might analyze how students collaborate on coding projects, exchange ideas in online forums, or participate in live coding sessions led by an instructor. They can also monitor engagement with interactive programming environments, track peer review activities, or assess student participation in virtual

group computational problem-solving. Through these insights, educators gain a deeper understanding of how interaction enhances informatics learning and can tailor their teaching strategies accordingly.

2.2.4 Communication model

The communication model centers on how information is exchanged between individuals and the impact of different communication channels and tools on the learning process (Teplovs et al., 2011; Pinnell et al., 2017). These models explore not only the meanings embedded in messages, but also the choices learners and teachers make regarding mediums—such as spoken conversation, phone calls, emails, instant messaging, or social media. By analyzing the nature and frequency of communication, educators can gain valuable insight into student engagement, collaboration, and course effectiveness.

Communication models recognize that the tools used to share information—ranging from traditional face-to-face interaction to digital platforms—can significantly influence learning experiences and outcomes (Kent et al., 2016; Yang et al., 2016). Effective communication tools help students stay focused on relevant tasks, encourage participation, and foster a collaborative environment.

In informatics education, communication models might analyze interactions within programming forums, group messaging platforms, or collaborative document sharing. For example, the use of a CI (Collective Intelligence) Dashboard can present visual analytics highlighting crucial aspects of online debates or collaborative coding sessions facilitated by CCI (Computer Supported Collaborative Intelligence) discussion tools. By examining patterns in digital communication, educators can assess how students discuss coding problems, exchange solutions, or provide peer feedback, ultimately supporting improved learning outcomes and more effective group collaboration.

2.2.5 Data model

The data model in Learning Analytics focuses on the systematic collection, organization, and interpretation of information related to learning activities. These models are designed to be platform-independent, meaning they can operate across different educational technologies and environments (Lukarov et al., 2015). By gathering a wide range of data—including student performance metrics, feedback, progress measurements, completion rates, and scores—data models provide a comprehensive and flexible framework for analyzing educational outcomes (Siemens & Baker, 2012).

Data models often incorporate sophisticated tools and techniques, such as in-game and stealth assessment methods, user modeling, adaptive learning controls, and visual analytics dashboards. They can organize raw data into meaningful clusters or patterns, track pedagogical actions within digital environments, and generate visual representations that help educators make sense of complex learning processes. For example, factors like contextualized attention metadata and idea ratings based on parameters such as importance and feasibility are commonly included to enrich understanding.

In informatics education, data models can be used to capture a wide spectrum of learner behaviors within digital platforms such as coding environments, simulations, and interactive software. For example, a data model might record the number of coding assignments completed, track error rates and debugging efforts, and monitor progress through programming modules. Visual analytics can reveal trends in student performance, such as which algorithms students struggle with most, or how quickly they move from syntax errors to functional code. Adaptive controls within the model can personalize programming challenges based on a student's prior achievements and interaction patterns, while clustering techniques can identify groups of students who share similar learning trajectories or challenges. By organizing and interpreting these diverse data points, a data model helps informatics educators tailor

instruction, support targeted intervention, and improve overall teaching effectiveness in computer science classrooms.

2.3 Process-Oriented Learning Analytics Models

Learning Analytics models can be categorized according to the processes they use, including data collection, analysis, reporting, and prediction. This process-oriented perspective highlights the sequence of operations that turn raw data into actionable insights. By examining the underlying methods and workflows, educators and researchers gain a clearer understanding of how data informs educational decisions. Sciarrone and Temperini (2019) reviewed Learning Analytics systems from 1996 to 2015, illustrating varied approaches to these processes and how mechanisms for reporting and prediction have evolved. This classification offers valuable insight into the development and diversity of LA tools used to extract meaningful information from educational data.

2.3.1 5-steps Oblinger Model

The 5-Steps Oblinger Model proposed by Campbell et al. in 1996 is regarded as the first LA model for planning real-world LA systems. The model follows five linear steps (Figure 3):



Figure 3: The 5-steps Oblinger Model (Image from Sciarrone & Temperini, 2019, p. 289)

1. **Capture:** This initial step focuses on collecting data—from deciding what information to gather and how often, where to securely store the data, and what is the right format to represent learning events.
2. **Report:** Here, the collected data is organized into reports for stakeholders. Key questions include who receives the reports, how often, what specific information should be included, and how reports will be accessed.
3. **Predict:** This step applies prediction algorithms to anticipate future outcomes. Attention is given to the accuracy and input requirements of the algorithms, and to determining which predictions will be shared with stakeholders.
4. **Act:** Based on insights from the previous steps, this phase involves deploying targeted actions within the learning environment to enhance student learning process and outcomes or address emerging challenges.
5. **Refine:** The final step is dedicated to evaluating the results from prior steps. It is a process of reflection and continuous improvement, considering the usefulness and impact of earlier actions.

2.3.2 LA Cycle Model

Proposed by Clow in 2012, the LA Cycle Model builds on earlier model by establishing a theoretically-grounded, cyclical process for LA. A key innovation of this model is its emphasis on the final feedback to the system. The LA Cycle Model comprises four main dimensions (Figure 4):

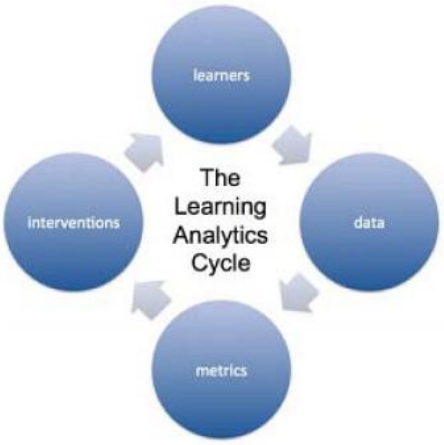


Figure 4: The LA Cycle Model (image from Sciarrone & Temperini, 2019, p. 289)

1. **Learners:** First, identify the participants enrolled in a course, focusing on who is involved in the learning process.
2. **Data:** Here, data is generated and captured as students interact with the course, encompassing all relevant activities and actions during learning.
3. **Metrics:** In this phase, data is analyzed to produce metrics that provide insights into the progress and patterns of learning. Visualization tools, such as dashboards, play a crucial role by making complex information accessible and helping students and educators understand learning trends.
4. **Intervention:** Based on the findings from metrics, targeted feedback and interventions are introduced to improve the learning process, creating a loop for ongoing refinement.

2.3.3 4-dimensions LA Model

Introduced by Chatti et al. in 2012, the 4-Dimensions LA Model offers a holistic framework for analyzing educational data by considering four essential aspects (Figure 5):

1. **What:** This dimension explores the types of data that the system collects, manages, and uses for analysis. It recognizes both centralized and distributed approaches to data gathering, accommodating diverse learning platforms and environments.
2. **Who:** Here, the model identifies all stakeholders who are targeted by the analytics process, including students, teachers, tutors, and educational institutions. Each group plays an active role in leveraging analytics to enhance learning process and outcomes as well as minimize student risk.
3. **Why:** This dimension addresses the purpose behind LA, ranging from monitoring and assessment to prediction, intervention, tutoring, feedback, adaptation, recommendation, and reflection. By clarifying the goals, it ensures that LA directly supports educational objectives.
4. **How:** In the final dimension, the model considers the methods used to analyze the collected data. Techniques such as statistical analysis, information visualization, data mining, classification, clustering, association rule mining, and social network analysis are emphasized for uncovering meaningful patterns and insights within educational datasets.

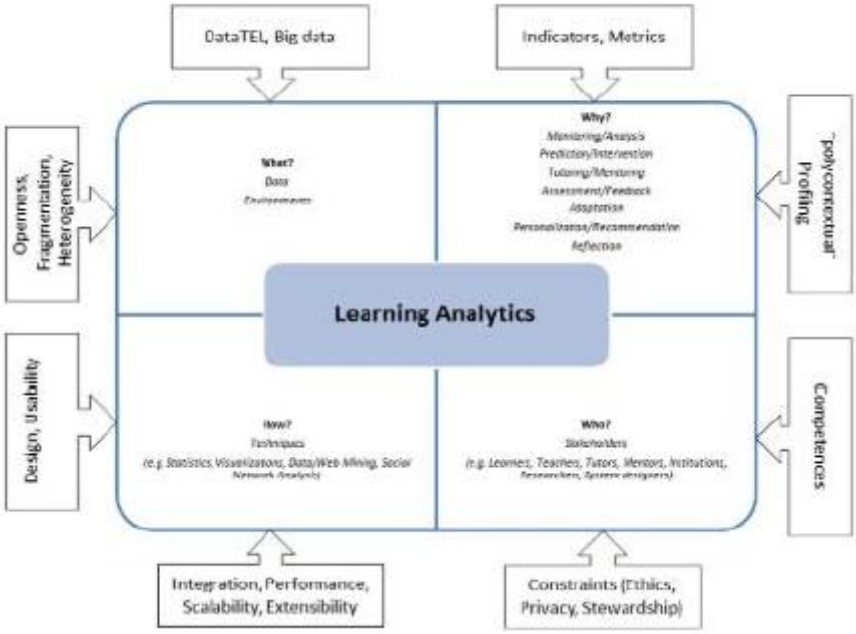


Figure 5: 4-dimensions LA Model (image from Sciarrone & Temperini, 2019, p. 289)

2.3.4 7-steps LA Model

Developed by Siemens in 2013, the 7-Steps Learning Analytics Model presents a comprehensive, systemic approach to analytics in educational settings. The model consists of seven key components: collection, storage, data cleaning, integration, analysis, representation and visualization, and action. Each step builds upon the previous, ensuring that raw data is transformed into meaningful insights and then used to inform decisions and interventions (Figure 6).

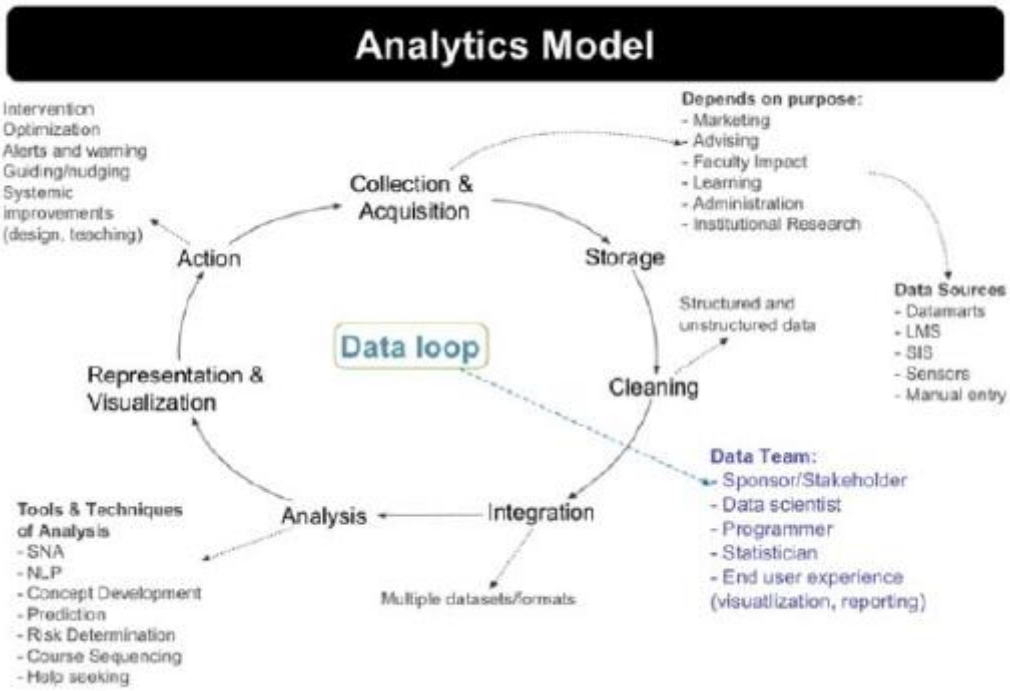


Figure 6: 7-steps LA Model (image from Sciarrone & Temperini, 2019, p. 289)

A notable feature of this model is its emphasis on the importance of a dedicated data team. Effective LA requires a diverse set of skills and knowledge rarely found in a single individual. By encouraging a collaborative, systemic approach, the model highlights the need for education institutions to coordinate resources across roles—data specialists, educators, analysts, and administrators—to fully support analytics-based interventions or the development of predictive models.

2.3.5 Dynamic LA Model

Developed by Freitas et al. (2015), the Dynamic LA Model offers a set of guiding principles to help higher education institutions enhance decision-making and operational practices using analytics. The model is organized around nine key principles (Figure 7):

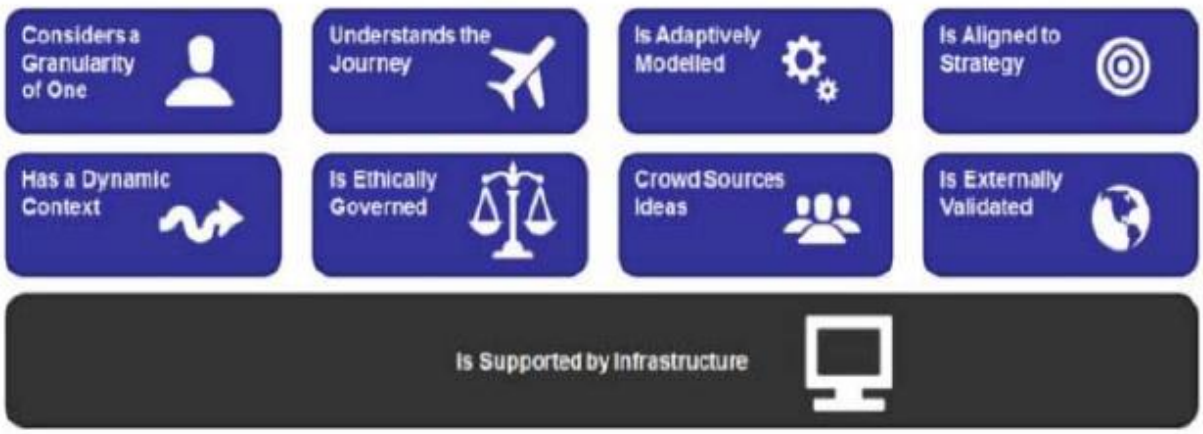


Figure 7: Dynamic LA Model (image from Sciarrone & Temperini, 2019, p. 290)

1. **Develop a LA Strategy:** Establish a university-wide approach to analytics to improve student retention, enrich their learning experiences, elevate teaching quality, and personalize support.
2. **Commit to Big Data Integration:** Build robust infrastructure that enables real-time, always-on, fully-integrated data collection across the institution.
3. **Learner-Centered Service Ethos:** Place the student at the heart of analytics, aiming for adaptive responses that improve individual learning experiences and outcomes.
4. **Dynamic Student Journey Monitoring:** Continuously observe and manage lage quantity of constantly produced data throughout the student lifecycle—spanning marketing, admissions, enrollment, retention, graduation, and employment.
5. **Adaptive Modeling of User Behavior:** Enable the system to dadaptively respond to student needs, recommending personalized learning pathways using behavioral modeling.
6. **Integrate LA in a Wider Dynamic Context:** Analyze diverse data sources—including academic performance, resource utilization, economic factors, market data, socio-economic status, and demographics—to understand student behavioral similarities.

7. **Qualitative Driven Crowd-sourced Hypotheses Formation:** The model leverages qualitatively driven crowdsourced ideation to generate various hypotheses, which has proven more effective for engaging stakeholders and fostering understanding than solely research-focused or quantitative methods.
8. **Rigorous Ethics and Ethical Procedures:** Uphold strict ethical standards for data anonymity, identity protection, and secure data storage, complying with legal requirements.
9. **Continuous Validation and Review:** Apply both internal and external review processes, using scientific and machine learning methods, to continuously validate and adapt learning pathways for students.

Summary:

LA models offer diverse frameworks for collecting, analyzing, and interpreting educational data, each with unique goals, purposes, functions, and processes. Whether oriented toward performance, cognition, interactivity, communication, data management, or analytical purpose—descriptive, diagnostic, predictive, and prescriptive—these models empower educators and institutions to make informed decisions, personalize learning, and enhance outcomes. Process-focused frameworks further shape how data is handled and acted upon. Together, these approaches highlight the evolving role of LA in informatics education, supporting evidence-based, adaptive practices for both students and teachers.

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3 Visualization and interpretation of data for learning analytics in informatics

Turning numbers into insights

By measuring, collecting, analyzing, and reporting digital traces from learning environments, LA offers valuable insights into student abilities, highlights potential obstacles, and predicts future learning trajectories. Visualization and interpretation are essential components of LA, as they transform complex educational data into clear, actionable information. Ultimately, this chapter explores how data visualization and interpretation enable all stakeholders to optimize educational outcomes, making learning more responsive, personalized, and evidence-based.

3.1 The Role of Data Visualization in Learning Analytics

Why visualization matters

Data in LA can be reported through various approaches, including machine learning methods and visualization techniques. While machine learning methods can provide powerful insights, they are not always a realistic or suitable option for all stakeholders (e.g., teachers, students, administrators, and policy-makers), as their use often requires specific expertise and technical skills (TRILA, 2021). Visualization techniques offer a more accessible and practical alternative, making it easier for users in most situations to interpret and understand data.

Data visualization—the graphical representation of information using charts, graphs, heat maps, timelines, network diagrams, and interactive dashboards—plays a pivotal role in LA by transforming large and complex datasets into clear, actionable insights. These visual methods make it possible to quickly see patterns and relationships within the data, supporting both descriptive and illustrative reporting. They are particularly effective for presenting existing data, capturing prior events, and enabling stakeholders to make informed decisions regarding teaching, learning, and organizational strategy.

By turning learning data into visual summaries, stakeholders can quickly gain a clear understanding of what has taken place (OKM, 2024). This transparency supports ongoing reflection and action, helping to identify trends, detect at-risk students, monitor participation, and evaluate learning outcomes. Students can use visualizations to review their progress, set learning goals, and take ownership of their learning paths. Teachers are empowered to pinpoint key performance indicators, recognize areas for improvement, and adapt instruction to student needs. Administrators benefit from an expanded view of institutional learning processes and outcomes, which supports planning and quality assurance across the organization.

Effective visualizations are essential because they significantly reduce cognitive load by presenting complex information in an accessible format, allowing users to focus on interpretation and decision-making rather than data processing (Khosravi et al., 2021; Masiello et al., 2024). Without visualization, stakeholders must sift through large volumes of raw data—a process that is both time-consuming and prone to error. Visual representations make patterns, trends, and anomalies stand out, enabling teachers, students, and administrators to quickly interpret critical information (Kirk, 2024). Instead of spending energy parsing datasets, users can concentrate on understanding what the data reveals and making informed decisions to support student learning. For instance, an interactive dashboard can instantly show changes in student engagement levels, pinpoint topics that present difficulties, and flag learners who may need additional support.

Moreover, visual analytics tools play an important role in formative assessment and real-time feedback. By making progress and learning outcomes visible, visualizations encourage timely intervention, adaptive instruction, and continuous improvement. Visual feedback helps teachers adjust their strategies, students refine their learning behaviors, and institutions fine-tune their support systems to meet evolving needs. Ultimately, data visualization

forms the backbone of LA by bridging the gap between data collection and meaningful action. It ensures that information is not only accessible but also practical and impactful for improving educational outcomes at all levels.

Common visualization techniques in learning analytics

Table 1 describes various visualization methods commonly used in LA, alongside practical examples of how each technique can be applied in educational contexts. These methods include bar charts and line graphs for displaying trends in student performance over time, heat maps for visualizing engagement levels across course materials, and scatter plots for exploring relationships between variables such as participation and achievement. Network diagrams can illustrate interactions among students in collaborative learning activities, while dashboards integrate multiple visualizations to provide an overview of key metrics and indicators at a glance.

Table 1: Common visualization techniques in learning analytics

Visualization Technique	Description & Purpose	Example Use Case
Bar/Column Charts (Figure 8)	Compare categorical frequencies or distributions; Display trends	Number of submissions per assignment; Trends in student performance among individuals or groups over time,
Dashboards (Figure 9)	Integrate multiple visualizations to provide an overview/summary of key metrics and indicators into a single interface	Teacher dashboard on student performance
Heatmaps (Figure 10)	Use color-coded matrix to show engagement, clicks, etc.	Highlight resource usage in a course
Histograms (Figures 11–12)	Visualize distribution of numeric data	Distribution of quiz score
Network Graphs/Diagrams	Visualize interactions, collaborations, social ties among students in collaborative learning activities	Group work patterns in discussion forums
Sankey Diagrams	Show flow and transitions between states	Student pathways through learning resources
Scatter Plots (Figure 13)	Show correlations and outliers for exploring relationships between variables such as participation and achievement	Relating time spent vs. grade achieved
Time Series/Line Charts (Figures 14–15)	Track student progress over time	Monitoring student activity throughout semester

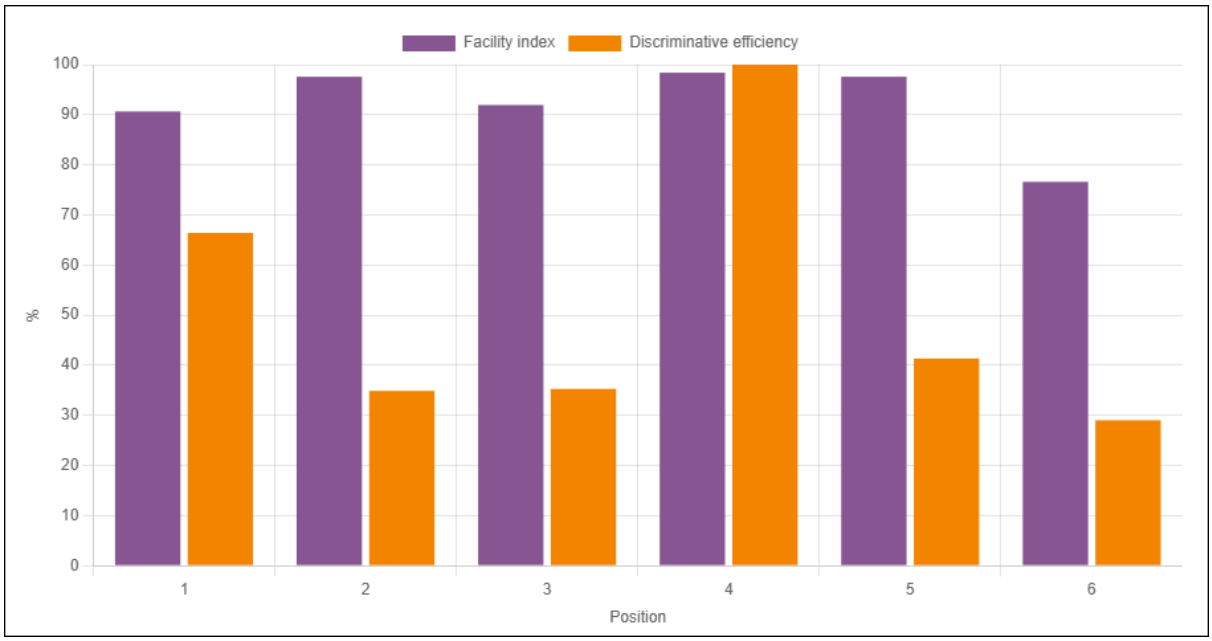


Figure 8: Column chart from a teacher's view in the Moodle learning platform, showing statistics for a quiz with 6 questions. The "Facility Index" indicates how easy each question is—higher values mean more students answered correctly. "Discriminative efficiency" shows how well each question distinguishes between students who know the material well and those who do not.

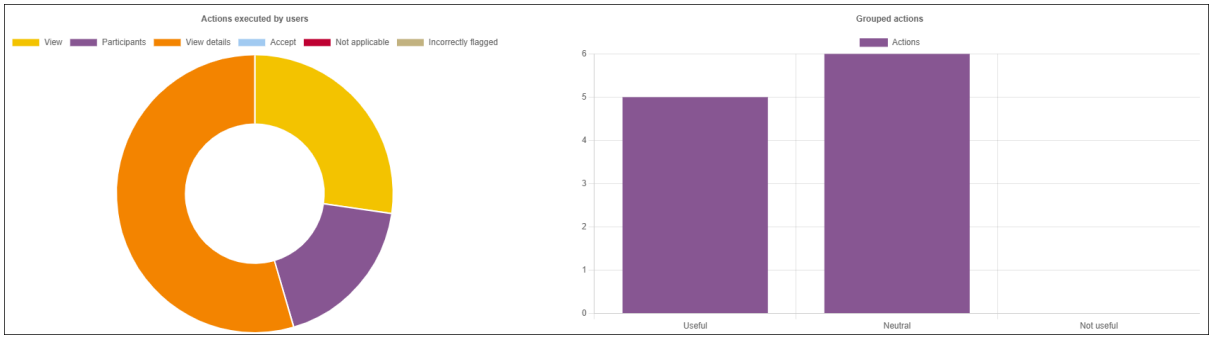


Figure 9: Administrator dashboard view in Moodle learning platform, displaying actions taken by users for courses flagged as "at risk of not starting" by the insight model.

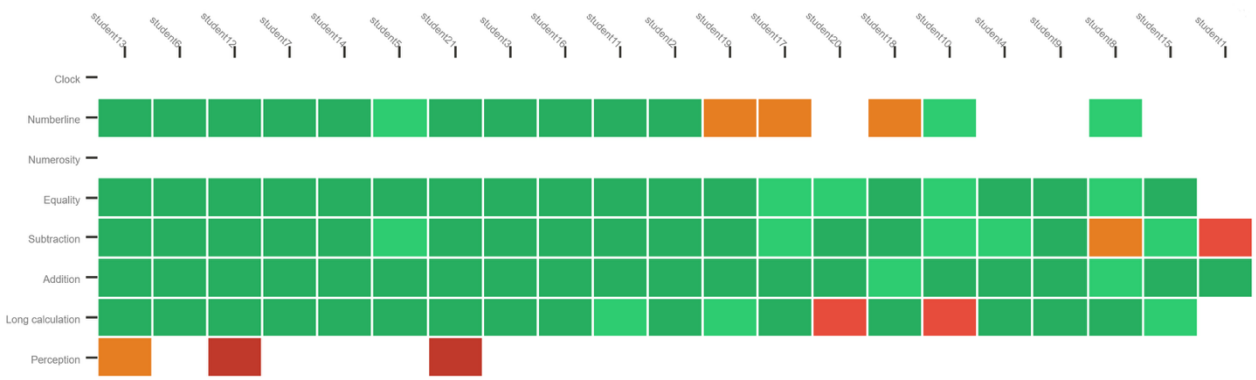


Figure 10: Heatmap from a teacher's view in the ViLLE learning platform, showing how many tasks each student has completed in different math content areas. Green indicates more completed tasks, while red indicates fewer completed tasks.

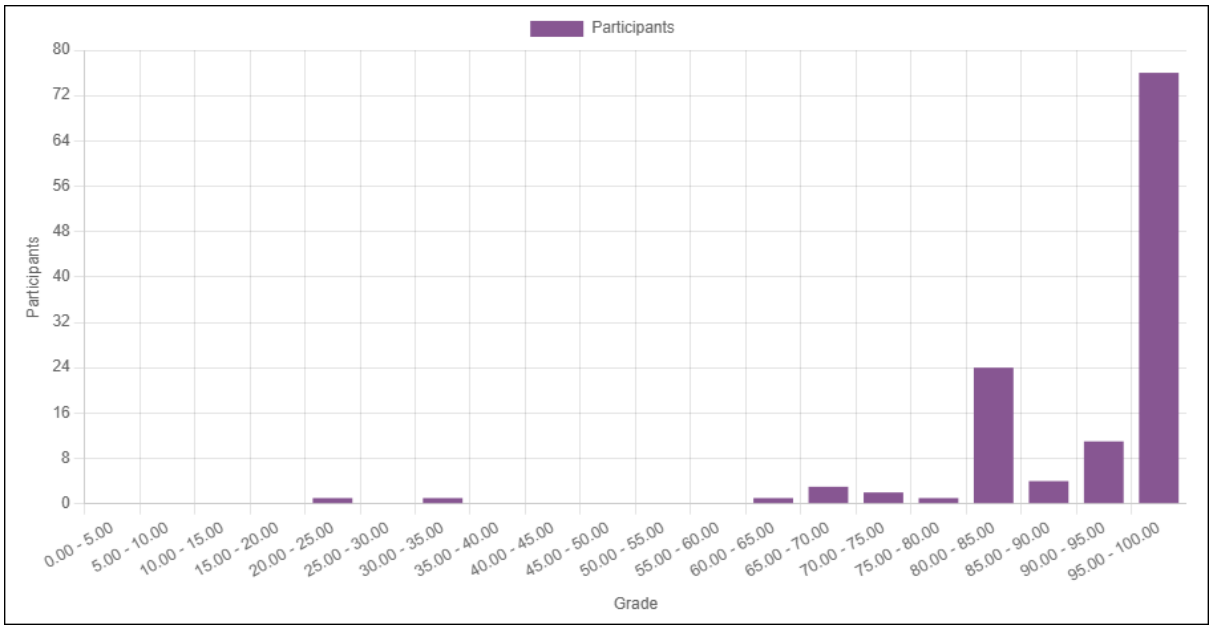


Figure 11: Histogram from a teacher's view in the Moodle learning platform, showing the number of students in each grade range (0–100) for a graded activity, such as a quiz or lesson.

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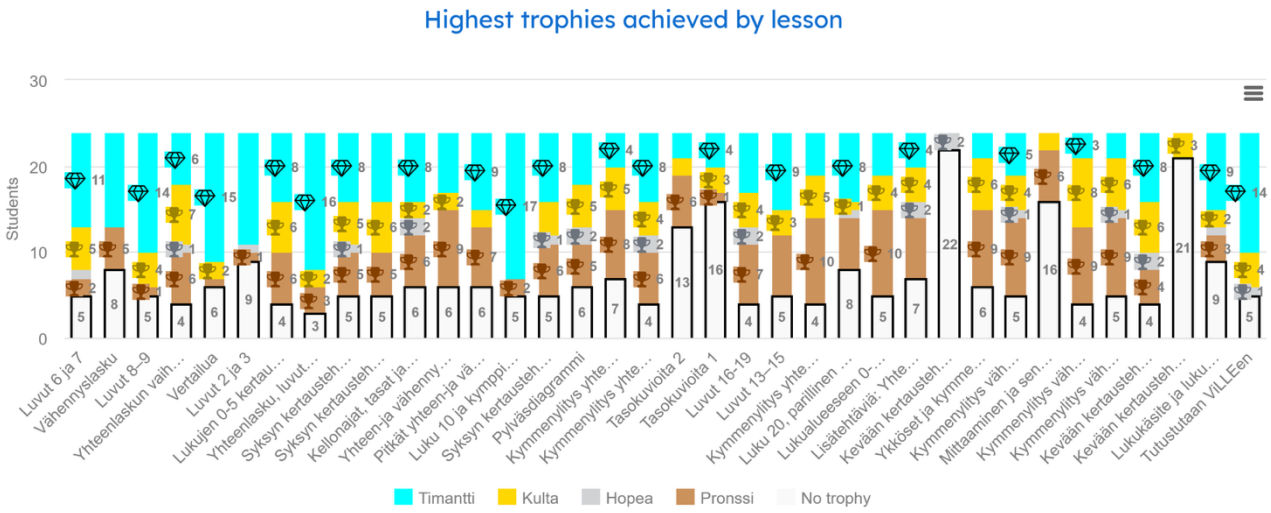


Figure 12: Histogram from a teacher's view in the ViLLE learning platform, showing how many students earned each type of trophy—none, bronze, silver, gold, or diamond—based on the number of tasks they completed in each math lesson.

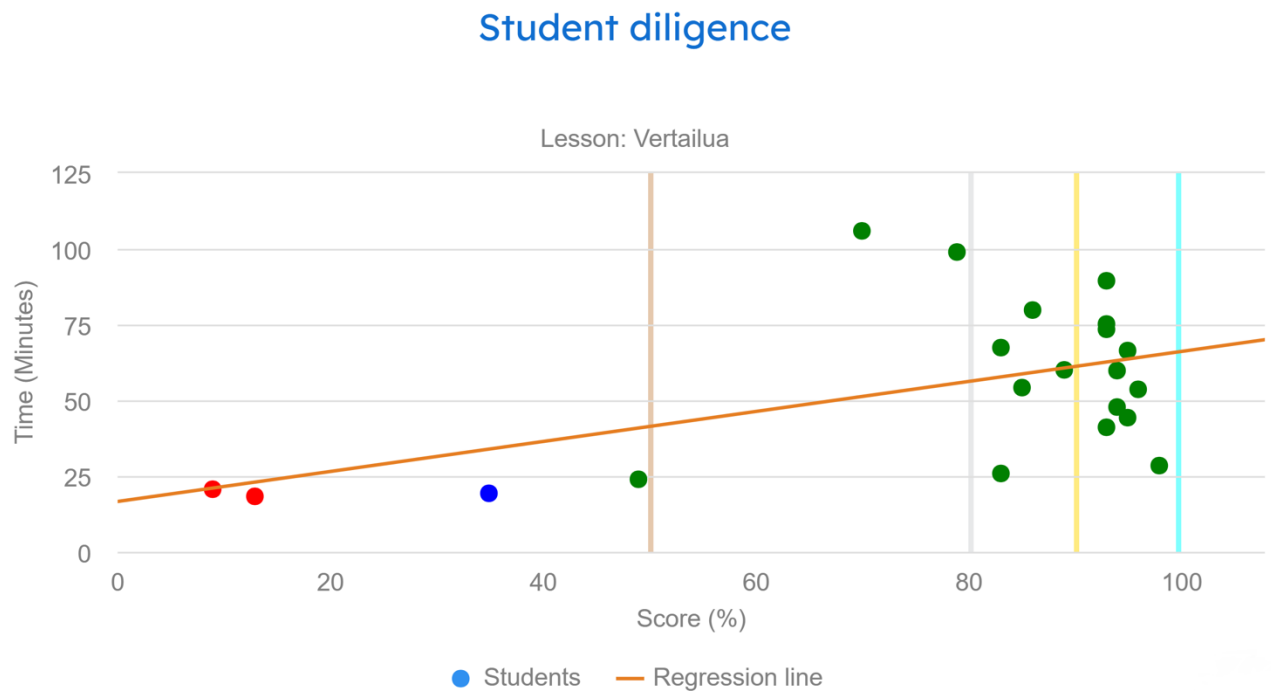


Figure 13: Scatterplot from the teacher's view in the ViLLE learning platform, showing each student's diligence in a lesson by plotting their time spent and scores received.

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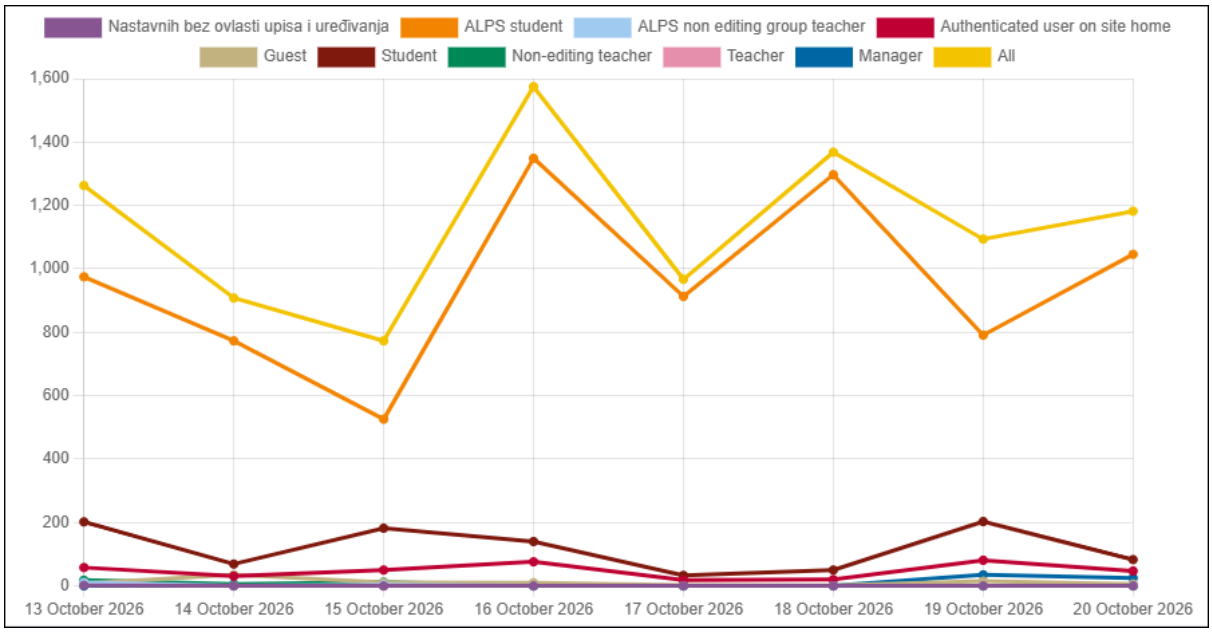


Figure 14: Time series from a teacher's view in the Moodle learning platform, showing user activity in a course over one week. Each line indicates a different user role, and the vertical axis shows how many actions were performed by users, based on log entries.

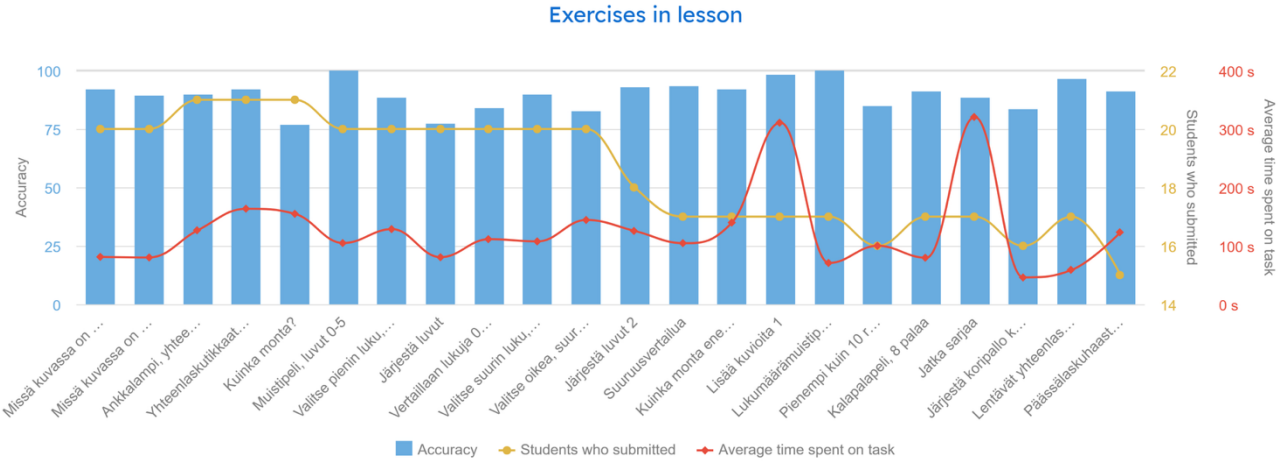


Figure 15: Combined column and line charts from a teacher's view in the Moodle learning platform, showing the number of students who submitted exercises in a lesson, their accuracy, and the average time spent on the task.

Table 2 presents several examples of visualization methods that have been applied to different assessment purposes in LA, along with references to key sources. While many of these techniques will be familiar to readers, the accompanying references can provide new perspectives and ideas for how visualizations can be used in teaching and learning contexts. Reviewing these examples may inspire educators and researchers to experiment with different visualization approaches, adapting them to better suit their own educational environments and analytical needs.

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Table 2: Visualization methods for teaching and learning evaluation (TRILA, 2021, p. 14).

Evaluation	Visualization Method	References
Collaboration	Mathematical graph (*node-link diagram*), Statistical (*bar plot, line plot, pie chart, scatter plot*), Timeline, Interaction Matrix, Heatmap, Radar	(Aramo-Immonen et al., 2015; de Laat & Schreurs, 2013; Hernández-García et al., 2015; Hu et al., 2016; Kim & Lee, 2012; Lockyer et al., 2013; Martinez-Maldonado et al., 2016; Schneider & Pea, 2014; Thompson et al., 2013; van Leeuwen et al., 2014; Verbert et al., 2013; Xing et al., 2015)
Relationships	Statistical, Spiral timeline	(Agudo-Peregrina et al. 2014; Gómez-Aguilar et al., 2015; Iglesias-Pradas et al., 2015)
Instructional Design	Mathematical graph, Statistical, Timeline, Word cloud, Interaction matrix, Circular graph, Bubble plot, Concept map, Glyph, Geomap	(Ali et al., 2012; Bull et al., 2016; Hsiao et al., 2016; Khan & Pardo, 2016; Kotranza et al., 2012; Ruipérez-Valiente et al., 2015; Schwab et al., 2017; van Leeuwen et al., 2014; Wang et al., 2011)
Reflection	Statistical, Word cloud, Heatmap, Bubble plot, Concept map, Radar	(Beheshitha et al., 2016; Bull et al., 2016; Hillaire et al., 2016; Hsiao et al., 2016; Nagy, 2016; Ruiz et al., 2016)
Usage Patterns	Statistical, Word cloud, Bubble plot, Concept map	(Bull et al., 2016; Cruz-Benito et al., 2015; Muñoz-Merino et al., 2015; Warner et al., 2015)
Learning Progress	Statistical, Circular graph, Heatmap, Radar	(Jacovina et al., 2015; Jugo et al., 2015; Minović et al., 2015)
Learning Paths	Mathematical graph, Statistical, Timeline	(Davis et al., 2016; Eagle et al., 2015; Faucon et al., 2016; Jugo et al., 2016)
Discussion Forums	Statistical, Word cloud, Bubble plot, Concept map	(Atapattu et al., 2016; Bull et al., 2016)
Retention	Statistical, Timeline, Word cloud, Glyph	(Chen et al., 2016; Freeman, 2016)
Motivation	Statistical	(Lonn et al., 2015)

Selecting the right visualization technique depends on the purpose of the analysis and the audience. Simple charts and graphs are ideal for quick summaries, whereas interactive dashboards facilitate deeper exploration and support decision-making by teachers, administrators, and even students. Advanced methods, such as timeline visualizations, can be used to track learning progress or highlight specific moments where interventions may be needed.

These visualization approaches not only make complex data more accessible but also enable timely insights and actions. By providing clear visual representations, LA supports ongoing reflection, targeted support, and continuous improvement of teaching and learning processes.

Dashboards

Dashboards also known as Learning Analytics Dashboards (LADs) are among the most widely adopted visualization tools in LA, providing a centralized and often real-time interface for accessing and exploring learning data through interactive visualizations (Pozdniakov et al., 2024). By aggregating diverse indicators about learners, learning processes, and learning contexts into one or more visualizations, dashboards offer users a comprehensive overview that supports monitoring, interpretation, and decision-making (Schwendimann et al., 2017). As the primary bridge between LA systems and end users, dashboards transform complex learner data into interpretable visuals that support decision-making for students, teachers, and other educational stakeholders. They can be customized to display a range of educational indicators—such as performance, progress, competency development, identified support needs, affective measures (e.g., motivation, anxiety, satisfaction), behavioral metrics (e.g., time-on-task, participation, resource use, see Figure 16), and sequences of learning actions (Masiello et al., 2024; Sahin & Ifenthaler, 2021). Most dashboard visualizations present descriptive information—like student engagement with online materials, task completion, and progression through a course. Many dashboards also allow users to compare individual results with class averages, learning goals, or other benchmarks, supporting self-monitoring and reflection.

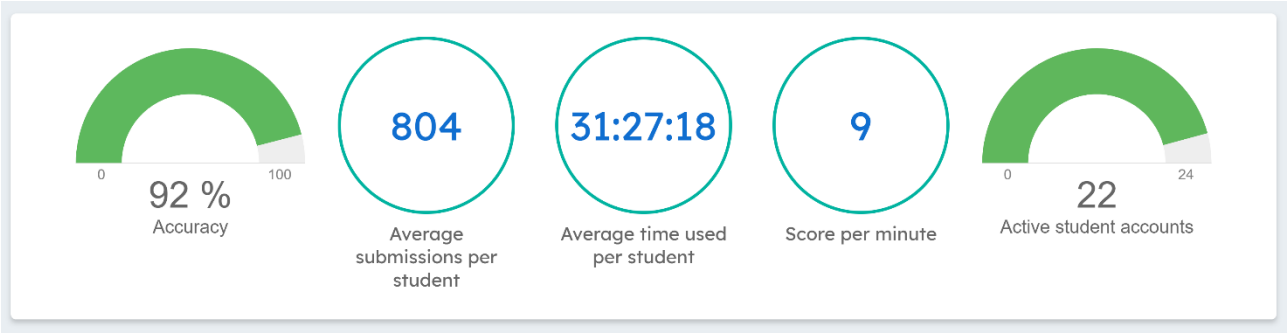


*Figure 16: **Administrator dashboard in the ViLLE learning platform, showing whole-class data over an academic year: accuracy percentage, average number of submissions, average time spent, score per minute, and the number of active student accounts.***

The true educational value of dashboards lies in their role as tools for promoting meaningful action. By providing timely and accessible information, dashboards encourage self-regulated learning, increase learners' awareness of their progress, and help educators identify students who may need additional support. Dashboards provide flexibility for teachers to view information either at the individual student level or for the entire class. This capability empowers educators to make informed decisions tailored to the needs of individual learners—such as providing targeted feedback or identifying students requiring additional support—as well as addressing broader trends and patterns within the class as a whole. By enabling both granular and holistic perspectives, dashboards facilitate responsive teaching, support differentiated instruction, and enhance overall classroom management.

As assessment and feedback tools, dashboards complement teaching and learning activities across educational contexts. However, their implementation has been more common in higher education than in primary and secondary schools, partly due to greater access to centralized data systems and digital infrastructure at universities.

Despite their advantages, interpreting dashboard visualizations isn't always straightforward. Users may find it challenging to recognize relevant patterns, understand relationships between indicators, or interpret the significance of presented data. To overcome these challenges, recent research has focused on **visualization guidance**—computer-assisted features that help users make sense of visualized data by directing attention to significant elements and reducing cognitive effort (Ceneda et al., 2017). Visualization guidance is often delivered through visual cues, annotations, highlights, alerts, and textual prompts that clarify important trends, anomalies, or relationships within the data (Barral et al., 2021). These features simplify the interpretation process, communicate insights more effectively, and reduce the chance of missing key information. This is especially valuable for users with limited visualization literacy, who may struggle to interpret educational dashboards effectively. As a result, contemporary dashboard research emphasizes not only creating informative visualizations, but also providing guidance to help users transform LA data into actionable educational insights.

3.2 Best Practices for Data Visualization

Effective data visualization in LA is more than simply displaying data—it is about creating representations that support meaningful interpretation and inform educational decisions. Visualizations should be thoughtfully designed to align with educational goals, helping stakeholders focus on what matters most for student learning and development. In addition, well-crafted visualizations draw attention to key trends, highlight areas of concern or interest, and support cognition by reducing complexity and enabling users to process information efficiently.

First and foremost, visualizations need to connect directly to key **educational objectives**. This means selecting **relevant indicators** that reflect learning, engagement, progress, and achievement, rather than simply presenting every available data. By focusing on relevant data, visualizations provide clarity and avoid overwhelming users with unnecessary information.

Designing data visualizations for **attention** requires careful consideration of how visual features guide users to the most important information. Drawing user attention in data visualizations requires thoughtful choices in both content and design. Visual elements should actively support, rather than distract from, the understanding of key information (Theeuwes, 2010). Designers should take into account established conventions within their specific research or practice domain, choosing visualization strategies that complement users' familiarity and scaffolding the narrative to enhance data comprehension (Anderson & Yantis, 2013; Theeuwes, 2010). Applying visual design principles, such as grouping related features by color or shape, promotes chunking and supports generative processing, making complex relationships clearer—sometimes by using small multiples to visualize recurring patterns or connections (Gobet, 2005). Equally important is the exclusion of irrelevant material, such as excessive detail, decorative embellishments, or cluttered layouts, which can hinder users' focus and reduce cognitive efficiency (Baldassi et al., 2006). By carefully balancing clarity, relevance, and visual structure, data visualizations in LA can effectively capture users' attention and facilitate meaningful interpretation.

Designing data visualizations to support **cognition** means thoughtfully combining text and visuals to foster deeper understanding. Presenting information in alignment with familiar mental models offers readers cues that make it easier to organize and retrieve knowledge, leading to more effective interpretation and inference (Anderson & Yantis, 2013; Theeuwes, 2010). Keeping explanatory text and visual elements close together helps users connect concepts and visuals, reinforcing comprehension (Mayer & Fiorella, 2014). Well-placed textual highlights also guide attention

toward the most important data points, ensuring that viewers focus on the insights that matter most (Mayer & Fiorella, 2014). Presenting information in a way that is easy to understand at a glance helps users quickly grasp key findings. This integrated approach enables LA visualizations to actively engage cognitive processes and transform complex data into actionable educational understanding.

Beyond drawing attention and supporting cognition, well-designed LA visualizations should provide ample **context** to clarify the meaning of each metric, incorporating legends, labels, and concise explanations. Comparisons to benchmarks, historical trends, or peer performance help users interpret data more accurately and meaningfully. Incorporating **interactivity**—such as filtering, zooming, or segmenting data by group or date—enables users to investigate underlying patterns and analyze data at varying levels of detail. **Accessibility** is also crucial; visualizations should employ color-blind-friendly palettes, accessible fonts, and thoughtful design considerations to ensure all users can interpret and benefit from the visuals. **Drill-down functionality** enhances flexibility, allowing educators and administrators to explore data in greater depth, such as tracking trends across groups, subjects, or time periods, and examining the specific factors underlying observed patterns. Together, these features promote deeper analysis and empower educators to uncover the causes of learning challenges and respond with targeted interventions.

Most importantly, visualizations must facilitate **actionable insights**. They should not only inform but also inspire targeted intervention, guiding pedagogical decisions, and supporting continuous improvement. Features such as clear indicators, risk alerts, or tailored recommendations help teachers to quickly identify students in need and adapt instructional strategies. Features such as summary dashboards, comparative benchmarks, and school-wide performance alerts help administrators and schools monitor progress toward institutional goals, identify emerging trends or areas requiring attention, and inform strategic planning, resource allocation, and quality assurance efforts.

Other best practices include collaborating with educators and end-users during the design process to increase relevance, maintaining ethical standards in data presentation, and ensuring visual formats fit the audience's needs. By following these guidelines, LA visualizations become powerful tools for enhancing teaching, learning, and organizational planning, ultimately leading to better educational outcomes.

3.3 Interpreting Learning Analytics Data

Although visualization is an essential tool in LA, insight emerges only through interpretation. Users must analyze visualized data in its educational context, recognizing that graphical representations alone do not provide meaning. Interpretation requires identifying patterns, explaining their significance, and determining appropriate actions based on what is observed (Khosravi et al., 2021; Masiello et al., 2024).

For example, a downward trend in student engagement may signal motivational challenges, difficulties with course content, or external factors impacting participation. Conversely, high activity on a digital platform might not reflect genuine learning, reminding educators to combine quantitative indicators with a nuanced pedagogical understanding. Interpretation is not simply about reading charts—it is about connecting visualized data to classroom realities and educational goals.

Interpreting LA data requires a thoughtful approach to recognizing patterns and drawing actionable conclusions. Educators should look for **patterns and trends**, for example, in assignment submissions, which may signal periods of challenge or disengagement. Consistently low participation can help identify students at risk and those in need of extra support. **Identifying outliers**—such as spotting students with unusually low engagement but high performance, or vice versa—can reveal unique learning needs or hidden obstacles. **Comparative analysis** across cohorts, demographic groups, or instructional methods can uncover disparities and highlight effective practices.

Effective interpretation also creates **feedback loops**; for example, real-time alerts can be triggered when a student misses multiple activities, prompting timely intervention. Through careful analysis, educators can harness LA data to provide meaningful feedback and adapt instruction for better learning outcomes.

Research indicates that an educator's ability to interpret analytics visualizations is closely tied to their **visualization literacy**—their skill at understanding, interpreting visual elements, and drawing conclusions from visual representations of data (Lee et al., 2017). Teachers with greater visualization literacy tend to offer more nuanced and sophisticated interpretations of educational data, while those with less experience may struggle to move beyond surface-level observations. Providing visual guidance. Features, including annotations, highlights, and narrative elements (often called data storytelling) can further support users in making sense of the information (Pozdniakov et al., 2024).

Ultimately, meaningful interpretation of LA data encourages critical reflection and informed decision-making. It enables educators to select appropriate interventions, refine instructional approaches, and better support student learning. As visualization tools become more widespread, fostering visualization literacy among all educational stakeholders—through training, clear annotation, and accessible design—will be increasingly important for maximizing the value of learning analytics.

3.4 Challenges and Considerations

Although LA visualizations offer significant promise, their effective use is accompanied by several challenges. One major concern is the risk of **misinterpretation**: users may misunderstand graphical representations, focus only on superficial metrics, draw conclusions from limited data, or struggle to convert insights into meaningful educational action. These issues can lead to misguided decisions or missed opportunities for intervention.

Data privacy and ownership are also critical considerations. Ensuring the ethical use of student information requires strict protocols, such as anonymizing data, to protect sensitive information and clarify who is responsible for managing and safeguarding it. Inclusiveness must be addressed as well, making sure visualization tools and data analysis approaches are accessible to all stakeholders, regardless of background or ability.

Variability in **data literacy and visualization literacy**, especially among educators, directly impacts the quality of interpretation and decision-making (Pozdniakov et al., 2024). Without adequate training and support, users may over-rely on automated LA reports or misinterpret key indicators, resulting in inequitable or ineffective outcomes. Ongoing professional development, clear communication, and opportunities for collaborative analysis are essential for bridging these literacy gaps and improving the ability of all stakeholders to draw meaningful conclusions from LA visuals.

Ethical awareness remains central to responsible use of LA. Educators and administrators should carefully consider how data is presented, take steps to avoid reinforcing bias, and actively engage students in understanding and using their own data. **Transparent communication** about the goals and methods of LA visualization fosters trust, promotes accountability, and encourages active participation among all stakeholders.

Technical limitations—such as incomplete data, software constraints, or lack of integration with existing educational platforms—can further hinder the effectiveness of LA visualizations. Addressing these challenges calls for collaboration among teachers, administrators, technical specialists, and policymakers to ensure that tools and practices are robust, reliable, and aligned with educational needs.

By thoughtfully navigating these challenges and maintaining a commitment to ethical, inclusive, and literate use of LA data, schools and institutions can unlock the full potential of LA visualizations to enhance teaching, learning, and educational outcomes.

Summary

Visualization and interpretation are essential for turning LA data into meaningful insights that drive educational improvement. Well-designed visual representations help educators and learners gain a clear understanding of learning processes, spot areas for growth, and make evidence-informed decisions. However, the impact of LA goes beyond the quality of visualizations; it also depends on users' ability to accurately interpret data and integrate insights into pedagogically relevant actions. By focusing on both the design of visualizations and building users' data literacy, schools and institutions can ensure that LA truly empowers stakeholders to enhance teaching, learning, and student success.

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