Advances in Analytics for Learning and Teaching

Muhittin Sahin
Dirk Ifenthaler *Editors*

Assessment Analytics in Education

Designs, Methods and Solutions

Springer

Advances in Analytics for Learning and Teaching

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This book series highlights the latest developments of analytics for learning and teaching as well as providing an arena for the further development of this rapidly developing field.

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Editors

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Preface

Online assessment has been advancing rapidly in the context of higher education, and its growth is set to accelerate with emerging opportunities for data collection and analysis. Yet, the future of online assessment faces significant challenges, including, perhaps most importantly, the extent to which assessments, when enabled by technology, can simultaneously serve the needs of learners, teachers, and those of the enterprise of education. Online assessments may involve, for example, a pedagogical agent acting as a virtual coach patiently tutoring someone and providing feedback on anything they would like to learn; scaffolding students to complete a task and measuring how much support they need; an analysis of a learner's decisions during a digital game or simulation; students reviewing and commenting on each other's digital creations through an online discussion; a multimedia-constructed response item created with an online animation and modeling application; students receiving remote asynchronous expert feedback about how they worked with each other via IT to solve a problem and communicate their understanding; an emotionally engaging virtual world experience that unobtrusively documents the progression of a person's leadership and ethical development over time; or semantic rich and personalized feedback as well as adaptive prompts for reflection through data-driven assessments.

As a result, this edited volume, *Assessment Analytics in Education: Designs, Methods, and Solutions*, presents a collection of contributions focusing on analytics-based indicators or measurements centering on learning processes and related behavior, (meta-)cognition, emotion, and motivation, as well as social processes. In addition, implications on design, analytics procedures, and related indicators are addressed. It features two major parts: Part 1 – Perspectives on Behavior, Engagement, and Interaction, and Part II – Perspectives on Analytics, Design, and Indicators.

Without the assistance of experts in learning analytics, the editors would have been unable to prepare this volume for publication. We thank our reviewer board for their tremendous help reviewing the chapters and linguistic editing. In addition, we

would like to thank the series editors of Advances in Analytics for Learning and Teaching for guiding the publication process and including our work in the book series.

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Editors

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Part I
Perspectives on Behavior, Engagement, and Interaction

Chapter 1
Foundations of Assessment Analytics

Muhittin Sahin and Dirk Ifenthaler

Abstract Assessment analytics (AA) emerges as a subset of learning analytics (LA), focusing on collecting and interpreting assessment data to guide recommendations and feedback. AA specifically targets assessment systems, analyzing metrics like time spent on questions. The chapter explores AA's definitions, frameworks, stakeholders, and research, emphasizing its importance in refining assessment processes and understanding learner experiences.

Keywords Learning analytics · Assessment analytics · Formative assessment · Feedback

1.1 Introduction

Instructional techniques are important in facilitating, making effective, and supporting learning and teaching processes. In this context, in recent years, learning analytics (LA) offers important opportunities to support learning and teaching (Lang et al., 2022; Johnson et al., 2013). LA is an emerging learning technology that aims to provide an individualized learning experience and, for this purpose, uses student-related data obtained from multiple sources (Wu et al., 2021). LA is defined as the use, analysis, and assessment of data obtained from learning environments and

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learners in order to optimize learning environments and learning processes, and make educational decisions (Ifenthaler, 2015). The application fields of LA consist of dropout prediction, enhancing learners' learning outcomes, study success, providing support and personalization, reflection, support decision making, analyzing the learning process of the learners, support writing activities, real-time feedback, and visualization (Sousa et al., 2021; Ifenthaler & Yau, 2020). On the other hand, learning analytics is also used for assessment purposes such as (a) monitoring and analysis, (b) automated feedback, (c) prediction, prevention, and intervention, and (d) providing new assessment forms (Caspari-Sadeghi, 2023). In the literature, it has been stated that learning analytics will also benefit the field of assessment (Milligan, 2020) and that research on using log data and analytical techniques in the field of assessment has started to be conducted (Ifenthaler & Greiff, 2021). It is suggested that assessment should be moved beyond the testing paradigm and utilize LA in assessment (Redecker et al., 2012).

Most research on learning analytics has examined the impact of learning analytics on learner achievement (Sahin & Ifenthaler, 2021). Kew and Tasir (2022); Yang and Ogata (2022); Aguilar et al. (2021); Russell et al. (2020); Kia et al. (2020); Cha and Park (2019); and Arnold and Pistilli (2012) are examples of studies examining the impact of learning analytics on learner performance. In addition, the research conducted by Sahin and Ifenthaler (2021) observed that feedback was added as a keyword in 8%, and assessment was added as a keyword in 7% of the studies in which learning analytics was included as a keyword. This situation in the literature can be interpreted as the significant contribution of learning analytics to the assessment field. From all these studies, it can be stated that feedback and assessment are essential concepts for learning analytics.

Through assessment, it is possible to determine what learners know about the subject and the gaps between where they should be and where they are. Massive Open Online Courses (MOOC), learning analytics, and assessment analytics are in the future of assessment (Jordan, 2013). Technology and enhanced analytics assessment systems can guide the learner's learning, reduce punctuation time, provide diagnostic reports, and provide individual feedback (Irons & Elkington, 2021). However, in addition to these, with the contributions of assessment analytics, it is possible to discover the assessment patterns of learners and thus improve the assessment processes and become even more effective. In this way, it will not only contribute to the development and optimization of these environments but also make it possible to discover assessment experiences and understand these processes in a better way.

Assessment analytics (AA) is monitoring, collecting, tracking, organizing, and interpreting assessment data and using this to make recommendations and provide feedback as well as guidance (Economides, 2009). Assessment data is crucial for assessment analytics. However, using analytics and methods in assessment needs to be treated as a separate field. Assessment analytics (AA) has been handled as a part of LA. At the same time, assessment data is the best predictor of achievement, among other metrics. However, some assessment metrics are related to assessment, not directly learning. The time spent by the learner on each question, the number of repeated turns to the question, the type of feedback the learner needs in any assessment task, etc., can be given as an example of these assessment metrics. It is important to associate AA with assessment and testing theories, such as linking LA with learning and teaching theories. Another important reason for separating LA and AA concepts is that assessment plays an important part in the learning process. Therefore, there are assessment modules within the learning systems (in the context of formative assessment), such as Learning Management System (LMS) and Massive Open Online Courses (MOOC).

On the other hand, there are standalone/independent testing or assessment systems (e.g., Adaptive Mastery Testing—AMT, Computer Adaptive Testing—CAT). Such systems have no learning content; the metrics produced from these systems cannot be called LA. Therefore, AA should be handled under another research topic (another type of analytics).

In this chapter, to better understand assessment analytics, the concept of assessment, definitions, and frameworks in the field of assessment analytics, stakeholders of assessment analytics, a summary of research in the field of assessment analytics, and the importance and contribution of assessment analytics to the literature are discussed.

1.1.1 Assessment

Assessment is an important construct linked to learners' learning process (Bayrak, 2022; Wisniewski et al., 2020; Nouira et al., 2019; Earl & Katz, 2006; Bransford et al., 2000). In fact, assessment is located at the heart of the learning process (Knight et al., 2013; Gikandi et al., 2011). Assessment gathers information about the learning and teaching process (Hanna & Dettmer, 2004).

Assessment is used for different purposes, and the literature has many different assessment classifications. Assessment is divided into summative and formative assessment according to its purpose (Sadler, 1998). Summative assessment is the assessment conducted at the end of a unit or semester to determine the performance level of the learner through achievement tests or to determine the effectiveness of the curriculum. Formative assessment is defined as a process of identifying what students know and what they lack in order to improve learning (Pinchok & Brandt, 2009). Summative assessment is the assessment conducted at the end of the semester to ensure student progress. In contrast, formative assessment is the assessment conducted during instruction to make adjustments in the teaching process (Earl & Katz, 2006). Nowadays, however, assessment is not divided into formative and summative assessment but into assessment of learning, assessment as learning, and assessment for learning (Earl & Katz, 2006). Detailed information about these assessment types is presented in Fig. 1.1.

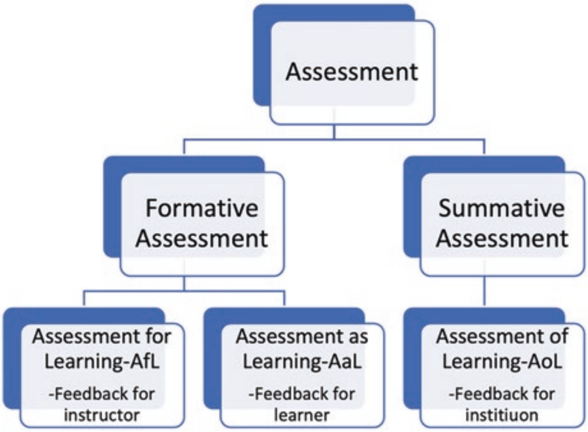

Fig. 1.1 Summary of assessment types (Bayrak, 2022)

In the new classification, assessment of learning corresponds to summative assessment, while assessment as learning and assessment for learning correspond to formative assessment. Assessment of learning is used to determine an individual's level of learning and to certify or prove it. Assessment as learning is a type of assessment that enables the learner to identify strengths and weaknesses in the learning process and to make a self-assessment. It aims to support the learning experience by providing information about the learner's performance (Yorke, 2003). Finally, assessment for learning aims to optimize the teaching environment and the learning process, and the results are presented to the instructor or administrator. Recently, with the development of technology and its use in teaching and learning processes, formative assessment systems have started to be used in addition to summative assessment systems. The indispensable part of the formative assessment process is feedback.

Feedback, which is one of the most important factors in increasing learner success, is the presentation of information about an individual's performance through an agent (instructor, peer, etc.) (Hattie & Timperley, 2007). In another definition, it is defined as information provided to the learner to regulate the learner's behavior in order to improve learning (Shute, 2008). Feedback should provide information that can fill the gap between the current state and the desired state of individuals related to the learning task or process (Sadler, 1989). Feedback has essential functions such as (a) improving learning, (b) informing, (c) guiding, (d) increasing motivation, (e) organizing, (f) reinforcing, (g) guiding, (h) evaluating, (i) validating, (j) suggesting, and (k) reconstructing (Narciss & Huth, 2004). However, Hattie (1999) reported that not all feedback has the same effect. On the other hand, it is known that feedback is more effective when it provides information about correct answers rather than incorrect answers, and it is also affected by the difficulty of the goals/task (more effective when the complexity of the task is low and specific) (Kluger &

DeNisi, 1996). Effective feedback must answer three questions (Hattie & Timperley, 2007):

- Where am I going—Feed Up?
- How am I going—Feed Back?
- Where to next—Feed Forward?

On the other hand, the characteristics that good feedback should have are as follows (Nicol & Macfarlane-Dick, 2006):

- Clarifying what the expected performance is,
- Facilitating self-assessment,
- Providing quality information about the learning process,
- Encouraging learner-learner and learner-instructor interaction,
- Motivating and promoting self-confidence,
- Providing opportunities to close the gap between current and desired performance,
- Providing instructors with information they can use to shape the teaching process.

Many different types of feedback can be provided to learners through technology, and analytics-enhanced systems. Detailed information about feedback types and their descriptions are presented in Table 1.1.

As seen in Table 1.1, there are many types of feedback. Various feedback is provided to students, both formative during the learning process and summative at the

Table 1.1 Detailed information about the feedback types (Shute, 2008)

Types of feedback	Explanation of feedback types
No feedback	Presenting no information about the correctness of the student's response.
Verification	Presenting to the student that correctness of the response (right or wrong, percentage of the correct response).
Correct response	Presenting the correct response without additional information.
Try again	If the response is incorrect, allow the student one or more response chances to answer the question.
Error flagging	Highlighting the errors in the solution without the correct response.
Elaborated	Providing explanations for why the correct response is the correct one. It can be in different forms, such as; attribute solution (presenting basic characteristics of the concepts or the skill), topic contingent (providing information about the subject), response contingent (presenting a specific response that explains why the wrong response is wrong and why the correct response is correct), hints/prompts (presenting detailed feedback that guides to the students to find the correct response), bugs/misconceptions (informing about the misconceptions and the mistakes), and informative tutoring (presenting of metacognitive and strategic information about the completion of the task to the student without sharing the correct response).

end of the learning process, via technology and analytics to enhance the assessment environment. The impact of both the feedback and feedback types provided in assessment systems and the impact of assessment metrics on learning and the assessment process can be examined in depth through assessment analytics. Thus, the environment can be optimized.

1.1.2 Assessment Analytics

The information gathered during the assessment process is important in guiding decisions about instruction and curriculum (Erwin & Knight, 1995). By analyzing the data obtained during the assessment process, relationships between (a) learner errors/misconceptions and learner interactions (Jordan, 2014), (b) students' behavior in different questions (Jordan et al., 2012), and (c) learner performance can be revealed (Ding & Beichner, 2009). At this point, assessment analytics provides essential contributions to researchers and stakeholders in analyzing the data obtained in assessment processes, discovering patterns, and optimizing assessment environments.

Redecker et al. (2012) stated that learning analytics should also be used in assessment processes with the slogan "move beyond the testing paradigm." At this point, the concept of assessment analytics was introduced. AA is a sub-field of LA and an emerging field by itself (Ellis, 2013; Papamitsiou & Economides, 2016; Bayrak, 2022). Assessment analytics has a remarkable potential to contribute to learning analytics (Ellis, 2013). While learning analytics aims to provide personalized learning experiences (Ifenthaler & Widanapathirana, 2014), assessment analytics aims to provide personalized assessment experiences. Assessment analytics can be defined as using the data obtained from the assessment processes, processing assessment data, and discovering patterns in these data in order to optimize assessment processes and environments and create individual assessment processes with individual interventions and recommendations.

Assessment and feedback theory are the most appropriate starting point for assessment analytics (Ellis, 2013). This is because the type of assessment to be used (assessment of learning, assessment as learning, assessment for learning) and the types of feedback (e.g., no feedback, verification, try again, elaboration feedback, etc.) to be used according to these assessment types should be handled within the scope of these theories. In addition, assessment and feedback theory will guide researchers in interpreting the analysis results and patterns obtained and optimizing the systems in the next step. Providing appropriate and individual feedback according to the behavioral data in the online learning environments is crucial (Chatti et al., 2012). In this point, AA has an important potential to the stakeholders. Because AA aims to improve the learners' learning performance by providing appropriate feedback to the students according to the assessment data. The ultimate goal of the AA is to provide an efficient and effective assessment process (Papamitsiou & Economides, 2016).

Learners at the micro-level, instructional designers and course facilitators at the meso-level, institutions at the macro-level, and governance at the mega-level are the stakeholders of learning analytics (Ifenthaler, 2015). In addition to these stakeholders in assessment analytics, assessment designers and experts in measurement and assessment fields are also stakeholders. At the mega-level, policymakers and decision-makers can plan the next step by deciding what to do about the outcomes and performance of the learning process and policies. At the macro-level, organizations and institutions can determine the effectiveness of their programs, identify what is working well and what needs to be revised, and then decide and take steps for the future. At the meso-level, instructional designers, course facilitators, assessment designers, and experts in the measurement and assessment field can work on optimizing the system by discovering patterns in the assessment processes. They can also help institutions and decision-makers to make policy by providing information. At the micro-level, learners can see their strengths and weaknesses and recognize their gaps. At this level, they can decide how to strengthen their weaknesses and what strategy they can use in the next step with the intervention and feedback they receive based on their assessment processes through assessment analytics.

Assessment needs to be an ongoing process of collecting data from different contexts (DiCerbo et al., 2016). AA can provide data from various sources, just like learning analytics. Data related to AA can be collected in Learning Management Systems (LMS), Student Information Systems (SIS), and stand-alone assessment environments. In LMSs and stand-alone systems, information/metrics about students' assessment tasks can be collected, while in SIS, information about students' individual and demographic characteristics can be collected. In addition to LMSs, stand-alone technology and analytics-enhanced assessment environments were added for assessment analytics data sources. Because in these environments, only data about the assessment processes of the learners are collected, and these data can be used to optimize the systems within the scope of assessment analytics.

1.1.3 Significance of Assessment Analytics

Digital learning environments enable learners to continuously monitor their progress (Gikandi et al., 2011). With assessment analytics, learners will be provided with information about their assessment processes through dashboards, and interventions can be made for them to decide on the next step. This will enable learners to make self-assessments. The main purpose of self-assessment is to improve learning by identifying the strengths and weaknesses in the learner's own performance (McMillan, 2007). Self-assessment, which is known to increase learner success when done regularly (Boud, 2000), is seen as an important skill for university students (Nicol, 2009). However, self-assessment is an important skill not only for university students but also for pedagogy and andragogy. Today, students are expected to be self-directed learners and learners who know where and when to work and how to work. At this point, technology and analytics-enhanced systems create important opportunities. With assessment analytics, both the hidden patterns in the assessment process are revealed, and the assessment processes are improved. In this way, both learners' learning outcomes and learning processes are improved.

Teaching and learning processes should be a student-centered assessment to show learners their abilities and improve their learning (Bransford et al., 2000). Students' assessment processes contain important information about students' learning. Vast amounts of data and many different types of data can be collected in assessment environments via technology and analytics assessment environment. However, discovering patterns in the data stored in these environments and optimizing the system is possible with assessment analytics. By discovering patterns, students can identify their strengths and weaknesses, the topics they need to emphasize, and the strategies they can apply in the assessment process. Technology and analytics enhance the assessment environments that will have a student-centered structure.

It is difficult for instructors to identify the learning deficiencies of learners and provide one-to-one feedback to individuals in high school institutions (Boud, 2000; Pardo et al., 2019). In his meta-analysis study, Bloom (1984) stated that providing one-to-one tutorial support to learners increased learner achievement by two standard deviations (*two sigma problem*). At this point, technology and analytics enhance the assessment environment and offer important opportunities. Assessment analytics has an essential role in taking these opportunities one step further. Because with assessment analytics, learners' behavioral patterns toward assessment processes can be revealed, and assessment processes can be individualized. This way, assessment environments will be optimized and individualized, and learning success will be increased by providing one-to-one support to individuals.

It has become possible to intervene in learners' learning processes with LA. In this context, intervention and intervention engine designs based on learning analytics are also made (Şahin & Yurdugül, 2019; Tlili et al., 2018; Arnold & Pistilli, 2012; McKay et al., 2012). In addition, intervention designs are also made according to assessment metrics in learning environments (Şahin & Yurdugül, 2019). Assessment metrics are included in both digital learning environments and standalone assessment systems. With assessment analytics, appropriate interventions can be made, and different types of feedback can be provided to learners in all environments where metrics for the assessment process are included. The contribution and significance of assessment analytics can be summarized as follows:

- Designing assessment environments that can provide one-to-one support to learners,
- Enabling learners to self-assess and supporting learner autonomy,
- Supporting learning and assessment processes,
- Exploring behavioral patterns in assessment processes,
- Designing and examining interventions for assessment processes,

- Identify metrics, characteristics, and constructs that are important in assessment processes,
- Significance contributions to assessment and feedback theories,
- Optimizing assessment environments to make them more effective and efficient.

1.2 Literature Review

In this section, a literature review has been conducted in order to reveal the situation regarding assessment analytics. As a result of the literature review, it has been seen that there is still a very insufficient number of studies on assessment analytics. One of the aims of this chapter is to provide a theoretical background, insights, and future directions for those who will conduct research on assessment analytics. When we look at the studies, it is possible to say that there are studies that put forward a theoretical framework (Nouira et al., 2019; Papamitsiou & Economides, 2016; Ellis, 2013) and studies in which the system is developed and tested (Bayrak, 2022; Hooda et al., 2022; Papamitsiou & Economides, 2017).

It would be appropriate to state that research on AA started to be conducted in 2013 and has started to increase in recent years. In 2013, Ellis explained the concept of AA in order to expand the scope of learning analytics and increase its usefulness. In this context, Ellis stated that assessment data can consist of individual assessment results, end-of-semester grades, rubric results, and student strengths and weaknesses.

In another study by Papamitsiou and Economides (2016), an AA framework was put forward to enhance students' learning development. In the study, where it is stated that the field of AA is a subfield of LA, it is noted that the AA framework consists of four phases: input, process, output, and feedback. The input phase answers the questions of what, why, who, when, and where in terms of why monitoring and evaluation are conducted. The process phase answers the questions of how data is collected, analyzed, and interpreted. The output phase answers the questions of what, why, who, when, and where in terms of how outputs will contribute to assessment processes. Finally, the feedback phase answers the questions of what, why, when, and where for feedback to use the cycle effectively.

In another study by Papamitsiou and Economides (2017), an e-assessment system was presented to students. The developed environment is called the Learning Analytics and Educational Recommender System (LAERS). The research aims to apply assessment analytics and provides a methodology for creating student models during the web-based self-assessment process. In student modeling, 17 different metrics were collected, and four of them were used. These metrics are total time spent to answer correctly, total time spent to answer wrongly, level of certainty, and response time effort. Different algorithms were employed to analyze these data, and the findings were presented within the scope of the study.

Nouira et al. (2019) proposed a model inspired by xAPI for assessment analytics. They used log data from a MOOC platform to validate the model. In terms of assessment metrics, they used score, time spent, attempt, number of total response items, number of non-response items, number of wrong responses, completion, and success metrics. In their study, 750,000 learning activities of 3470 learners from 70 different countries were collected as log data. They developed a semantic web application to convert the assessment data into Ontology Web Language (OWL) files according to the ontological model.

Bayrak et al. (2021) examined the interaction between learners and feedback provided after assessment tasks. The system provided to students with criteria-referenced feedback, elaboration feedback, self-referenced feedback, and norm-referenced feedback on assessment tasks. The study was conducted with 100 first-year students at a state university, and the students had a four-week experience. Lag sequential analysis was used to analyze the data. When the findings were analyzed, it was seen that the students switched to the feedback in the order in which they were presented. They also found that the transitions between feedback types were statistically significant and that the transitions between feedback types of master and non-master students were similar.

Bayrak (2022) developed a web-based system for students to assess themselves, presented it to students, and discussed the findings within the scope of assessment analytics. The system that was developed was named Web-Based Self-Assessment System (WebS-AS). The system presented the exam results to the students with different feedback and visualization methods. The study, which was structured as a one-shot case study, was attended by 214 undergraduate students enrolling in the measurement and evaluation course. It was concluded that students used feedback at a high rate to evaluate themselves and follow their learning processes. Additionally, summary information about the studies in the literature is presented in Table 1.2.

As can be seen in Table 1.2, it is noticeable that the studies from the past to the present are theoretical structure, framework, and then the development of systems and the implementation of these developed systems. It is thought that with a better understanding of the concept of assessment analytics, studies will increase, and assessment processes will become more effective and efficient.

Table 1.2 Assessment analytics in the literature

Author(s)	Year	Aim of the research
Ellis	2013	Identify assessment analytics
Papamitsiou & Economides	2016	Assessment analytics framework
Papamitsiou & Economides	2017	Develop and apply an assessment environment—Learning Analytics and Educational Recommender System (LAERS)
Nouira, Cheniti-Belcadhi & Braham	2019	Develop assessment xAPI for MOOC
Bayrak, Aydın, & Yurdugül	2021	Examine the learners' interactions according to the feedback
Bayrak	2022	Develop and apply an assessment environment—Web-Based Self-Assessment System (WebS-AS)

1.3 Discussion and Conclusion

Analyzing and understanding data and data quality are the main challenges of data obtained from digital learning environments (Kuosa et al., 2016). At this point, learning analytics provides important opportunities. Learning analytics can potentially change and support the learning process (Ferguson et al., 2016). On the other hand, the important component of the learning process is assessment (Earl & Katz, 2006). Collecting and analyzing the data during the assessment process is crucial. In order to both optimize and individualize assessment environments and experiences, assessment processes need to be well understood. In order to understand assessment processes, assessment analytics, which aims to optimize environments by discovering patterns in the data involved in this process, provides important opportunities. Assessment analytics involves using data from assessment processes first to identify latent patterns and behaviors in assessment data. Design based on these patterns, present these designs to stakeholders so they can experience them, and finally test and optimize them. Assessment analytics provides important contributions to stakeholders and researchers in all these processes. The contributions, stakeholders, and process outputs of assessment analytics are detailed in the challenges and future directions section at the end of the book.

In this chapter, the concepts of assessment and assessment analytics are introduced. It also discusses why assessment analytics should be considered as a separate concept from learning analytics and the reasons for this. Assessment environments can be designed both as an additional module to learning environments and as stand-alone systems. For example, in assessment environments developed as a stand-alone system, it would be more appropriate to use assessment analytics rather than learning analytics. Because the data obtained from this environment and the patterns based on these data are relevant to the assessment processes. In addition, some metrics obtained from assessment environments are only related to assessment processes. Therefore, assessment analytics is a concept that needs to be considered and focused on separately.

Assessment is one of the most important elements of the learning process. With assessment analytics, latent patterns in assessment processes are discovered; thus, both assessment environments and assessment processes are optimized. In addition, assessment analytics contributes to (a) providing one-to-one support in assessment environments, (b) supporting learner autonomy, (c) supporting learners' assessment processes, (d) identifying behavioral patterns, (e) creating individual assessment processes, and (f) structuring interventions.

It is possible to say that the assessment analytics concept was first introduced by Ellis in 2013. In the following years, it is possible to see that conceptual framework studies on assessment analytics were conducted. In recent years, system development studies have been carried out for assessment analytics, and these systems have been implemented in real-time with students. However, it has been determined that the research on assessment analytics is very insufficient, and there is a need for more experimental evidence on assessment analytics. The lack of research on assessment analytics is because there is not much information, theoretical framework, and application examples for the concept. Challenges and future trends in assessment analytics are discussed in the book's last chapter.

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