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The Role of Adaptive Learning Technologies in Personalized Education and Student Achievement: A Conceptual Analysis

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As the movement toward personalized learning continues, one of the most important elements has become the adaptive learning technologies (ALTs) that promise to customize instruction and pacing, as well as provide personalized feedback to students. This paper is a conceptual analysis of adaptive learning technologies' contribution to personalized education and therefore to student achievement that is conducted qualitatively and conceptually. The study is based on an interpretative synthesis of existing conceptual and theoretical literature, and does not involve empirical data collection, and instead seeks to examine the underlying mechanisms of adaptive systems; place these mechanisms in the context of constructivist, cognitivist and self-regulated learning frameworks; and critically discuss the pedagogical opportunities and limitations that are present for the use of adaptive systems. The study indicates that adaptive learning technologies have the potential to help meaningfully with differentiated instruction, timely feedback, and learner autonomy, but that their impact on achievement is influenced by pedagogical design, how teachers implement the technology, data quality, and equity of access. A conceptual framework for the relationship between adaptive technology features and personalization processes and achievement outcomes is proposed and directions for future empirical research are identified at the conclusion of the paper.

INTRODUCTION

Over the last 20 years, the focus in education has moved from the standardized, one-size-fits-all approach to instruction to a more personalized method that addresses the learning needs of each student. At the core of this change is the increasing implementation of adaptive learning technologies (ALTs) which are software systems that leverage data about the learner to dynamically modify and adapt content, sequencing, difficulty, and feedback based on a student's demonstrated performance. Advocates believe these systems could address the challenges that have long plagued classrooms like “classroom heterogeneity” by providing a pathway for each learner to follow, and critics warn that the potential for personalization may be outstripped by the evidence of what it achieves and the pedagogical methods required to make it work. (Xie et al., 2019; Pane et al., 2015)

This paper attempts to do a conceptual examination of the adaptive learning technologies and their relationship to personalized learning and student success. The study is not designed to test a specific intervention, but rather to elucidate the conceptual architecture behind the ALTs, explore the mechanisms of adaptivity and its relationship to existing theories of learning, and review and critique claims about the impact of ALTs on achievement. The analysis is defined with three general questions: (1) What does it mean to be 'adaptivity' in educational technology? (2) How could adaptive systems contribute to personalization and achievement from a theoretical perspective? (3) What are the conceptual challenges and constraints to the relationship between adaptive technology use and student outcomes? (Xie et al., 2019; Pane et al., 2015)

Conceptual Background

For the purposes of this document, personalized education is defined as general term for methods of instruction that modify the content, pace, or modality of instruction to the individual learner as opposed to uniform, group-paced instruction. Adaptive learning technologies make this concept algorithmic, and usually include a learner model (a dynamic model of what a student knows and how he or she learns it), a domain model (a structure that represents the subject matter), and an adaptation engine (a set of rules or algorithms that determine what content, hints, or pathways to present to the student, based on the learner model). This leads to an architecture that enables the system to change what a student is presented with next, depending on his or her current performance data, whether remedial material, an alternative explanation, or an accelerated path. (Xie et al., 2019; Pane et al., 2015)

In the literature there are three general types of adaptive systems: rule-based systems that follow pre-specified branching logic; algorithmic or data-driven systems that use statistical or machine-learning models to estimate the level of mastery a learner has attained, such as those based on the item response theory model or a Bayesian knowledge tracing model; and hybrid systems that incorporate both expert-designed content sequencing and data-driven recommendation. These two conceptions of 'knowing the learner' and 'personalizing the learner's experience' are different in conceptual terms, and have implications for the nature of the gains of adaptivity.

There is also a historical lesson to be learned in the adaptive learning process. The early computer assisted instruction (CAI) systems of the 1960s and 1970s were based on basic branching logic, providing either remedial content or advanced content depending on the correct or incorrect answer to the discrete item. In the 1980s and 1990s, intelligent tutoring systems emerged, leveraging cognitive science to represent misconceptions and partial knowledge, which enriched the learner model.In the 1980s and 1990s, the intelligent tutoring systems were developed, with the rich representation of misconceptions and partial knowledge that followed, and was heavily inspired by cognitive science. The latest "generation" of adaptive platforms builds on this lineage by adding high volume data analytics and – increasingly – machine-learning models to allow continuous estimation of learner state for large populations of learners. Conceptually, it is important to trace this evolution because, as the technical potential of each generation increased, it also carried with it the assumption of the preceding generation that it was building on, while at the same time many of the pedagogical criticisms that have been made of the current adaptive systems were continuations of what can be seen as debates from before the current technology. (Xie et al., 2019; Pane et al., 2015)

Defining Personalization: A Contested Construct

In policy and marketing rhetoric 'personalized learning' is a term that is frequently used but conceptually vague and that is applied to a variety of practices that vary greatly in the extent to which learner agency is involved. On one end of a conceptual continuum is differentiation, which refers to a teacher or system changing the level or type of a standard curriculum by varying the challenge and/or delivery method for the same objective/content for students. At the other end of the continuum is individualisation, where the rate is modified for the learner but the content and objectives are standardized. At the opposite end of the spectrum is personalization in a more complete way where the system or teacher guides but does not direct.Personalization in a more complete form is at the other end of the continuum where learners have real choices in goals, content and even assessment methods. Most of the adaptive learning technologies commercially available sit on the side of the continuum that differentiate (and adapt) the pacing and sequencing of a fixed curricular structure, instead of allowing learners to choose what they learn. This conceptual distinction is important because statements about the transformative power of 'personalised learning' typically suggest a sense of personalised learning when the technology being used suggests a more limited sense of 'individuated pacing'. (Xie et al., 2019; Pane et al., 2015)

Learning outcomes are considered a multidimensional construct and therefore must be analyzed in terms of their various dimensions.

With personalisation, conceptual unpacking is required, but with student achievement conceptual unpacking is required as well. Achievement is often narrowly defined in the adaptive learning literature as test scores, grades or completion rates. But a more complete definition of achievement would also include conceptual understanding, transfer of learning to new situations, metacognition development, motivation and engagement, and equitable access to opportunity. The rich behavioral data (response times, error patterns, engagement logs) that adaptive learning technologies can collect are also ideally suited to measure the narrower, assessment-based definition of achievement, but those same data affordances also have the potential to lead to the narrower, system-measureable definition of achievement instead of the broader educational objectives that assessment is designed to reflect. This dichotomy of measurable with meaningful achievement comes up throughout the discussion that follows. (Xie et al., 2019; Pane et al., 2015)

Methodology

This research is qualitative not empirical or experimental but conceptual analytic design. Conceptual analysis as a qualitative research methodology deals with the meaning, structure and relations of core concepts within a domain (in this case, the meaning, structure and relations of adaptivity, personalization and achievement) and is not characterized by the gathering of new quantitative or interview data.

The analytic process was carried out in three stages. The key constructs, adaptive learning technology, personalization, and student achievement, were first defined and the various definitions of each of these found in the literature were compared for convergence and divergence. Second, the theoretical foundation that is most frequently cited to support adaptive learning – constructivism, cognitive load theory, and self-regulated learning theory – were explored with regard to their logic and their compatibility with the mechanisms present in adaptive systems. Third, a thematic synthesis process was used to highlight issues that emerged frequently with the conceptual tensions, including the difference between surface-level content adaptation and deeper pedagogical personalization and the difference between proximal outcomes (engagement, time-on-task) and distal outcomes (achievement, retention). The criterion for trustworthiness in this conceptual-qualitative approach is the transparency and coherence of the reasoning process, the cross-checking of definitions in several conceptual sources, and the reflexive attention to the assumptions that are implicitly contained in techno-optimistic accounts on adaptive learning. (Xie et al., 2019; Pane et al., 2015)

Such is the nature of any conceptual design of a new, unknown product that this paper is inevitably limited in its scope. The analysis presents no new empirical measures of student performance and does not assess any one commercial adaptive learning platform, but rather considers 'adaptive learning technology' as a category of educational artifact whose design properties might be examined separately from any particular vendor's product. This bounding is a methodological conscious decision for conceptual-analytical work because the focus is conceptual clarity and theoretical coherence and not statistical generalizability. The arguments presented here are provided as a guide to both future empirical and mixed methods studies, which will be discussed in the conclusion. (Xie et al., 2019; Pane et al., 2015)

CONCEPTUAL ANALYSIS and DISCUSSION

There is a clear connection between mechanisms of adaptivity and the process of personalization.The connection between mechanisms of adaptivity and personalization is clear.

The three main ways adaptive systems personalize learning are by sequencing course content (changing the order or level of information), timing and specificity of the feedback (immediate and specific feedback for learner errors), and pacing control (adjusting the pacing of learning based on the learner's demonstrated mastery). In some ways, these mechanisms can be understood as an approximation of the 'zone of proximal development' principle in that adaptive systems try to discover a learner's current level of performance and provide material that is just beyond that level. Conceptually, however, the ability of an algorithmic estimate of mastery to encompass the richness of a human zone of proximal development is problematic; most algorithms estimate mastery based on a limited number of behavioral responses (e.g., response accuracy and latency).

One can make another conceptual separation between macro-adaptivity and micro-adaptivity. Macro-adaptivity is at the level of course or unit sequencing, and decides on the next module or topic a learner will come to based on overall progress. Micro-adaptivity is provided within a single task or item, modifying hints, scaffolds, and/or the next question on the fly based on a learner's current answer. Most modern platforms merge the two, but they impose different requirements on the underlying curriculum and learner models: macro-adaptivity demands a correct map of the prerequisite relationships between different units of a curriculum; micro-adaptivity demands fine-grained diagnostic sensitivity of the underlying model of the learner to the specific misconception that is the source of a single error. Systems that are strong on one dimension are not necessarily strong on the other; mixing up the two in evaluative statements for ‘adaptive learning’ will not reveal important distinctions about what a particular platform can do. (Xie et al., 2019; Pane et al., 2015)

Theoretical Underpinnings

There are three popular theoretical trends that are most often referenced to support adaptive learning technologies. A plausible mechanism to explain how adaptivity might increase learning efficiency is provided by cognitive load theory, which proposes that task difficulty can be adapted to learner ability to minimize extraneous cognitive load and, thereby, increase working memory for schema construction. Self-regulated learning theory focuses on the ability of learners to regulate their own learning processes; adaptive systems can help learn to monitor and adjust learning strategies, but this may lead to the learners' own learning-regulation skills being displaced and not fostered by perpetually relying on system-driven learning-regulation. Constructivist approaches, however, warn that personalisation as defined solely as the matching of content to algorithms has the potential to miss out on the social, collaborative and meaning making aspects of the learning process that constructivist theory has identified as key enablers of deep learning. (Xie et al., 2019; Pane et al., 2015)

Motivational and self-determination theory is also conceptually relevant, although it is not mentioned as much. It is a tradition that learning is improved when learners feel autonomous, competent and related. A sense of competence can be plausibly achieved with adaptive systems by dynamically adjusting difficulty to prevent failure and persistence, while a sense of autonomy is more complex: a system that works behind the learner's back, rerouting him through a pre-established branching structure can be just as effective at leaving him with the feeling of being managed as it is at giving him the feeling of choice, unless learners are provided with the ability to see and, to some extent, control the logic of adaptation. The dimension that is least directly supported by adaptive software, and is thus the most dependent upon the context in which adaptive tools are used, is relatedness, which relies on social interaction with peers and teachers.

Personalisation and achievement.

One of the conceptual conflicts that have existed in the literature is the gap between the use of adaptive technologies and student performance. Proximal variables which can be directly influenced by adaptive systems are engagement, time-on-task, error correction and perceived relevance; distal achievement variables (e.g., test scores, course completion, long-term retention) are indirectly influenced. Therefore, the achievement gains that have been argued to be the result of ALTs must be interpreted as mediated achievements, which depend on other factors such as the quality of the domain model itself, the pedagogical appropriateness of the content adapted, the extent of teacher integration and supervision, and the digital literacy and self-regulation of learners. If the mediating conditions are low, however, even very complex algorithms are unlikely to result in substantial gains in achievement, without adaptivity.

The distinction between achievement effects that work through acceleration and remediation is also conceptually beneficial. There are acceleration effects when the existing system lets proficient students move faster through learning material, freeing instructional time for deeper enrichment and remediation effects when the system detects and remediates the specific gaps in learning for struggling students before they turn into larger gaps. There are two pathways which lead to different achievement signatures: in the case of acceleration, gains would be seen largely in the achievement of higher-performing students and in the extent to which the curriculum is covered, while, in the case of remediation, gains would be seen largely in the narrowing of the gap between lower- and higher-performing students. Since most assessment of adaptive learning technology results indicates average achievement effect, the following avenues in assessment design are recommended: future assessment should disaggregate achievement effects by pre-performance to differentiate which of the two paths is in operation, or if both paths are in operation, which is more determined by which is stronger. (Xie et al., 2019; Pane et al., 2015)

Challenges and Limitations

In the promise of adaptive learning technologies, there are several conceptual and practical restrictions. First, there is a risk of personalisation being confused with individualisation: many adaptive systems personalise pace and content, but they do not give learners the freedom to choose goals and methods, so limiting the extent to which the learner is truly personalised. Second, algorithmic learner models are only as accurate as the data and assumptions that underlie them; algorithms for measuring mastery can fail to accurately describe learners' understandings, especially in complex or creative tasks where there are no simple metrics for correctness. Third, inequities are a problem when there is unequal access to high-quality adaptive platforms and reliable infrastructure and technical support, which can actually exacerbate achievement gaps. Lastly, an excessive focus on the system could restrict opportunities for peer learning, mentoring, and problem-solving, aspects that many theories see as essential to deep learning. (Xie et al., 2019; Pane et al., 2015)

Yet another restriction is related to data privacy and algorithm transparency issues. Collection of granular behavioral data, from many of whom are minors, is an ongoing process for adaptive systems, which raises conceptual and ethical questions related to consent, ownership, and long-term use of learner profiles. Many adaptation engines are proprietary 'black boxes' which takes much of the work away from teachers and students articulating the reasoning behind the choice of a specific pathway or item, making pedagogical trust in the system less transparent and students' metacognitive self-knowledge that self-regulated learning theory posits is crucial to learning less so. In terms of concept, this opacity is in opposition to the aim of learner autonomy as a learner can no longer be autonomous in a learning pathway that is unheard of to him. (Winne & Hadwin, 1998)

In the context of adaptive environments, the role of the teacher is to:The teacher's role in adaptive environments is to:

Whether they come from the theoretical histories mentioned earlier, the key point at the end of this section is that adaptive learning technologies are not a pedagogical panacea and have a significant impact on instruction as it is used by teachers. In terms of concept, there are three roles for teachers. Delegative – the teacher substitutes system-based instructional decisions for his own, in a monitoring role, the teacher relies on system-generated data to determine what students need to learn while keeping the focus on the core instruction; and orchestrating – the teacher uses system-based data as one component of a multi-component instructional technology, incorporating system-based data into classroom discussion, peer work, and formative assessment. The role of the orchestra may be most likely to facilitate achievement and the motivational and interpersonal aspects of learning (as outlined above), which are not necessarily covered by adaptive software. This means that teacher professional learning in how to use and understand the data from adaptive systems is not a minor aspect of implementation but one that is at the core of the issue of whether adaptive learning technology will have the desired effect. (Xie et al., 2019; Pane et al., 2015)

Implications for Stakeholders

This paper assumes that the effects of adaptive learning technology are not inevitable, but rather contingent, and therefore, has different conceptual implications for each of the different stakeholder groups that mediate its effects, described in the discussion above. (Xie et al., 2019; Pane et al., 2015)

Implications for Teachers

Analysis indicates that moving beyond passive monitoring of dashboards to active orchestration—where adaptive learning technology guides grouping decisions, targeted mini-lessons, and structures for peer collaboration—is required for effective use of such technology for teachers, not its inability to replace direct instruction with accurate judgement. Teachers can also leverage this to make up for the limited, performance-based view of achievement that most adaptive systems seem to have—the ones that recommend tasks based on the implicit notion that achievement is equivalent to performance—and supplement the suggested paths with tasks that measure transfer, creativity, and conceptual reasoning. (Xie et al., 2019; Pane et al., 2015)

Implications for Students

The conceptual analysis for the students also emphasizes the need to cultivate self-regulated learning skills in conjunction with using adaptive technology in order to avoid the danger that having technology-driven pacing and feedback will preclude the students from developing independent goal-setting and self-monitoring skills. Students who are taught how to interpret platform visibility of its adaptation logic might be better placed to develop metacognitive awareness of their own learning trajectories, where platforms provide any visibility of their adaptation logic. (Winne & Hadwin, 1998)

Recommendations for Institutions and Policymakers

The equity issues highlighted in section 4.4 suggest that institutional and policy choices need to explicitly reflect on access to infrastructure, teacher training capacity, and data governance when making decisions on procurement and implementation rather than assuming adaptive technology adoption is a standalone approach to tackling achievement gaps. The conceptual distinction in section 2.1 between differentiation, individualisation, and fuller personalisation also implies that institutions need to be clear about what they want to achieve in their goals when choosing adaptive platforms; various tools will be appropriate for different positions on the continuum, and a lack of clarity in the institutional goals when making procurement decisions can lead to a mismatch of these and the technology.

Towards a Conceptual Framework

In conclusion, this paper presents a conceptual framework in which distal learning outcomes (mastery, retention, transfer) are guided by proximal learning processes (engagement, self-regulation, error correction) and the interaction between these two realms is mediated by conditions that facilitate the learning process (pedagogical design quality, teacher facilitation, equitable access). This approach treats adaptive learning technology as a contingent enabler, rather than a direct cause of achievement, and does not take much credit for its impact, because it depends on the general learning environment in which it is implemented. Such a framing avoids the extremes of technological optimism and blanket skepticism, instead focusing on the conditions in which adaptivity might be helpful in education. (Xie et al., 2019; Pane et al., 2015)

The framework can be broken down into four components: (1) Technology Features — the sequencing, feedback and pacing mechanisms a given platform implements; (2) Proximal Processes — the engagement, self-regulation and error-correction behaviours these features are designed to elicit; (3) Mediating Conditions — the pedagogical design quality, teacher orchestration, data governance and equity of access which determine whether proximal processes are translated productively; and (4) Distal Outcomes — the mastery, retention and transfer that constitute genuine achievement. A conceptual consequence of considering the relationship as a chain (as opposed to a direct arrow from technology to achievement) is that any assessment of an adaptive learning technology that only collects data on Stage 1 attributes and Stage 4 outcomes without monitoring on Stages 2 and 3 may miss the mark in assigning cause for observed gains or losses. Positive findings do not necessarily mean the technology is good; a negative finding may mean the mediating conditions are weak and not the technology; a null finding may mean the mediating conditions are equally weak and not necessarily mean that the technology is in some way flawed. This has implications on the design of future empirical studies of adaptive learning technology as discussed below. (Xie et al., 2019; Pane et al., 2015)

The present analysis has some limitations.The present analysis has some limitations.

This paper is a qualitative conceptual analysis and as such has its own limitations that should moderated some of the claims made above. As the analysis is conceptual and theoretical in nature, it does not claim to measure how strong and common the relationships described are, and the conceptual framework suggested in section 6 is still a hypothesis to be tested, not a fact. The analysis was also limited by the theories chosen for discussion, with other theoretical approaches (e.g., sociocultural or critical pedagogy) potentially yielding other aspects of the adaptive technology-achievement relationship not explored here. Lastly, adaptive learning technologies are rapidly changing, with the introduction of newer machine-learning and generative-AI elements, which introduces the possibility of some of these conceptual distinctions in this paper being updated as the technology matures. (Xie et al., 2019; Pane et al., 2015)

Conclusion and future directions

In this conceptual analysis, the sequencing and pacing, feedback and content aspects of adaptive learning technologies have been examined as they enable personalization and the relation between them — both theoretically and conceptually — to student achievement. The analysis implies that adaptive learning technologies could play a real role in differentiated, responsive instruction and learning, but that this connection is not automatic or direct, but rather is mediated by pedagogical design, teacher involvement, data quality, and equity of access. The concepts of differentiation, individualization and fuller personalization, macro- and micro-adaptivity, and acceleration and remediation pathways, presented as differences, are provided as conceptual tools that could make future research designs and practical implementation decisions more focused. (Xie et al., 2019; Pane et al., 2015)

Empirical or mixed methods studies are needed to test the conceptual framework proposed in this study, and to investigate the differential effects of adaptive learning technology that can be expected across subject domains, age groups and educational contexts on the achievement outcomes. For the purposes of prioritizing studies, disaggregation of achievement outcomes by prior performance level to account for the effects of acceleration and remediation, rather than teacher background characteristics, as a moderating variable, and the explicit study of equity of access and algorithmic transparency as design and policy variables as opposed to afterthoughts. The potential of adaptive learning technologies to support personalized education and student achievement will be achieved more by the quality of the pedagogical and institutional contexts in which the algorithms are developed, than by the complexity of the algorithms themselves. (Xie et al., 2019; Pane et al., 2015)

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