Refocusing Educational Measurement: Understanding Student Learning Through Adaptive Learning

Che Yee Lye[1]

[1] Teaching & Learning Centre, Singapore University of Social Sciences, 463 Clementi Road, Singapore 599494
cylye@suss.edu.sg

Abstract. Adaptive learning is a promising technology that is transforming higher education by personalising instruction to meet the diverse needs of adult learners. This technology leverages data-driven algorithms and continuous assessment to tailor content and pace to individual needs, enhancing learning outcomes. Traditional methods of assessment and measurement tend to focus on the starting and ending performance points, with less attention to the progression of student development. Furthermore, a significant tension exists between using assessment data for institutional accountability and for improving learning and teaching. This paper argues that adaptive learning pedagogy provides an opportunity to adopt a broader approach to measuring student progress by prioritising learning processes and growth, and by integrating human-machine collaboration in both the development of adaptive learning content and the nuanced interpretation of student data. It further considers the role of Rasch measurement in relating student proficiency to task difficulty and translating assessment evidence into actionable information for supporting learning.

Keywords: Adaptive learning, Rasch measurement, educational measurement, Zone of Proximal Development, feedback on learning, higher education.

1 Introduction

The changing landscape of higher education presents significant challenges for conventional approaches to teaching, assessment and educational measurement. Higher education increasingly serves adult learners, part-time students and lifelong learners whose educational history, professional experiences, prior knowledge and learning circumstances can differ considerably [1, 2, 3]. At the same time, personalisation and generative artificial intelligence (AI) are becoming increasingly prominent features of contemporary education [4, 5]. These developments create a strong context for reconsidering how student learning should be understood and measured.

Educational measurement has traditionally provided systematic methods for determining what students know and can do. Scores, grades, proficiency estimates and achievement levels support decisions about certification, progression, selection, programme evaluation and institutional accountability [6]. Advances in Classical Test

© The Author(s) 2026
C. Y. Lye et al. (eds.), *Proceedings of the Pacific Rim Objective Measurement Symposium (PROMS 2025)*, Atlantis Highlights in Social Sciences, Education and Humanities 56,
https://doi.org/10.2991/978-94-6239-834-4_7

Theory (CTT), Item Response Theory (IRT), Rasch measurement, computerised adaptive testing (CAT), multistage adaptive testing (MST) and other psychometric approaches have further increased the precision with which student performance can be estimated. Nevertheless, much educational assessment continues to rely on observations made at particular points in time, especially for summative judgements about achievement and attainment [7, 8]. Students may complete a diagnostic or placement assessment at the beginning of a course and an examination or other summative assessment at its conclusion. Comparison of these observations can provide evidence of achievement and, under appropriate measurement conditions, evidence of growth [7, 8]. Yet much of what happens between the beginning and end of learning may remain largely unobserved [8].

This creates an important conceptual limitation. Learning is not simply the difference between two test scores. Students may follow markedly different developmental trajectories [7, 8]. A student may progress gradually, while another student may experience an extended plateau followed by rapid improvement. Some students may successfully master a concept after a small amount of feedback, while some others may require substantial additional explanation or practice. Still, others may demonstrate apparent mastery temporarily but fail to retain or transfer learning. These differences matter educationally. They provide evidence not only whether learning has occurred, but also how learning is developing [9, 10, 11]. This distinction reflects a longstanding concern within formative assessment. Black and William [9, 11] argued that assessment becomes formative when evidence of student achievement is elicited, interpreted and used to make better decisions about subsequent learning and teaching. Similarly, Sadler [12] emphasised that students require information about the gap between present and desired performance and ways of closing that gap. Shepard [10] subsequently argued that for a learning culture in which assessment is integrated into curriculum and instruction rather than functioning predominantly as a mechanism for external judgement.

Adaptive learning creates particularly favourable conditions for extending these arguments into educational measurement. Adaptive environments can continuously gather information about student performance and use this evidence to modify subsequent learning opportunities [13, 14]. The central argument of this paper is that adaptive learning provides an opportunity to refocus educational measurement from primarily measuring student performance towards understanding student learning. This does not diminish the importance of psychometric measurement; rather it broadens the scope of measurement to include developmental progression, patterns of difficulty, responsiveness to scaffolding, repeated evidence of mastery and the relationship between measurement information and subsequent pedagogical action. Particular attention is given to Rasch measurement because placing student proficiency and task difficulty within a common measurement scale [15, 16, 17, 18] creates possibilities for translating psychometric evidence into information about what students have mastered, where they experience difficulty and what learning might appropriately follow. The paper first conceptualises adaptive learning and outlines its pedagogical foundations. It

then advances the argument for refocusing educational measurement, with particular attention to Rasch measurement and feedback on learning, and considers the implications for human-machine collaboration for both the development of adaptive learning environments and the interpretation of student learning evidence.

2 Conceptualising Adaptive Learning and Its Pedagogical Foundations

Adaptive learning is often described in technological terms: algorithms select tasks, alter sequence or difficulty, and personalise content according to student data [13, 14, 19]. This description is incomplete. Adaptation becomes educationally meaningful only when it is grounded in a defensible account of what is being learnt, what evidence indicates current learning and why a particular subsequent activity is appropriate. Adaptive learning should therefore be conceptualised as an integrated learning, assessment and measurement environment rather than as an automated delivery mechanism.

Within this environment, four forms of adaptation are particularly important: adaptive diagnostic assessment, adaptive assessment, adaptive content and adaptive sequencing. Diagnostic information provides an estimate of what students are likely to know already. Embedded adaptive assessment then supplies updated evidence about developing mastery. Content can be differentiated according to identified learning needs, while sequencing determines where the students should proceed next. The resulting cycle can be represented as diagnose, learn, assess, interpret, adapt and learn again. Measurement is therefore embedded within a recursive decision process rather than positioned only at the end of instruction.

The adaptive learning approach requires a clear substantive structure. Curriculum mapping provides the initial architecture by identifying key concepts and skills, and representing how they are related [20, 21]. Such mapping provides a basis for learning progressions, which describes increasingly sophisticated forms of knowledge, understanding or performance within a domain and can connect curriculum, instruction and assessment [20, 21]. In an adaptive environment, intended learning outcomes and key concepts can be represented as linked nodes or bands, making hypothesised pre-requisite relationships visible. Wilson's [21] construct-mapping approach provides a useful measurement analogue by linking qualitatively ordered descriptions of a construct with assessment tasks and empirical estimates. However, an empirical hierarchy of item difficulty should not be assumed to constitute a developmental progression. Rather, the progression should be treated as substantive hypotheses informed by expert judgement and refined using student response evidence.

Mastery thresholds create decision points within the progression. Mastery learning assumes that students may require different amounts and forms of support while working towards common educational expectations [22]. In adaptive learning, evidence

of mastery can trigger progression, while insufficient evidence can trigger additional practice, differentiated resources or instructor support. However, mastery should not be reduced to crossing a numerical threshold once. Immediate success may reflect temporary recall, guessing or assistance [23]. Stronger claims require repeated and appropriately varied evidence, including later independent performance and, where relevant, transfer to new contexts [23].

The zone of proximal development (ZPD) adds a further developmental perspective. Vygotsky [24] distinguished between what a student can accomplish independently and what can be accomplished with guidance. In adaptive learning, hints, feedback, worked examples and differentiated resources can operate as scaffolds when independent performance is not yet successful. A student who succeeds after a modest conceptual hint is in a different educational position from one who remains unsuccessful after substantial support. For measurement purposes, assisted and independent performance should be distinguished, while both can provide complimentary evidence about learning development [25, 26].

Learning gaps can also be incorporated into the design, for instance, using distractor-level information to identify misconceptions or specific areas of incomplete understanding that may require targeted intervention [27]. In this way, assessment responses provide information not only about success or failure, but about the nature of students' difficulties.

These foundations can support different learning models: bridging, flipped learning and revision models. A bridging model can identify pre-requisite gaps before students begin a course; a flipped learning model can use adaptive activities for pre-class concept acquisition while aggregated evidence informs classroom teaching; and a revision model can diagnose which previously learnt concept remain secure and which require relearning. The same measurement evidence may therefore lead to different actions depending on the pedagogical purpose.

3 Refocusing Educational Measurement

The significance of adaptive learning for educational measurement lies not only in its ability to generate more frequent assessment data, but also in how evidence is interpreted and used. Within an adaptive learning environment, measurement is embedded in an ongoing process of learning, interpretation and pedagogical response. This creates an opportunity to refocus educational measurement from primarily documenting performance towards generating evidence that supports decisions about what students have mastered, where difficulties remain and what learning should follow.

Educational measurement has traditionally supported decisions about achievement, progression and certification [6], and these functions remain essential. However, when

assessment is embedded within learning, measurement can also generate evidence that informs learning while it is still taking place [9, 10, 11]. This aligns with formative assessment, in which evidence of student learning is elicited, interpreted and used to inform subsequent learning and teaching [9, 10, 11]. In this context, assessment extends the purpose of measurement by emphasising how assessment evidence is used to identify the knowledge and skills students have mastered, areas of non-mastery, areas requiring remediation and strategies for improving learning [11, 12]. The emphasis therefore shifts from reporting performance alone towards using measurement evidence to support pedagogical decision-making.

Measurement can also help identify where instructional support may be most productive. When student proficiency and task difficulty are considered together, tasks close to a student's current level can provide useful information about areas in which additional support may facilitate further learning. This provides a measurement basis for informing pedagogical decisions related to the ZPD [24], where appropriately targeted support can help students progress beyond what they can accomplish independently.

A further implication concerns feedback on learning. Measurement evidence should support subsequent learning, so reports need to extend beyond scores or proficiency estimates [11, 12]. Students and instructors require information that can be interpreted in relation to curriculum and used to guide action. Learning data should therefore be translated into actionable information on which students and instructors can act on.

Refocusing educational measurement in this way places psychometric qualities within a broader educational purpose. Accurate and robust measurement remain necessary, but its value is strengthened when the resulting evidence contributes to understanding student learning and informing appropriate pedagogical responses. Adaptive learning therefore offers opportunities not only to measure students more frequently, but also to make measurement more informative for identifying learning needs, directing support and informing subsequent learning. This broader purpose provides the basis for next section, which examines how Rasch measurement can contribute to the interpretation of student proficiency, task difficulty and feedback on learning.

4 Rasch Measurement and Feedback on Learning

Rasch measurement provides a useful foundation for adaptive learning because it places student proficiency and item difficulty on a common measurement scale [15, 16, 17, 18]. This allows assessment evidence to be interpreted in relation to task difficulty and supports the calibration of item banks, the identification of appropriate levels of challenge and the generation of feedback on learning.

4.1 Rasch Measurement for Adaptive Learning

A central feature of Rasch measurement is the construction of a common scale on which student proficiency and item difficulty can be represented [15, 16, 17, 18]. This provides a basis for examining the relative position of students and assessment tasks, and therefore the level of challenge that particular tasks represent for individual students. Tasks located below a student's estimated proficiency are generally more likely to be within reach, whereas tasks located above that level are likely to present greater challenge [15, 16, 17, 18]. This relationship is particularly useful in adaptive learning, where students may encounter different assessment tasks according to their current proficiency and learning needs rather than completing the same fixed set of tasks.

Calibrated item difficulties provide the measurement foundations for this adaptive process. By locating assessment tasks along a common continuum, an adaptive system can draw from an item bank at levels that are appropriate to the students' current proficiency [28]. This supports more targeted assessment while maintaining a common frame of reference across different adaptive pathways [28]. The use of calibrated items is therefore important not only for item selection, but also for ensuring that performance can be interpreted consistently when students encounter different sets of tasks.

Rasch measurement can also support the development and maintenance of adaptive item banks. A person-item map provides information about the distribution of student proficiency and item difficulty on the same scale [18, 29], making it possible to examine whether the available tasks adequately cover the range of students using the system. Gaps in the item distribution may indicate areas where additional assessment tasks are needed, while clusters of items at similar difficulty levels may signal redundancy [18]. Such evidence can inform decisions about expanding, revising or rebalancing an adaptive item bank.

The relationship between student proficiency and task difficulty can further support adaptive sequencing and differentiated learning. Tasks that are relatively accessible may provide evidence of established knowledge or skills, while more demanding tasks may indicate areas for subsequent learning. Tasks closer to a student's current proficiency are particularly relevant to the ZPD, where learning can be advanced through appropriate guidance and scaffolding [24]. In an adaptive environment, Rasch measurement evidence can therefore help identify concepts or skills for which targeted practice, explanation, hints or other forms of support may facilitate progression, and inform decisions about the next assessment task, learning resource or level of support.

4.2 Response Patterns, Learning Gaps and Mastery

By locating students on a proficiency continuum, Rasch measurement can support the interpretation of response patterns. Responses can be examined in relation to model expectations to identify performances that are consistent with, or depart from, the estimated relationship between student proficiency and item difficulty [29, 30]. Such

response patterns are especially useful when items have been deliberately linked to curriculum concepts and potential learning gaps. Distractors can be designed to represent specific misconceptions or errors in reasoning [27], allowing incorrect responses to provide more diagnostic information than a binary score alone. When recurring distractor is selected by many students, the pattern can identify a concept that warrants targeted instructional attention. At the individual level, unexpected responses can be examined alongside other evidence such as previous attempts, use of hints and performance on other items assessing the same concept or skill, to identify areas where additional practice or explanation may be needed.

Mastery decisions can also be informed by Rasch evidence. Rather than interpreting mastery through the number or percentage of correct answers, person measures and the difficulty of relevant items can provide a common frame for considering whether a student has demonstrated sufficient proficiency on the target construct [29, 30]. The mastery standards remain linked to curriculum expectations and the intended consequences of decision. Rasch measurement contributes by making the relationship between the standard, student proficiency and item difficulty explicit and empirically examinable.

Repeated assessments can strengthen the interpretation of learning evidence by showing whether students demonstrate improved performance after additional learning or support [31]. Within adaptive learning, students who have not yet reached the mastery threshold may receive further resources, practice, hints or feedback before being assessed again. Subsequent evidence can then be used to determine whether previously identified areas of non-mastery have improved and whether students are ready to progress to the next concept or level.

4.3 Translating Rasch Evidence into Feedback on Learning

The educational value of Rasch measurement depends on how psychometric evidence is translated into feedback that students and instructors can understand and use. Logit measures, standard errors, item difficulties and fit statistics are important for psychometric analysis, but they provide limited pedagogical value unless they are interpreted in relation to curriculum expectations, areas of mastery and possible next steps for learning. Recent work has similarly argued that Rasch analysis should extend beyond instrument validation towards formative applications that provide diagnostic information about student learning [32, 33]. In an adaptive learning context, this means using Rasch evidence not only to estimate proficiency, but also to identify areas requiring support, remediation and future learning goals.

One useful approach is to translate person and item measures into interpretable regions of learning. Lye and Lim [30], for example, used Rasch-derived person ability and item difficulty estimates to construct a Guttman scalogram and person-kid-map (KIDMAP) for students in an adaptive mathematics course. The Guttman scalogram was used to identify areas in which groups of students were likely to require support,

while the KIDMAP provided individual-level diagnostic information by locating responses within regions such as mastery, need-consolidation, need-scaffolding, mistakes or special learning needs, non-mastery future goals and beyond-ability [30]. These representations illustrate how Rasch outputs can be converted into more pedagogically meaningful information than a single proficiency estimate.

Such feedback can support different users in different ways. For students, it can highlight areas already mastered, concepts requiring further consolidation or scaffolding and possible future learning goals [30]. For instructors, it can identify broader patterns of difficulty and areas where targeted remediation or instructional intervention may be needed [30].

The use of Rasch evidence is consistent with established principles of effective feedback, which emphasise helping students understand their current performance, the intended learning goal and the actions required for improvement [12, 34]. Within adaptive learning, the contribution of Rasch measurement is therefore not limited to producing more precise proficiency estimates, its greater value lies in supporting feedback that connects assessment evidence with mastery, learning needs and appropriate next steps.

5 Human-Machine Collaboration and Implications for Educational Measurement

The increasing use of AI adds another layer to the relationship between adaptive learning, educational measurement and pedagogy. AI can support a range of functions within adaptive learning environments, including curriculum mapping, item and content generation and report generation [19]. These capabilities are attractive because adaptive learning requires substantial quantities of structured learning materials, calibrated assessment items [28] and repeated analysis of student data [19]. However, greater computational capability does not reduce the need for construct definition, expert review, validity evidence and pedagogical judgement. Rather, effective adaptive learning requires a complementary division of roles: machines can support scalability, consistency, automation and pattern detection, while humans remain responsible for construct definition, pedagogical judgement, interpretation and consequential decisions.

Curriculum mapping provides one example. Subject matter experts and course developers propose an initial representation of relationships among learning outcomes, concepts and skills. Student data generated through the adaptive platform can then be analysed to identify discrepancies between the hypothesised map and observed response patterns. Machine-supported analysis can reveal relationships, but refinement of the curriculum map requires human judgement about whether those relationships are substantively meaningful. The process is therefore iterative: human specification, data collection, analytic feedback and expert revision.

Content and item development represent another important area for human-machine collaboration. Generative AI can assist in producing draft assessment questions, explanations, examples, hints and differentiated learning resources, thereby reducing some of the workload associated with developing and maintaining large adaptive item banks. Yet AI-generated materials require review for accuracy, construct relevance, cognitive demand, ambiguity, bias and alignment with the learning progression. Where AI is used to generate or extend assessment content, calibrated existing data can provide an important empirical anchor for constraining generation and supporting consistency with the established measurement framework. Psychometric evidence provides a further layer of quality assurance by examining difficulty, fit and response pattern [18, 29], allowing generated items to be evaluated empirically before they are incorporated into adaptive learning pathways.

Report generation is similarly suited to automation. Rasch analysis and learning analytics can generate information rapidly, and AI may help summarise complex patterns for students and instructors [35]. However, automated summaries are not equivalent to educational judgement. An unexpected response can have at least two explanations: (1) repeated attempts can represent persistence but may also be associated with uncertainty or guessing [30]; and (2) a long response time may reflect sustained engagement, but it may also be influenced by inactivity, interruption or contextual factors [36]. Human users need sufficient measurement literacy to interpret such evidence, recognise uncertainty and decide when automated recommendations should be questioned or overridden.

These requirements have implications for professional development. Adaptive learning and Rasch measurement may be unfamiliar to many instructors. Effective implementation therefore requires more than training in tool operation [37]. Instructors need to understand why adaptive assessment is embedded within learning, how person and item measures should be interpreted, why assisted and independent performance differ, how mastery decisions are made and how feedback can inform instructional intervention.

This need for professional development is closely connected to stakeholder engagement. Adaptive learning is more likely to become meaningfully integrated into pedagogy when course teams understand its educational purpose, have confidence in the evidence it generates and recognise how that evidence can inform learning and teaching [37, 38]. Buy-in is strengthened when stakeholders can see how the system responds to identified educational needs, how measurement evidence supports pedagogical action and how instructors retain agency over decision [37, 38]. Implementation is therefore likely to be sustained when course teams are actively involved in co-designing the adaptive learning model, rather than having technological solutions imposed on established teaching practices.

6 Summary

Adaptive learning provides an opportunity to reconsider what educational measurement is intended to accomplish. Reliable estimates of attainment remain essential for progression, certification, quality assurance and accountability. Yet learning cannot be fully represented by isolated performance points. Students begin from different positions, encounter different difficulties, respond differently to feedback and scaffolding, and develop at different rates. Adaptive environments make these processes more visible because evidence can be generated repeatedly and linked to subsequent learning action.

The paper has argued for refocusing educational measurement from primarily documenting performance towards understanding learning development. Learning progressions and curriculum maps provide substantive representations of development; mastery thresholds create decision points; learning gaps identify areas needing attention or further support; the ZPD and scaffolding make emerging capability visible; and repeated assessment provides evidence about whether support has changed performance. Rasch measurement is central to this argument because it places student proficiency and item difficulty on a common scale, supports person-item targeting and makes expected and unexpected responses available for diagnostic interpretation.

The value of Rasch measurement in adaptive learning therefore lies not merely in producing more sophisticated scores, but in supporting feedback on learning. Measurement can identify where the student is and where the difficulty occurs; pedagogy determines the form of support; reassessment then supplies new evidence about development. Human-machine collaboration can strengthen this cycle when automation is governed by human judgement, psychometric evidence and clear educational purposes. Adaptive learning thus offers opportunity not only to measure students more frequently, but also to enhance the educational value of measurement by generating evidence that supports more nuanced interpretations of learning development and informs subsequent pedagogical decisions. Refocusing educational measurement in this way shifts the central question from what a student can demonstrate at one point in time towards a broader concern with what has been learnt, how learning is developing, what support has been effective and what should happen next.

Acknowledgments. The paper was presented as a Keynote address at the Pacific Rim Objective Measurement Symposium (PROMS) in Singapore (July 2025).

Disclosure of Interests. The author has no competing interests to declare that are relevant to the content of this paper.

References

1. Chong, G., Ding, D., & Ho, K. W. E-learning in higher education for adult learners in Singapore. International Journal of Information and Education Technology, 5(5), 348-353 (2015). DOI: 10.7763/IJIET.2015.V5.528
2. Burns, R. Adult learner at work: The challenges of lifelong education in the new millennium. Routledge. (2020).
3. Broek, S., Kuijpers, M. A. C. T., Semeijn, J. H., & van der Linden, J. Conditions for successful adult learning systems at local level: creating a conducive socio-spatial environment for adults to engage in learning. International Journal of Lifelong Education, 43(2–3), 200–223 (2024). https://doi.org/10.1080/02601370.2024.2338366
4. du Plooy E, Casteleijn D., Franzsen D. Personalized adaptive learning in higher education: A scoping review of key characteristics and impact on academic performance and engagement Heliyon, 10(21), e39630 (2024). DOI: https://doi.org/10.1016/j.heliyon.2024.e39630
5. Hooshyar, D., Weng, X., Sillat, P. J., Tammets, K., Wang, M., & Hämäläinen, R. The effectiveness of personalized technology-enhanced learning in higher education: A meta-analysis with association rule mining. Computers & Education, 223, 105169 (2024). DOI: https://doi.org/10.1016/j.compedu.2024.105169
6. Archer, E. The assessment purpose triangle: Balancing the purposes of educational assessment. Front. Educ. 2(41) (2017). DOI: 10.3389/feduc.2017.00041
7. Boud, D., & Falchikov, N. Aligning assessment with long-term learning, Assessment & Evaluation in Higher Education, 31(4), 399-413 (2006). DOI: 10.1080/02602930600679050
8. French, S., Dickerson, A. & Mulder, R.A. A review of the benefits and drawbacks of high-stakes final examinations in higher education. High Educ 88, 893–918 (2024). https://doi.org/10.1007/s10734-023-01148-z
9. Black, P., & Wiliam, D. Assessment and classroom learning. Assessment in Education: Principles, Policy & Practice, 5(1), 7–74 (1998). https://doi.org/10.1080/0969595980050102
10. Shepard, L. A. The role of assessment in a learning culture. Educational Researcher, 29(7), 4–14 (2000). https://doi.org/10.3102/0013189X029007004
11. Black, P., Wiliam, D. Developing the theory of formative assessment. Educ Asse Eval Acc 21, 5–31 (2009). https://doi.org/10.1007/s11092-008-9068-5
12. Sadler, D.R. Formative assessment and the design of instructional systems. Instr Sci 18, 119–144 (1989). https://doi.org/10.1007/BF00117714
13. Wang, X., Maeda, Y., & Chang, H.-H. Development and techniques in learner model in adaptive e-learning system: A systematic review. Computers & Education, 225, 105184 (2025). https://doi.org/10.1016/j.compedu.2024.105184
14. Xie, H., Chu, H.-C., Hwang, G.-J., & Wang, C.-C. Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. Computers & Education, 140, 103599 (2019). https://doi.org/10.1016/j.compedu.2019.103599
15. Rasch, G. Probabilistic models for some intelligence and attainment tests. Copenhagen: Danish Institute for Educational Research. (1960). (Expanded edition, Chicago: The University of Chicago Press).
16. Wright, B. D., & Stone, M. H. Best test design. MESA Press. (1979).
17. Andrich, D. Rasch models for measurement. SAGE Publications, Inc. (1988). https://doi.org/10.4135/9781412985598

18. Bond, T. G., Yan, Z., & Heene, M. Applying the Rasch model: Fundamental measurement in the human sciences (4th ed.). Routledge. (2021).
19. Kabudi, T., Pappas, I., & Olsen, D. H. AI-enabled adaptive learning systems: A systematic mapping of the literature. Computers and Education: Artificial Intelligence, 2, 100017 (2021). https://doi.org/10.1016/j.caeai.2021.100017
20. Harden, R. M. AMEE Guide No. 21: Curriculum mapping: a tool for transparent and authentic teaching and learning. Medical Teacher, 23(2), 123–137 (2001). https://doi.org/10.1080/01421590120036547
21. Wilson, M. Constructing measures: An item response modeling approach (2nd ed.). Routledge. (2023).
22. Bloom, B. S. Learning for mastery. Evaluation Comment, 1(2), 1–12 (1968)
23. Soderstrom, N. C., & Bjork, R. A. Learning Versus Performance: An Integrative Review: An Integrative Review. Perspectives on Psychological Science, 10(2), 176-199. (2015). https://doi.org/10.1177/1745691615569000
24. Vygotsky, L. S. Mind in society: The development of higher psychological processes. Harvard University Press. (1978).
25. Allal, L., & Ducrey, G. P. Assessment of—or in—the zone of proximal development. Learning and Instruction, 10(2), 137–152 (2000). https://doi.org/10.1016/S0959-4752(99)00025-0
26. Poehner, M. E., & Lantolf, J. P. Vygotsky's teaching-assessment dialectic and L2 education: The case for dynamic assessment. Mind, Culture, and Activity, 17(4), 312–330 (2010). https://doi.org/10.1080/10749030903338509
27. Toh, P. G. What can the Taxonomy of Learning Gaps tell us about learning and assessment? In P. G., Toh & S. C., L. (eds). Assessment in Singapore: Volume 1, Perspectives for Classroom Practice. Singapore Examinations and Assessment Board. (2014).
28. van der Linden, W. J., & Glas, C. A. W. (Eds.). Elements of adaptive testing. Springer. (2010).
29. Andrich, D., & Marais, I. A course in Rasch measurement theory: Measuring in the educational, social and health sciences. Springer. (2019).
30. Lye, C. Y., & Lim, L. Interpreting Rasch ability and difficulty estimates to inform mathematics learning through an adaptive learning system. In Q. Zhang (Ed.), Proceedings of the Pacific-Rim Objective Measurement Symposium (PROMS 2023) (pp. 502–509). Atlantis Press. (2024). https://doi.org/10.2991/978-94-6463-494-5_33
31. Wiklund-Hörnqvist C., Jonsson B. & Nyberg L. Strengthening concept learning by repeated testing. Scandinavian Journal of Psychology 55, 10–16 (2013). https://doi.org/10.1111/sjop.12093
32. Bond, T. G. The Rasch model: Empowering educational achievement in the developing world. Vietnam Journal of Educational Sciences, 19(4), 2-9 (2023). http://vjes.edu.vn/rasch-model-empowering-educational-achievement-developing-world
33. Yan, Z. Applications of Rasch measurement in research and practice. Vietnam Journal of Educational Sciences, 19(4), 10-21 (2023). http://vjes.edu.vn/applications-rasch-measurement-research-and-practice
34. Hattie, J., & Timperley, H. The power of feedback. Review of Educational Research, 77(1), 81–112 (2007). https://doi.org/10.3102/003465430298487
35. Paulsen, L., & Lindsay, E. Learning analytics dashboards are increasingly becoming about learning and not just analytics - A systematic review. Educ Inf Technol 29, 14279–14308 (2024). https://doi.org/10.1007/s10639-023-12401-4

36. Kovanovic, V., Gašević, D., Dawson, S., Joksimovic, S., & Baker, R. Does time-on-task estimation matter? Implications on validity of learning analytics findings. Journal of Learning Analytics, 2(3), 81-110 (2016). https://doi.org/10.18608/jla.2015.23.6
37. Mirata, V., Bergamin, P. Role of organisational readiness and stakeholder acceptance: an implementation framework of adaptive learning for higher education. Education Tech Research Dev 71, 1567–1593 (2023). https://doi.org/10.1007/s11423-023-10248-7
38. Alajlani, N., Crabb, M. & Murray, I. A systematic review in understanding stakeholders' role in developing adaptive learning systems. J. Comput. Educ. 11, 901–920 (2024). https://doi.org/10.1007/s40692-023-00283-x

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (http://creativecommons.org/licenses/by-nc/4.0/), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

