# From Clicks to Clues: A Learning Analytics Approach to Formative Assessment in a Digital Reading Environment

Judith Hanke
*University of Flensburg*
*Germany*

## Abstract

*Learning analytics (LA) uses data to understand and optimize learning. This article investigates how data from a digital reading tool, reading packages, can function as both a formative assessment mechanism and a source for learning analytics. An intervention study with elementary school students was conducted to track engagement with digital reading packages. Data on task completion times and interaction with feedback functions (e.g., "skip," "second attempt") were collected and analyzed. Initial findings revealed that a 'skip' button, intended to reduce frustration, was potentially encouraging students to avoid challenging content. Based on this diagnostic analysis, a clear prescriptive action was identified: modifying the platform by removing the skip button. This study demonstrates a practical LA cycle where student interaction data is used for diagnostic purposes to inform evidence-based platform refinement. It illustrates how a data-driven feedback loop can be created to guide improvements aimed at enhancing the efficacy of the learning tool itself.*

## 1. Introduction

The proliferation of digital learning environments has created unprecedented opportunities to collect data on student learning processes. Learning Analytics (LA) has emerged as a powerful field focused on using data from learners to understand and optimize their learning and the environments in which it occurs [18]. By applying data-driven methods, educators can move from generalized instruction to personalized learning pathways, identify at-risk students earlier, and continuously refine the educational tools they use.

However, the effective implementation of LA requires more than just data collection; it demands a clear connection between the data gathered and pedagogical goals. Digital learning tools, such as the interactive reading packages [LesePfad; 9], are rich sources of such data. They function not only as instructional materials but also as formative assessment tools that generate a constant stream of information about student behavior, from time spend on a text to problem-solving strategies revealed through button clicks [15].

The primary objective of this article is to demonstrate a practical application of the learning analytics cycle. The study explores how student interaction data from the reading packages can be used to diagnose learning behaviors, inform pedagogical interventions, and drive evidence-based improvements to the digital platform itself. Specifically, this paper addresses the following questions:

*What patterns of student engagement emerge from interaction data (e.g., reading time, button usage) within the learning platform of the reading packages?*

*How can this data be used to diagnose potential issues in platform design and student learning strategies?*

*How can this diagnostic analysis inform evidence-based improvements to the learning platform?*

By analyzing the results of an intervention study, this paper illustrates how learning analytics can

*"close the loop"[6],*

turning raw data into actionable insights that benefit both learners and learning environment designers.

## 2. Literature Review

Learning Analytics (LA) is formally defined as “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” [18, p. 33]. At its core, the purpose of LA is to use data to make invisible learning patterns visible. Its importance in modern education is growing rapidly, as it provides a methodology for improving learning outcomes, enabling personalized education at scale, and refining the digital tools students use every day. As a field, LA encompasses a wide range of applications. For example, a key use is providing real-time feedback to both students and teachers by tracking digital interactions to predict performance and identify at-

 | DOI: 10.20533/ijds.2040.2570.2025.0248 

risk students, allowing for early and targeted intervention before they fall behind [11].

## 2.1. Foundational Educational Theory: Learning from Experience and Reflection

Before detailing the technical processes of learning analytics, it is crucial to ground them in foundational educational theory. The concept of an iterative learning cycle is not new; it is deeply rooted in theories of experiential and reflective learning.

A landmark paper in education, Assessment and classroom learning by Black and Wiliam [3] presents a powerful case for the importance of formative assessment—the practice of assessing students during the learning process to provide feedback and adjust teaching. After reviewing hundreds of studies, the authors concluded that effective formative assessment practices (like providing constructive feedback, encouraging self-assessment, and using assessments to adapt instruction) lead to significant and often substantial learning gains. This work is foundational to the modern "assessment for learning" movement.

A foundational document by the Organisation for Economic Co-Operation and Development (OECD) [16], defines formative assessment as a central element of effective teaching and learning. It is not about grading but about generating feedback to modify and improve the learning process itself. The key idea is that assessment and teaching are intertwined. Formative assessment involves teachers, students, or peers providing information about student understanding to guide future learning steps. This report emphasizes that for assessment to be truly formative, the feedback must be used to adapt teaching strategies and help students become more autonomous learners by understanding their own progress and how to improve.

To translate these principles into action, Wylie's [20] report, Formative assessment examples of practice, serves as a practical guide for educators published by the Council of Chief State School Officers. Unlike a theoretical research paper, its main purpose is to provide concrete, real-world examples of how to implement formative assessment in the classroom. The principles of formative assessment—providing feedback, adapting instruction, and empowering student autonomy—are central to what educators hope to achieve with modern technology. Kollom et al. [13] found in a cross-country analysis that academic staff's primary expectation for learning analytics is precisely this: to better support their teaching by identifying struggling students early and understanding their engagement. This shows a clear demand from educators for tools that facilitate formative practices.

This aligns with emerging branches of LA designed to directly support the learner. For instance, Heilala's [10] work on "student agency analytics" focuses on providing students with data about their own learning patterns. This directly serves the formative goal of making students more autonomous learners, as they can use these insights to self-reflect and regulate their study strategies.

Furthermore, Shum and Ferguson [17] extend these ideas into collaborative settings with Social Learning Analytics. Their approach uses data from student interactions not for grading, but to provide formative feedback on the process of collaboration itself. This allows instructors to understand how knowledge is being co-constructed and intervene to improve group dynamics, perfectly illustrating how analytics can make the invisible processes of social learning visible for formative purposes.

David Kolb's [12] Experiential Learning Theory provides a direct pedagogical ancestor to the modern LA cycle. Kolb proposed a four-stage cycle of learning: 1. Concrete Experience (doing something), 2. Reflective Observation (reviewing or reflecting on the experience), 3. Abstract Conceptualization (concluding or learning from the experience), and 4. Active Experimentation (planning or trying out what you have learned). This cyclical process of doing, reflecting, thinking, and trying forms the theoretical bedrock for data-driven optimization. This model mirrors the core purpose of the LA cycle, where data analysis prompts educators and learners to reflect on learning events and modify their strategies accordingly. This theory establishes that effective learning is an active, cyclical process of action and reflection—a principle that learning analytics aims to support and accelerate with data.

## 2.2. Learning Analytics Life Cycle

At the heart of applying learning analytics is the Learning Analytics Cycle, a conceptual process that translates learner data into actionable improvements. While several models exist, such as Campbell and Oblinger's [5] five-step framework (Capture, Report, Predict, Act, Refine), a particularly influential model is the four-step cycle proposed by Clow [6]. This framework conceptualizes the process as follows:

i. Learners generate data through their interactions within a learning environment.

ii. This data is collected and analyzed to produce metrics, analytics, or visualizations.

iii. These outputs are fed back to learners or educators through interventions.

iv. This final step "closes the loop," impacting the learning process and leading back to the generation of new data.

This is not a single, linear event but an iterative process designed for continuous optimization. This process is often visualized as a cycle, as illustrated in Figure 1. In this cycle, each stage is essential:

*Data Generation*: Learners produce data through their interactions with a learning environment. In the context of this study, this occurs when students use the digital reading packages (LesePfad) on the Levumi platform [14].


Figure 1. The Learning Analytics Cycle.

The model in Figure 1 illustrates the iterative process of data generation, tracking, analysis, and action used to optimize learning (Author's own creation).

*Data Tracking and Analysis*: The platform collects and analyzes this interaction data to identify patterns in student behavior.

*Action*: The insights from the analysis inform interventions. These actions can be taken by educators (e.g., providing targeted support to a student) or by developers (e.g., modifying the platform itself), leading to an improved learning environment and the generation of new data.

The present study is designed to enact one full iteration of this cycle. However, the effectiveness of this entire cycle hinges on the quality and nature of the data generated in the first step. Gašević, Dawson, and Siemens [7] offer a crucial caution, arguing that for LA to be truly about learning, it must move beyond easily captured metrics like clicks and login times. They stress the importance of collecting pedagogically meaningful data—information that is grounded in learning theory and reflects the underlying cognitive and metacognitive processes of the learner.

The presented study addresses this challenge directly, as the digital reading packages are intentionally designed to capture data that offers insight into the learning process itself. For example, rather than simply tracking task completion, it monitors indicators of task persistence (e.g., use of a 'second attempt' button) and reading strategies (e.g., use of a 'repeated reading' function to revisit the text). This focus ensures that the subsequent analysis and interventions are grounded in a deeper understanding of student behavior, making the feedback loop more effective.

### 2.3. Four Types of Learning Analytics

The outcomes of the LA cycle are often categorized into four types, each answering a progressively more complex question.

Descriptive Analytics answers "What happened?" It summarizes past data to provide a snapshot of learning. The most common examples are learning dashboards that visualize student quiz scores or activity levels [19].

Diagnostic Analytics asks "Why did it happen?" This involves drilling down into descriptive data to understand the root causes of a phenomenon, such as analyzing why a specific group of students consistently failed a particular quiz question.

Predictive Analytics seeks to determine "What will happen?" It uses historical data to forecast future outcomes. A classic example is the "Course Signals" project at Purdue, which used student data to predict in real-time which students were at risk of failing, allowing for early intervention [1].

Prescriptive Analytics provides an answer to "What should be done?" This is the most advanced stage, where the system provides automated recommendations or interventions. This can involve suggesting specific resources to a struggling student or guiding them on what actions to take next to improve their learning [4].

While all four types are valuable, this study focuses primarily on using descriptive and diagnostic analytics (analyzing button clicks and reading times) to inform prescriptive actions (making concrete improvements to the reading packages).

## 3. Methodology

This section outlines the research design, participants, materials, and procedures used in the study to evaluate the impact and usage of the digital reading packages.

### 3.1. Research Design

This study employed a descriptive analysis of user interaction data collected during a four-week educational intervention. Elementary school students in an intervention group engaged with digital reading packages on tablets approximately three times per week during regular class sessions. The analysis presented in this paper focuses specifically on the interaction data (e.g., button usage, time on task) generated on the Levumi platform to understand student engagement and inform platform refinement.

### 3.2. Materials and Instruments

The primary instrument for the intervention was the digital reading packages, integrated into a learning platform to enhance reading comprehension for elementary school students, with a primary focus on Grade 3. The content consists of eleven distinct packages, each containing literary texts and accompanying exercises. The reading exercises were comprehension questions aligned to the texts. To cater to diverse learning needs, the packages were offered at three adaptive digital ability levels, ensuring that students were presented with appropriately challenging material. While the narrative text remained the same across levels, the difficulty of the vocabulary and the complexity of the accompanying comprehension exercises were adjusted to fit each level. This design choice was crucial, as keeping the core narrative consistent allowed the entire class to participate in shared activities, such as introductions and group discussions, regardless of their individual reading levels. The reading packages contain topics and interests of elementary school students, and the difficulty was aligned with the LIX [2] as well as common exercise practices.

As illustrated in the Figure 2 below, each of the eleven packages is structured to build foundational literacy skills by combining literary texts with corresponding reading exercises. This integrated approach is designed to foster primarily reading comprehension, and secondary reading fluency, and the use of effective strategies (such as the w-questions) for reading comprehension.

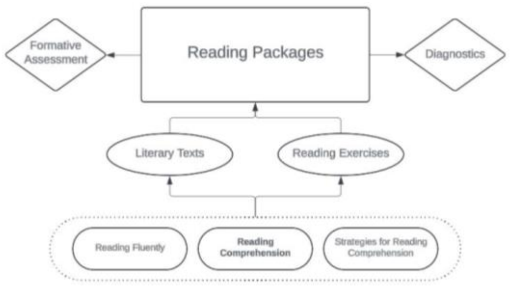


Figure 2. The digital reading packages [8]

The core design principle of the packages is to facilitate formative assessment. The platform provides students with immediate feedback on their performance and includes several interactive features designed to support learning and generate valuable analytics data:

*Second Attempt Button*: This feature encouraged persistence by allowing students to retry an exercise after an incorrect answer.

*Repeated Reading Button*: This allowed students to navigate back to the literary text at any point during the exercises, promoting the key comprehension strategy of revisiting a source text to find or confirm information.

*Reveal Solution Button*: After multiple attempts, this option provided the correct answer, preventing excessive frustration and creating a learning opportunity.

*Skip Exercise Button*: This feature allowed students to bypass a particularly difficult question to maintain momentum, though its impact on learning was a key focus of our analysis.

*Check Button*: students were able to check their answers.

# 4. Results

The study collected data on student interaction with the digital reading packages, including reading times and the use of interactive buttons. A total of 58 students were included in this analysis.

## 4.1. Reading Time and Platform Interaction

The average time spent on the initial reading of the literary texts varied across the three adaptive ability levels. As shown in Table 1, students in Level 2 had the longest average reading time at 2.82 minutes, followed by Level 1 at 2.68 minutes. Students in Level 3 had the shortest average reading time at 1.86 minutes.

Table 1. Average Reading Time per Ability Level

| Level 1 (N = 4) | Level 2 (N = 15) | Level 3 (N = 39) |
|---|---|---|
| 2.68 minutes | 2.82 minutes | 1.86 minutes |

## 4.2. Feature Usage

Analysis of the button usage data (Table 2) reveals patterns of student engagement. All 58 students used the "Second Attempt" and "Reveal Solution" features.

Table 2. Button Usage

| N = 58 | Repeated Reading | Skip Exercise | Second Attempt | Reveal Solution |
|---|---|---|---|---|
| students who used | 33 | 39 | 58 | 58 |
| M (SD) | 4.40 (9.41) | 25.79 (38.12) | 30.74 (19.17) | 146.88 (41.61) |

*Note: M = Mean, SD = Standard Deviation*

The "repeated reading" function was used by 33 students (57%), with an average of 4.40 uses among those students. The "skip-button" was used by 39 students (67%), with a high average of 25.79 uses. The extremely high standard deviation for the 'skip-button' (SD=38.12) is particularly noteworthy, as it suggests that while the mean usage was high, individual student behavior varied dramatically.

# 5. Discussion

The results of this study offer valuable insights into how learning analytics can be practically applied within a digital reading environment to understand and enhance student learning. The analysis of

 | DOI: 10.20533/ijds.2040.2570.2025.0248

interaction data from the reading packages and the platform (Levumi) moves beyond simple performance metrics, providing a rich, diagnostic view of student engagement and strategy use.

### 5.1. Student Persistence and Strategy Use

The finding that 100% of students used the "Second Attempt" and "Reveal Solution" buttons (Table 2) is a strong indicator of both student persistence and the platform's ability to function as a formative assessment tool. Rather than disengaging after a mistake, students were motivated to retry and seek correct answers, a behavior essential for learning. Furthermore, the significant use of the "Repeated Reading" button (57% of students) provides direct evidence that students were actively employing a key reading comprehension strategy. This data offers a clear example of diagnostic analytics in action; it helps us understand how students approach problem-solving within the learning environment.

### 5.2. The Diagnostic Power of "Negative" Data: The Skip Button

Perhaps the most significant finding was the diagnostic insight gained from the "Skip Button." While used by a majority of students (67%), its high average use (25.79 times per user) suggested it might be functioning less as a tool to prevent frustration and more as a way to avoid challenging content altogether. However, the high standard deviation (SD=38.12) is also significant, indicating that usage was highly variable, with some students relying on it heavily while others used it sparingly. This observation led to a clear prescriptive recommendation: modifying the platform by removing the button. This practical application demonstrates the full learning analytics cycle [6] described in our literature review, where data was collected and analyzed to diagnose a problem, leading directly to a prescriptive recommendation - the removal of the skip button - to optimize the learning environment.

### 5.3. Implications and Future Directions

The implications of this study are twofold. For educators, the data provides a deeper, almost real-time understanding of student learning behaviors that would be invisible in a traditional classroom. For platform developers, it highlights the importance of grounding design choices in pedagogical theory and using analytics to continuously refine features. The high standard deviation in the usage of the skip and solution buttons also suggests that these features are used very differently by different students, warranting further investigation into learner-specific patterns.

While this study provides a strong proof-of-concept, its limitations include a relatively small sample size, especially for the level 1 group focused on a specific demographic. Future research should explore these patterns in a larger, more diverse student population. Additionally, the next step would be to develop predictive models based on this interaction data to identify students who may need real-time support before they fall behind.

## 6. Conclusion

In this study the researcher successfully demonstrated a practical application of the learning analytics cycle within a digital reading tool for elementary school students. The analysis of student interaction data enabled a progression from descriptive analytics (what actions students took) to diagnostic interpretations (offering potential reasons for their behavior), which informed a prescriptive, evidence-based platform modification. The key finding—that a seemingly helpful "skip" feature was potentially hindering learning focus—underscores the necessity of grounding tool design in pedagogical goals and continuously evaluating it with real-world data. Ultimately, this research affirms that embedding LA principles directly into the architecture of digital learning environments creates a powerful, iterative feedback loop. This loop not only enhances the efficacy of the tool itself but also provides educators with deeper insights, paving the way for more effective, data-informed support and personalized learning pathways for students.

## 7. References


[1] Arnold, K. E., and Pistilli, M. D. (2012). Course signals at Purdue: Using learning analytics to increase student success. Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, 267–270. DOI: 10.114 5/2330601.2330666.

[2] Björnsson, C. H. (1968). Lesbarkeit durch Lix. Pedagogiskt Centrum.

[3] Black, P., and Wiliam, D. (1998). Assessment and classroom learning. Assessment in Education: Principles, Policy and Practice, 5(1), 7–74. DOI: 10.1080/09695959 80050102.

[4] Bodily, R., and Verbert, K. (2017). Trends and issues in student-facing learning analytics reporting systems research. Proceedings of the Seventh International Learning Analytics and Knowledge Conference, 308–317. DOI: 10. 11 45/3027385.3027435.

[5] Campbell, J. P., and Oblinger, D. G. (2007, October). Academic analytics. EDUCAUSE Quarterly.

[6] Clow, D. (2012). The learning analytics cycle: Closing the loop effectively. Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, 134–138. DOI:10.1145/2330601.2330636.

[7] Gašević, D., Dawson, S., and Siemens, G. (2015). Let's not forget: Learning analytics are about learning. TechTrends, 59(1), 64–71. DOI:10.1007/s11528-014-0822-x.

[8] Hanke, J. (2024, June). Discerning students' reading skills - Teachers or tests? [Presentation]. International Conference on Innovative Research in Education (IRECONF). DOI: 10.13140/RG.2.2.17577.30565.

[9] Hanke, J., and Diehl, K. (2024). Handbuch - Beschreibung der Lesepakete LesePfad für dritte inklusive Klassen: Beschreibung der Konstruktion der Lesepakete sowie Beispiele der Lesetexte und Leseaufgaben in deutscher Sprache. https://nbn-resolving.org/urn:nbn:de:gbv:8:3-2024-00240-2 (Access Date: 2 March 2025).

[10] Heilala, V. (2022). Learning analytics with learning and analytics: Advancing student agency analytics [Doctoral dissertation, University of Jyväskylä]. JYU dissertations.

[11] Hernández-de-Menéndez, M., Morales-Menendez, R., Escobar, C. A., and Ramírez Mendoza, R. A. (2022). Learning analytics: State of the art. International Journal on Interactive Design and Manufacturing, 16, 1209 – 1230. DOI: 10.1007/s12008-022-00930-0.

[12] Kolb, D. A. (1984). Experiential learning: Experience as the source of learning and development. Prentice-Hall.

[13] Kollom, K., Tammets, K., Scheffel, M., Tsai, Y. S., Jivet, I., Muñoz-Merino, P. J., and Ley, T. (2021). A four-country cross-case analysis of academic staff expectations about learning analytics in higher education. The Internet and Higher Education, 49, 100788. DOI: 10.1016/j.iheduc.2020.100788.

[14] Gebhardt, M., and Mühling, A. (n.d.). Levumi. Retrieved September 2, 2025, from https://www.levumi.de/

[15] Nokelainen, P. (2006). An empirical assessment of pedagogical usability criteria for digital learning material with elementary school students. Educational Technology and Society, 9(1), 178–197.

[16] OECD - Organisation for Economic Co-Operation and Development. (2008). Assessment for learning: Formative assessment. https://www.oecd.org/site/educeri21st/4060053 3. pdf (Access Date: 5 April 2025).

[17] Shum, S. B., and Ferguson, R. (2012). Social learning analytics. Journal of Educational Technology and Society, 15(3), 3–26.

[18] Siemens, G., and Long, P. (2011). Penetrating the fog: Analytics in learning and education. EDUCAUSE Review, 46(5), 30–32. https://er.educause.edu/articles/2011/9/penetrating-the-fog-analytics-in-learning-and-education (Access Date: 9 May 2025).

[19] Verbert, K., Duval, E., Klerkx, J., Govaerts, S., and Santos, J. L. (2013). Learning analytics dashboard applications. American Behavioral Scientist, 57(10), 1500–1509. DOI: 10.1177/0002764213479364.

[20] Wylie, C. (2023). Formative assessment examples of practice. Council of Chief State School Officers. https://ccsso.org/resource-library/formative-assessment-examples-practice (Access Date: 14 May 2025).

 | DOI: 10.20533/ijds.2040.2570.2025.0248