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Toward a categorisation of indicators for assessment analytics

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Recent advancements in assessment analytics provide the potential to support learning processes and deliver relevant informative feedback when needed. Yet, few well-defined indications yield valid data points for assessment analytics. The categorisation of indicators that is presented here is designed to provide insights into the possible approaches to assessment and the meaningful connection to assessment analytics. Ethics, social responsibility, privacy, and data protection must be fully respected when following the categorisation of indicators for assessment analytics.

Keywords: adaptive feedback, assessment analytics, data indicators, formative assessment, learning analytics, online assessment, summative assessment

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Introduction

The use of online assessments has been increasing rapidly, as they offer the promise of more efficient ways of delivering and marking assessments as well as access to vast amounts of assessment data that could be used for a wide range of conclusions and recommendations relevant for students, teachers, schools, and education systems (Webb & Ifenthaler, 2018). A recent systematic review of online assessments identified and synthesised various modes, types, and forms of assessments (Heil & Ifenthaler, 2023). In a nutshell, modes of assessment include peer-, teacher-, automated-, and self-assessments; formats of assessment can either be formative or summative; assessment type refers to the implemented representation of the assessment. This could include, for example, quizzes, essays, e-Portfolios, and project-based tasks, but also other types are observed.

The various opportunities for online assessment also result in a large variety in design concerning the formats, modes, and types of online assessments. Online assessment allows for a wide range of implementation possibilities. This can range from adaptive quizzes, over peer-assessed essay writing to teacher-assessed case-based learning scenarios.

In addition to a critical reflection on the conceptual clarity of online assessments, assessment analytics is an emerging line of research. In the field of learning analytics, assessment analytics uses data obtained through assessments to inform learning processes (Ellis, 2013). Recent developments in this area bear opportunities for a better understanding of learning processes as well as for providing meaningful feedback and interactive support for learners across a variety of settings (Gašević et al., 2022). For instance, Ifenthaler and Greiff (2021) suggested a benefits matrix for analytics-enhanced assessment, which provides examples of how to harness data and analytics for educational assessment. The clear and comprehensive categorisation of assessment into mode, format, and type (Heil & Ifenthaler, 2023) allows a better understanding of individual aspects in assessment design and to identify and classify specific application contexts. Based on this classification, it is possible to draw conclusions about relevant data points that can individually support the subsequent assessment and learning processes.

However, clearly defined indicators that produce valid data points for assessment analytics across different modes, formats, and types are scarce. Therefore, this contribution introduces a categorisation of indicators for assessment analytics that is based on a matrix following the most frequent combinations of assessment mode (automated, peer, self, teacher), assessment format (formative, summative), assessment type (e.g., short-answer, quiz, essay, portfolio, etc.), and related feedback (e.g., rubric-based, narrative, correctness, reports, etc.). As a result, the categorisation of indicators will allow learning designs, data scientists, and educators to integrate meaningful and valid indicators into their assessment designs, thus providing a foundation for assessment analytics and ensuring transparency and fairness of data usage.

Assessment analytics

Over the past decade, there has been an increase in interest in gathering and processing educational data on student backgrounds and performance (Baker & Siemens, 2015). While the use of learning analytics in educational settings has advanced quite substantially (Buckingham Shum & McKay, 2018), research suggests that meaningful analysis of educational data requires a comprehensive theoretical foundation as well as robust evidence of validity, gained for instance in (quasi-)experimental or longitudinal evidence-based design processes (Ifenthaler & Yau, 2020; Marzouk et al., 2016). A specific focus on the usage of assessment-generated data and analytics-driven assessment can support learning in real-time and support stakeholders in improving their decisions on learning environments (Ellis, 2013; Webb & Ifenthaler, 2018).

Indicators based on directly observable behaviours in the digital learning environment, such as time spent online, access to different sorts of resources, or reading and making posts, remain the main emphasis of learning analytics approaches (Mah, 2016; Martin & Whitmer, 2016; Yau & Ifenthaler, 2020). Other learning analytics approaches are focused on learner characteristics such as demographic data to, for instance, predict study success or chances of dropout (Costa et al., 2017; Lacave et al., 2018) as well as noting potential ethical issues with such approaches. However, while new applications and approaches have brought forth new insights, there is still a shortage of research addressing the effectiveness and consequences of these endeavours. Vieira et al. (2018) emphasise that research on learning analytics focuses on analysing resource utilisation, with just a few researchers taking a process-oriented approach by attempting to assess learners' actual learning progress through carefully defined and validated indicators.

Therefore, learning analytics may yield only limited insights into students' actual learning, because the indicators collected are not pedagogically valid. For instance, specific indicators, such as 'time on task' might have different meanings depending on the learning contexts and the specific domain they are embedded into (Goldhammer et al., 2014). As a consequence, studies that report on "time on task" often yield inconsistent and also somewhat inconclusive results. To make adequate use of great amounts of data and learning analytics, more relevant and specific indicators need to be developed (Ifenthaler & Greiff, 2021). At the same time, assessment analytics has a yet-to-be-exploited potential to provide indicators that are tailored towards the learning setting and therefore provide further meaningful insights into the learning process. Assessment plays a central role in the design of learning environments and in motivating learners (Ellis, 2013). In addition, the provision of feedback that the learner can act upon plays a crucial role in facilitating learning (Carless, 2007). Given the impact of assessment and feedback on learning processes, a generic selection of indicators is not an appropriate solution for diverse learning scenarios.

This is in line with Ellis (2013), who called for the use of assessment data in the further analysis of learning processes. Especially when assessing in a formative format, the assessment data can provide indicators to analyse the ongoing learning process, whereas summative assessment can provide potential analysis of standards and comparisons (Ifenthaler & Greiff, 2021).

In summary, assessment analytics harnesses formative and summative data from learning processes and the context in which they occur to facilitate learning in (near) real-time (Ifenthaler & Greiff, 2021). To ensure the meaningful implementation of assessment analytics, choosing indicators that are aligned with the current learning design and related learning processes as well as learning outcomes remains a current challenge. The clear allocation of possible indicators for specific assessment design not only allows for more in-depth research into the effectiveness of assessment analytics and analytics-based feedback, but also bridges the gap between theory and practice by supporting practitioners in designing their learning environments.

Categorisation of indicators

The following categorisation of indicators is designed to provide first insights into the possible approaches to assessment and the meaningful connection between specific indicators and their use in assessment analytics. Table 1 provides an initial categorisation of indicators for assessment analytics which is based on a systematic review including 114 research articles with a specific focus on online assessments (Heil & Ifenthaler, 2023). The following sub-sections elaborate on the categorisation of indicators by mode, format, type, and feedback content as well as providing examples of indicators for assessment analytics developed based on the current state of scientific research.

Table 1. Categorisation of indicators for assessment analytics

Mode	Format	Type	Feedback Content	Indicators for Assessment Analytics
Peer & Teacher	Formative and Summative	Essay	Narrative	Rubric-based indicators of strengths and weaknesses Comparison between peers Deviations of different
		e-Portfolio	Rubric-based	Progress indicators
Automated	Formative	Quiz	Reports Fail/No Fail	Performance factors Temporal features Alignment of answers with common mistakes
		Short-answer questions	Reports Fail/No Fail	Sentiment analysis, closeness index
		Essay	Reports Fail/No Fail	Rubric-based indicators
Self	Formative	e-Portfolio	Self-comparison with Rubric	Improvement Persistence Attainment

Peer and teacher assessment

Peer- as well as teacher-assessments, are often used on essays or other types of writing tasks as well as on e-Portfolios (Heil & Ifenthaler, 2023).

Essays: In a formative as well as a summative format, indicators of the achievement of intended learning outcomes include an evaluation of the demonstrated competence by the assessed learner through a predefined rubric (Seufert et al., 2019). If multiple peers provide feedback, online assessment and methods of machine learning allow for a comparison of the peer feedback among each other (Divjak et al., 2016) to support the validity of the assessment (Darvishi et al., 2022). Such comparisons can serve as indicators to provide feedback on the quality of the peer feedback but also the actual performance of the learner by finding common ground on aspects covered frequently. Similarly, in the combination with teacher assessment or the assessment by an automated system, deviations from peer or teacher feedback can be discovered (Divjak et al., 2016). Methods of automated outlier detection can also investigate aspects of the given feedback by teachers or peers that do not align with other points or grading (Divjak et al., 2016). For example, in a rubric, the majority of peers may rate the structure of an essay well, but a single person disagrees with the assessment, which then does not factor in so strongly. Furthermore, one aspect of the rubric, such as the content, might deviate strongly from the actual overarching evaluation of the essay, including the other factors.

e-Portfolio: In e-Portfolios, which formatively track the learner's learning process, the observed alignment of improvement with previously marked strengths and weaknesses can serve as possible indicators of the learning process. Teachers as well as peers can document and assess these processes and provide indicators for feedback and further analysis. This might, for example, refer to a learner improving their work on a project and addressing previously identified issues in the planning or development.

Automated assessment

Automated assessment is not limited to but is frequently used on quizzes, short-answer questions, and essays.

Quiz: In many cases, quizzes are used formatively to support the learning process. Indicators of learners' progress and processes identifiable through an evaluation of behaviour include performance factors, such as the percentage of correct answers in tasks, as well as the number of submitted assignments (Veerasamy et al., 2021) or temporal features (Chen et al., 2018). This might include time spent on individual tasks or overall time spent in the assessment process. Another factor is the continuation of attempts (Zhang et al., 2021), which can indicate whether learners have abandoned the assessment process or continued, especially after giving incorrect answers. More advanced analysis methods also allow for the detection of the deviation or alignment of given answers with common mistakes (Barana et al., 2019). To support teachers in automated assessment scenarios, automated systems can also contribute by providing a discrimination index of questions (Barana et al., 2019).

Short-answer questions: Methods of Natural Language Processing (NLP) to assess short-answer questions include text-mining, sentiment and content analysis (Blikstein, 2013). Both sentiment and content analysis can provide insights into learner behaviour and attitudes towards the tasks and engagement with them. This can, for example, show that learners might have mentioned essential keywords but not clearly understood the assignment. Another factor is closeness indices to correct responses, which can be utilised as further indicators.

Essays: Automated assessment can also be applied to writing tasks such as an essay in the form of automated essay scoring. While the same indicators apply to short-answer questions, more advanced NLP systems might also check for originality and thus provide indicators (Ellis, 2013). As in peer or teacher assessment, automated rubric-based assessment can provide specific indicators of possible improvement through means of automated trait-specific automated essay scoring. An NLP system might provide singular values for factors such as content, word choice, sentence fluency, organisation and adherence to conventions in contrast to one overall score (Mathias & Bhattacharyya, 2020).

Self-assessment

Self-assessment is mostly used formatively on portfolios. Indicators of the learning process are, in the case of self-assessment, perceived by the learner themselves. This includes the self-perceived level of improvement or persistence and attainment (Ellis, 2013). Learners can concretely determine improvements in their performance, for example, in a case-based learning scenario, as well as identify their perseverance in completing tasks.

Conclusions

As there is currently a discrepancy between the potential and the actual implementation of assessment analytics in educational practice, a categorisation of how to use assessment data can be a useful support in closing this gap. Choosing indicators based on the design of the assessment can provide pedagogically valid insights and tailor the analysis to the respective learning processes and learning outcomes. Through the proposed categorisation, learning designers, data scientists, and educators can adapt analytics strategies based on valid indicators that are related to assessment formats, modes, and types as well as feedback. Hence, the accessibility for implementation of assessment analytics may be increased.

Open questions to consider include which indicators can simultaneously provide feedback and insight for the assessor (peer, teacher) and the learner. Another challenge is linked to how to use the indicators to provide a meaningful visual representation of the learning progress or achievement to support learning and teaching further. While online assessments allow for the combination of multiple formats, modes, and types, this level of freedom of choice also poses a new challenge in how to make use of a valid combination of modes such as automated/peer/teacher to compare the results, validate the assessment, or detect misconceptions. As a fundamental concept, it is important to ensure the fairness of data usage as well as to understand the dynamic nature of assessment data. Ethics, social responsibility, privacy, and data protection must be fully respected when following the categorisation of indicators for assessment analytics. Learners must provide consent for the use of their data (Ifenthaler & Schumacher, 2016) and the data used as indicators need to be handled with ethical care.

When considering formative assessment, a challenge opens in mapping which formative assessment indicators can provide insights into factors such as motivation, engagement, barriers to understanding, time management, or self-regulated learning strategies (Goldhammer et al., 2014; Ifenthaler & Greiff, 2021; Veerasamy et al., 2021). Additionally, it is important to consider how to build upon these issues to support the learning process, especially considering different tasks and modes of assessment.

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