Toward Asset-based Instruction and Assessment in Artificial Intelligence in Education

Jaclyn Ocumpaugh
Associate Director, Penn Center for Learning Analytics
Graduate School of Education
University of Pennsylvania
Philadelphia, PA, USA
Email: jlocumpaugh@gmail.com; ojaclyn@upenn.edu
ORCID ID: 0000-0002-9667-8523

Rod D. Roscoe
Associate Professor
Human Systems Engineering/The Polytechnic School
Arizona State University
Mesa, AZ, USA
ORCID ID: 0000-0001-8327-4012

Ryan Baker
Professor
Graduate School of Education
University of Pennsylvania
Philadelphia, PA, USA
ORCID ID: 0000-0002-3051-3232

Stephen Hutt
Assistant Professor
Department of Computer Science
University of Denver
Denver, CO, USA
ORCID ID: 0000-0002-7041-7472

Stephen Aguilar
Assistant Professor
School of Education
University of Southern California Rossier
Rossier, CA, USA
ORCID ID: 0000-0003-2606-067X

Toward Asset-based Instruction and Assessment in Artificial Intelligence in Education

Abstract

The artificial intelligence in education (AIED) community has produced technologies that are widely used to support learning, teaching, assessment, and administration. This work has successfully enhanced test scores, course grades, skill acquisition, comprehension, engagement, and related outcomes. However, the prevailing approach to adaptive and personalized learning has two main steps. First, the process involves detecting the areas of knowledge and competencies where students are deficient. This process also identifies when or how a student is considered "at risk" or in some way "lacking." Second, the approach involves providing timely, individualized assistance to address these deficiencies. However, a considerable body of research outside our field has established that such *deficit* framing, by itself, leads to reactive and less productive strategies. In deficit-based frameworks, powerful student strengths, skills, and schemas—their *assets*—are not explicitly leveraged.

In this paper, we outline an asset-based paradigm for AIED research and development, proposing principles for our community to build upon learners' rich funds of knowledge. We propose that embracing asset-based approaches will empower the AIED community (e.g., educators, developers, and researchers) to reach broader populations of learners. We discuss the potentially transformative role this approach could play in supporting learning and personal development for all learners, particularly for students who are historically underserved, marginalized, and "deficit-ized."

[208 words]

Keywords: artificial intelligence; asset-based; educational technology; equity; learner modeling

Toward Asset-based Instruction and Assessment in Artificial Intelligence in Education

After decades of intensive effort, there have been large strides in fulfilling the promise of artificial intelligence in education (AIED). Learning technologies that use artificial intelligence (AI) (e.g., intelligent tutors, intelligent simulations, and automated writing evaluation) are now used at scale in several countries to inform critical decisions, enable teaching, support learning, and more (Pinkwart & Liu, 2020; Gobert, 2023; Shermis & Hamner, 2013; Yang & Zhang, 2019). AIED systems have been particularly prevalent in science, technology, engineering, and mathematics (STEM) education (see Xu & Ouyang, 2022 for a review), but there has also been considerable progress in literacy (e.g., Jackson et al., 2012; Spiro et al., 2017).

Evidence suggests that AI-based learning technologies improve student learning outcomes, engagement, and motivation (Diwan et al., 2023). For example, several large-scale studies of intelligent tutoring systems (ITS) have documented their efficacy (Pane et al., 2014; Roschelle et al., 2020; Feng et al., 2023). VanLehn's (2011) meta-analysis compared the effectiveness of ITSs to other computer-based learning environments, finding that learning gains in ITSs were 0.32 to 0.40 standard deviations higher than in systems that simply offered accuracy feedback. A later meta-analysis (Kulik & Fletcher, 2016) reported a 0.66 standard deviation benefit for learners using ITSs over conventional instruction.

Similarly, a range of other AIED technologies have also been highly successful. For example, Kumar and colleagues (2010) deployed a conversational agent that scaffolded a conversation between students, leading to better learning than simply working on the learning task without scaffolding. Jackson and colleagues (2012) and McLaren and colleagues (2017) observed that educational games (teaching reading and decimals, respectively) performed as well or better than an ITS, and better than a control condition. Moussavi et al. (2016) demonstrated that adding AI-based scaffolding to an educational simulation contributed to learning that transferred beyond the simulation.

However, amidst these successes, growing discussion has emerged about whether and how AIED systems are serving all learners, particularly learners who have been historically underrepresented and marginalized (Roscoe, 2023; Roscoe, Salehi, et al., 2022; Bhimdiwala et al., 2021; Nye, 2015). For example, scholars have voiced concerns that AIED systems might be less available to less-resourced schools (e.g., the "digital divide," Warschauer, 2012; Aguilar et al., 2022), which has inspired technologies that work with limited-bandwidth mobile connections (Ijtihadie et al., 2012; Aguilar et al., 2020). Greater attention is also being paid to how AI algorithms participate in or perpetuate systemic biases (Finkelstein et al., 2013; Holstein & Doroudi, 2022; Karumbaiah et al., 2021; Kizilcec & Lee, 2022). There is a growing awareness that algorithms that assess students may produce inequitable results for different demographic populations (Baker & Hawn, 2022, Hutt et al. 2023) and more broadly (Cramer et al., 2018). When training data and corpora are compiled to develop algorithms, the data may not be equally or equitably sourced from multiple populations in ways that enable valid inferences for the range of populations students come from (Baker & Hawn, 2022). Such concerns have prompted research on factors that might produce biased technologies (Holstein & Doroudi, 2022; Karumbaiah et al., 2021) and how to address those biases (Finkelstein et al., 2013; Kizilcec & Lee, 2022; Roscoe et al., 2022). Further attention to these issues has been inspired by calls to examine and expand the populations who receive scholarly attention (Paquette et al., 2020; Roll & Wylie, 2016).

Despite these ongoing concerns, several studies have observed benefits for AIED systems among historically underserved populations. For instance, Huang and colleagues (2016) reported that using the ALEKS system in an after-school program in a small city contributed to stronger benefits for Black students than for White students. A similar effect was observed with ASSISTments, where gains were significantly higher for Black students, students receiving free or reduced-price lunch, and students with limited English proficiency than for students belonging to none of these categories (Koedinger, McLaughlin, & Heffernan, 2010). These examples do not establish that AIED systems are "just fine" and no further critique is warranted. However, these cases do demonstrate that AIED need not underserve anyone; the potential reach of AIED is vast.

In this paper, we grapple with yet another equity issue in contemporary AIED: the deficit-based focus that underlies many (or even most) of our technologies. Deficit-based models for detection and intervention focus on identifying problems that might be remediated by intervention or adaptation. The use of a deficit-based approach is rarely an intentional, deliberate design goal, but instead results when pedagogical goals emphasize what learners "lack," how their performance "fails" to attain normative standards, or "gaps" between learners and their peers (Smit, 2012; Davis & Museus, 2019). Deficit-based models identify problems that might be remediated by intervention, which is not inherently problematic, but they do so in a way that locates the problems within the individual student rather than considering the broader context (Dudley-Marling, 2015).

This "find and fix" approach underpins many highly effective AIED systems because it can guide students toward desired knowledge and strategies while also supporting students' individual needs. Nonetheless, we argue that this approach also incurs potential costs. Specifically, we contend that deficit-based approaches are incomplete and *constrain* technology affordances, potential benefits, and potential solutions. Deficit framing limits design features to reactive "filling gaps" and "fixing" students who have been (mis)categorized as "lacking," "low" knowledge or skill, "underprepared," "unmotivated," or otherwise broken. Consequently, positive and meaningful student strengths, skills, strategies, and schemas—their *assets*—are not adequately recognized or leveraged. Furthermore, this approach implicitly communicates to students (and other stakeholders) that certain assets do not matter.

Alternative approaches strive to recognize and build upon students' capacities more expansively. These *asset-based* approaches focus on the knowledge and capabilities that learners already have, whether such strengths stem from formal educational experiences, community and cultural experiences, or family and personal life (Moll, 1992; Esteban-Guitart et al., 2014, Verdín, et al., 2021). Asset-based approaches consider the prior knowledge, resources, interests, and histories that learners bring to their learning context in order to provide each learner with relevant growth opportunities. This paradigm empowers learners to develop and apply their strengths to other tasks, problems, domains, or even everyday life, while still allowing for addressing needs and problems. Scholarship in diverse domains has argued that students attain more enduring, positive outcomes when education embraces their existing strengths, cultures, and resources (e.g., Wolfram et al., 1999; Flint & Jaggers, 2021; Verdín et al., 2021; Montañez, 2023) as well as addressing opportunities for growth.

Importantly, the adoption of asset-based approaches does not mean overturning decades of AIED theory and practice (unlike, say, Selwyn, 2020). Adopting asset-based pedagogies does not require abandoning approaches such as offering corrections to wrong answers or misconceptions; it takes more than just offering corrections for an approach to be deficit-based (Davis & Museus, 2019). Instead, asset-based approaches extend the scope of learner resources that are worth considering; they emphasize strengths (e.g., alternative conceptions that afford analogical insights) instead of only "gaps" (e.g., misconceptions to be refuted or disengaged behaviors). Many tools are already available. AIED systems already seek to identify what skills learners know (Corbett & Anderson, 1995; Cosyn et al., 2021; Baker et al., in press), which can be used to determine where a student is "ahead" rather than where they are "behind." AIED systems can be designed to allow for different problem-solving strategies that empower students to use their knowledge (Aleven et al., 2016). AIED systems increasingly can identify whether students demonstrate functional strategies for self-regulated learning (Zhang et al., 2022), inquiry (Wang et al., 2023) and invention (Chase et al., 2019)—all of which can be used to identify and build on student assets. Finally, AIED systems have been used to personalize content based on students' personal interests and improve learning outcomes by building on those existing goals (Walkington & Bernacki, 2019). In sum, the seeds of asset-based approaches are already present in AIED. Our proposal is simply to (re)emphasize relevant aspects our field's rich history of research.

The remainder of this article is organized as follows. We begin with a brief overview and critique of deficit- and asset-based frameworks for understanding learners. We then consider how deficit-based approaches might manifest within classic student modeling methodologies. Importantly, our purpose is not to malign existing AIED systems, but rather to reveal points of articulation that might benefit from asset-based designs. We then articulate several potential principles for asset-based AIED. We argue that future AIED research and development should shift to better incorporate, detect, leverage, build, and appreciate learners' assets. Implementing these principles has the potential to move AIED beyond "finding and fixing" and toward "appreciating and advancing" in ways that better support students' long term growth and success.

1.0 Characterizing Learners and Learning

Learning is fundamentally an act of gaining, growing, transforming, and applying new knowledge and experiences. Learners may acquire new knowledge and strategies, deepen or modify their existing understanding, or may realize that expertise in one domain can be leveraged for success in other areas. Learners connect to the new knowledge and skills they are acquiring within contexts that are influenced by their socially, culturally, and linguistically diverse backgrounds. Consequently, a core goal within educational practice and research is the accurate characterization of learners' knowledge, skills, performance, and contexts (i.e., assessment, Bennett, 2011). In turn, these assessments inform diverse pedagogical strategies within a variety of settings (e.g., lectures, peer collaboration, serious games, intelligent tutoring, and much more) that empower learners to progress. Indeed, this connection between understanding and responding to learners is the cornerstone of individualized and personalized approaches for educational technology and learning analytics (e.g., Blanchard & Mizoguchi, 2008; Ellis, 2013; Dilllenbourg, 2016; Ogan et al., 2017; Walkington & Bernacki, 2019; Holstein et al., 2020; Schaldenbrand et al., 2021; Roscoe & Craig, 2022).

1.1 Deficit-Based Approaches

Within this broad assessment mission exist distinct mindsets for how learners are characterized. Importantly, no pedagogical theory or learning system that we are aware of self-identifies as a deficit-based approach. Instead, this label emerges as critique of how the systems frame and interact with learners. Commonplace *deficit-based* approaches emphasize what learners *lack*, what they *cannot* do, how their performance *fails to attain* normative benchmarks, or *gaps* between learners and their peers (Flores, 2007; Gutiérrez, 2008; Howard, 2019; Davis & Museus, 2019). Deficit-based models identify problems that must be remediated by intervention. We argue that many extant AIED systems can be characterized as enacting deficit-based approaches. In other words, our categorization of AIED research and technologies as deficit-based is intended as descriptive rather than pejorative.

As in other areas of education research, the term *deficit-based* emerges as critique, as opposed to being a term that researchers and developers apply to themselves. Researchers who criticize deficit-based approaches have highlighted that' these pedagogical practices are typically not deliberate, but often emerge when cultural or other demographic capital is not investigated. When this occurs, the practices and resources of dominant groups may be assumed to be normative and typical (Gutiérrez & Rogoff, 2003), and value judgments about "worthwhile" knowledge and skills can be socioculturally loaded. For example, in K-12 settings, the strengths that emergent bilingual learners have with respect to their home language often ignored in lieu of ensuring that they learn the dominant language of instruction (Garcia, 2009; Griesen et al., 2021; Lin, 2020). Likewise, research has shown that neurodiverse students often have exceptional skills that are overlooked when we focus on disability (see review in Grundwag et al., 2017).

The AIED community's efforts to personalize education often emphasize the need for responsive assistance and support. Numerous AIED technologies have sought to automatically identify misconceptions (Al-Shanfari et al., 2017), skill and knowledge gaps (Corbett & Anderson, 1995; Aleven et al., 2023), or disengagement (Paquette & Baker, 2019), which then guide adaptive support to provide key information, scaffolded practice, strategies, or motivating experiences. When learners are "missing something," the goal is to meet their needs to enable achievement. The need for these efforts can be found in almost all major learning theories—even those that express concerns about deficit-based approaches. However, there are consequences when students are defined exclusively by what they are missing, and those consequences are often more severe for students whose cultural backgrounds are not those that have shaped the culture of the school system they are assigned to (Davis & Museus, 2019; Alim & Paris, 2017; Humphries, 2013; Bacon, 2017; Johnson et al., 2020; Stockman, 2010).

We are not advocating that the AIED community abandon the successes of these approaches, many of which we have ourselves published. However, we do believe that the community has too often relied on models that compare the student to a single standard, which results in defining individual students as deficient in terms of that model. Overall, we believe that the community's reliance on deficit-based approaches is constraining or confounding the potential of AIED systems—limiting what we attend to and leverage in our support of learners. That is, *deficit approaches are incomplete*. Although learners may indeed lack prior knowledge, proficiency, and so forth, these "gaps" are only a *partial model* of learners' actual needs and competencies. There are often multiple ways to complete a learning task or solve a problem, involving task-specific, domain-general, cognitive, metacognitive, and motivational strategies. AIED systems that detect and remedy gaps may be missing critical context, opportunities, networks, or other resources for supporting learning (Garcia, 2009). Narrowly focusing on student deficits may *obscure alternative paths* that might be nurtured, leading to incomplete sets of possible interventions.

A related critique is that *deficit approaches are reductive* because they do not consider learners' backgrounds, interests, and identities. When learners' limitations are more salient than their strengths, learners become *defined by perceived deficiencies*. For example, it has been common practice to refer to learners categorically and perhaps disparagingly as "low knowledge," "low working memory," and "unmotivated" (Reeve, 2013), but emphasizing these traits may undermine efforts to recognize and support self-efficacy, goal-setting, engagement, and identity (Rocha et al., 2022). In parallel, concentrating on learners' deficiencies can undervalue them, as is often the case with English language learners (ELLs) when educators overlook opportunities to link new information to students' existing knowledge (Garcia, 2009; Greisen et al., 2021). By locating these traits in the individual learner, deficit-based approaches discourage us from examining the ways in which the learning environment is failing the students (Waitoller & King Thorius, 2016, see also Lipsky & Gartner, 1989). Deficit models run the risk of disparaging learners, their lived experiences, and their strengths.

Finally, we argue that deficit-based approaches may limit us in a key goal of education. Namely, *deficit-based approaches may obscure opportunities to foster transfer*, wherein learners recognize that their knowledge and skills in one domain apply elsewhere (and then apply them in that context). That is, when AIED systems exclusively define students by the gaps they show against a single normative model, we may be limiting and obscuring diverse resources and ways of succeeding. As far back as Piaget's (1926) foundational schema theory, it was recognized that learners' first instincts are to assimilate new knowledge within schema they already have. Only when disequilibrium occurs, and cannot be resolved through assimilation, do accommodation processes produce new schemas. That theory (and subsequent formulations used in the development of AIED technologies; e.g., Ting & Chong, 2006) defines learning as a process of connecting to and contrasting with students' prior knowledge and experience (Dumas et al., 2013; Jablansky et al., 2020), a process that is inhibited when only certain kinds of knowledge or experiences are considered "valid" while others are disregarded. Moreover, by only assessing a limited range of "gaps," deficit based approaches implicitly communicate that knowledge and other factors related to students' backgrounds, interests, and identities do not matter.

1.2 Asset-Based Approaches

In contrast to deficit-based approaches, *asset-based* frameworks (Celedón-Pattichis et al, 2018; Reynolds & Johnson, 2014), such as the funds of knowledge (FOK) model (Esteban-Guitart & Moll, 2014), have been proposed. Asset-based approaches highlight the knowledge, capabilities, and resources that learners *do have* or *can access*, which may stem from formal schooling or from informal experiences and networks among family, friends, communities, jobs, and more. Asset-based frameworks focus on the ways that learners succeed and thrive within their unique environments instead of how they "fail" or "struggle" within constrained contexts that overlook their strengths (Greenberg, 1989). For example, several scholars have urged colleagues to reframe learning and achievement "gaps" as "opportunity gaps" (e.g., Rodriguez, 1998; Gutiérrez, 2008) and to recharacterize learners based on strengths rather than weaknesses (e.g., describing students living in poverty as "resilient" rather than "deficient," Gorski, 2017). Likewise, theories of *culturally-relevant pedagogy* (Ladson-Billings, 1995), *culturally-responsive pedagogy* (Rychly & Graves, 2012), and *culturally-sustaining pedagogy* (Paris, 2012), all emphasize seeking strengths within learners (Fitzgerald et al., 2021; Young et al., 2018). In sum, asset-based models adopt an expansive and encompassing view of learners and how they can experience success.

Funds of knowledge frameworks (Esteban-Guitart & Moll, 2014) may reveal additional opportunities for assessment and support. Funds of knowledge include the "historically accumulated and culturally developed bodies of knowledge and skills essential for household or individual functioning and well-being" that learners might bring to their learning context (Esteban-Guitart & Moll, 2014). Longstanding evidence suggests that systematic performance differences emerge when the cultures of learners, educators and curriculum and assessment designers are mismatched (Labov, 1970; Houser & Chevalier, 1995; Rickford et al., 2004), but that valuable learning opportunities can be created for historically-minoritized learners when educators use "what the student knows and can do as the avenue to what needs to be learned" (Lipsky & Gartner, 1989). This framework notes that cultural participation equips learners with psychological tools and schemas needed to function in their world (Esteban-Guitart & Moll, 2014). Thus, by identifying the resources and schemas already employed by learners, educators may more deftly assess what leaders already know and can do. Subsequently, educators can also provide learners with relevant opportunities to connect new knowledge to a broader foundation of existing knowledge, skills, and experiences.

Embracing asset-based approaches facilitates the crafting of learning opportunities that are more personally and culturally meaningful by recognizing what schemas are already available to students (e.g., Saxe, 1988). For example, substantial research across a range of demographics and learning domains has found that learning outcomes are improved when educational environments account for the cultural linguistic practices of students' home environment (e.g., Wolfram, 1999; Edmonds-Wathen, 2013; Finkelstein et al., 2013; Adger et al., 2014; Shapiro & McDonald, 2017; Civil et al., 2019; Spycher et al., 2020; Rioux & Ewing, 2022; Byrd et al., 2023). These studies have covered a range of cultural and linguistic backgrounds, as shown in Table I.

Table I: Research using cultural linguistic backgrounds to improve pedagogy

Cultural Linguistic Background	Citation
Aboriginal Australian	Sarra & Ewing (2014)
African American	Labov (1970); Hilliard (1992); Murrell (1993); Lee (1994); Flood et al. (2004); Baker-Bell (2020)
American Indian/Alaskan Native	Swisher (1990)
Appalachian (US)	Cleveland et al. (2012); Johnson et al. (2009)
English learners (Taiwan)	Lu (2022)
Deaf students (US)	Cannon & Luckner (2016); Pedersen et al. (2021)
Hmong-American students	Spycher et al. (2020)
Iwaidja speakers (Australia)	Edmonds-Wathen (2013)
Indigenous US students	Brayboy & Castagno (2009)
Students from Spanish heritage background (US)	Fuson et al. (1997); Curtin (2006); Mejia et al. (2020); Chapman & McHatton (2022); Cammarato & Ronero (2009)
Maori (NZ)	Meany et al. (2016); Savage et al., (2011); Bishop et al. (2009); Penetito et al. (2011)
Native Hawaiian	Au & Jordan (1981); Au (2003)
Navajo	Watahomigie & McCarty (1994)
Odawa (US)	Mohatt & Erikson (1981)
Somali Bantu Refugees (US)	Shapiro & McDonald (2017)
Turkey and US students	Valencia Mazzanti & Karsli-Calamak (2022)

Work has also sought to assist educators with understanding how these group-based differences might emerge in the classroom and other places where students are assessed (Schleppegrell, 2004; Solano-Flores & Li, 2006; del Rosario Basterra et al., 2011; Carpenter Ford, 2013; Wheeler, 2016; Hendricks & Adlof, 2017; Chou et al., 2018; Sa'd & Eames, 2021). However, within this, asset-based approaches discourage treating everyone from the "same" demographic background as identical, with the same needs, goals, or preferences (Ladson-Billings, 2021; Paris & Alim, 2014). By providing developers and teachers with tools to conceptualize students' assets, these frameworks may help to mitigate stereotyped thinking about "deficient" populations (Boser et al., 2014; Guskey, 1982; Ferguson, 2003; Howard, 2003; Dedeoglu & Lamme, 2011).

In sum, although addressing students' "gaps" in knowledge, skills, motivation, and resources afford viable ways to support learning, this approach is restricted and restrictive—it limits whom we can serve and how. Asset-based approaches, by contrast, may offer a more expansive and inclusive way to "model" students' learning resources and thereby leverage them for richer instruction and support. In the following sections, we describe how student modeling approaches demonstrate deficit-based approaches and begin to explore asset-based alternatives.

2.0 From Deficits to Assets in Artificial Intelligence in Education Models

Many AIED systems tend to adopt a deficit-based approach. These approaches are often successful and improve learning for some, if not all, students. Indeed, AIED systems that detect and adapt to learner needs have driven decades of deficit-based (but beneficial) interventions that:

- identify when students have *not mastered* a skill, and then offer them more opportunities to practice that skill (Corbett & Anderson, 1995; Jones & Bomash, 2018; Doroudi, 2020)
- identify students who hold a specific *misconception*, and then explain or demonstrate to them why it is incorrect (Hirashima et al., 2017)
- identify students who are using help resources *ineffectively*, and then train them to make better use of these tools (Roll et al., 2011)
- identify students who are using an *ineffective* science inquiry strategy, and then teach them a better strategy (Moussavi et al., 2016)

- identify students who are demonstrating *negative affect* (e.g., boredom or frustration), and then motivate them to perform well despite these feelings (D'Mello et al., 2010) – although some of the approaches to do this have done so by reminding students of positive assets, such as their connection to a broader community (DeFalco et al., 2018)
- identify students who are *gaming the system* (i.e., succeeding in learning system despite *not following the desired behaviors;* using loopholes or system properties to complete tasks without thinking about the domain content; Paquette & Baker, 2019), and then implement responses to discourage or prevent that behavior (Xia et al., 2020; Li et al., 2022)
- identify the *weakest* components of a written essay, and then provide students with formative feedback and relevant writing strategies (Roscoe et al., 2013, 2014, 2017).

As the italicized text suggests, some degree of deficit framing (i.e., "ineffective" strategies and "negative" affect) is clear in many examples. For instance, Roscoe et al. (2013, 2014, 2017) have described how Writing Pal algorithms provide feedback to student essays "lacking in elaboration" or exhibiting "repetitiveness," and how feedback messages emphasize "problem identification" and "problem resolution." Although grounded in robust literature on formative feedback and writing instruction, this framing was nonetheless deficit-based—students' weaknesses and "problems" with writing were foregrounded rather than their potential strengths as writers. This framing is carried out despite the researchers' own findings that there are variable ways for students to write successfully (Crossley et al., 2014).

A variety of AIED approaches can incorporate deficit-based and/or asset-based framing. In the following subsections, we describe examples of how deficit-based paradigms might manifest in AIED via *mastery learning and misconception models*, *self-regulated learning* (SRL) *detection,* and *affect and engagement detection*. These few examples are not exhaustive of the myriad approaches used in AIED but represent classic and contemporary cases that many readers may be familiar with.

2.1 Mastery Learning and Misconception Models

One of the most common paradigms for AIED systems is "mastery learning," where learners continue to study or practice a given topic until they have demonstrated sufficient mastery (e.g., consistently able obtain correct solutions or express correct conceptions) (Corbett & Anderson, 1995; Jones & Bomash, 2018; Doroudi, 2020). Progress toward mastery (or the lack thereof) may be assessed via various metrics (or a combination thereof), for example, performance on quizzes, the correctness of actions taken while working, use of learning resources (e.g., hints and prompts). Many such systems implement very simple heuristics requiring students to continue working until they produce three correct responses consecutively (Doroudi, 2020; Cosyn et al., 2021). For example, in Cognitive Tutor (now MATHia), attainment of mastery is determined by probabilistic Bayesian algorithms that take into account a student's history of correct responses, errors, and hint requests, treating hint requests as evidence of a lack of mastery (Corbett & Anderson, 1995). This approach remains the most common method for assessing mastery (beyond simple heuristics such as three correct in a row) (Kang et al., 2022) despite evidence of complex relationships between hint-seeking and knowledge (Roll et al., 2011), some of which might be culturally conditioned (Karumbaiah et al., 2021).

Although generally effective for supporting learning (Corbett, 2001; Sales & Pane, 2019), mastery approaches have historically been deficit-based in their implementation. Specifically, mastery learning systems are often based on an *overlay model* (see also "expert model" and "domain model") wherein learners' knowledge, skills, and strategies are considered a *subset* of experts' domain knowledge (Carr & Goldstein, 1977). The system characterizes students' capabilities and competencies by subtracting them from models of what experts know (e.g., Brown & Carr & Goldstein, 1977; Burton, 1978; VanLehn 1988; Liang et al., 2022). When overlay models detect a misalignment between student and expert models (i.e., the student "lacks" knowledge or "cannot" solve a problem), the system requires learners to continue to study the material until the discrepancy falls below a threshold.

A parallel approach was developed to address learner "misconceptions" (Brown & Burton, 1978)—mental models that comprise multiple "incorrect" ideas or inferences that might nonetheless seem to coherently explain the world (Chi, 2005). Early misconception detection models sought to compile multiple types of errors and actions (e.g., missing information and incorrect solution steps) into pre-defined "bug libraries" (Brown & Burton, 1978; VanLehn, 1988; Zhang, 1991), which documented the ways in which students' incorrect answers or procedures might signal a known misunderstanding of the material. Others deconstructed misconceptions into components (Langley & Ohlsson, 1984; VanLehn, 1988; Zhang, 1991). For instance, a misunderstanding of the distributive property might be revealed by incorrect orders of mathematic operations, intermediate computations, or answers.

Mastery approaches, misconception detection, and overlay models embody a deficit-based approach in several ways. First, by establishing "expert" or "domain" models as the baseline, students can only ever be "less than" expert unless they exactly emulate the experts or express a canonical conceptualization. This formulation assesses learners and learning as an extent of imperfection. Learner knowledge, skills, conceptions, and resources that diverge from the expert model are defined as either "wrong" or "irrelevant." In addition, the identity of the expert is often unstated, but in practice is usually the cognitive scientist, learning scientist, or curriculum developer who built the expert model—often representing a historically empowered and well-represented population (see, for instance, the depictions of procedures in Lovett, 1998 or Rowe et al., 2021). The design of overlay models begs the question of what funds of knowledge, alternative ways of knowing and working, social networks, and other resources are embedded within the expert model. What and whose expertise and assets are considered good enough for mastery? Have students actually "fallen short" or are there alternative approaches that have not been acknowledged?

One indicator of the problematic aspects of mastery approaches emerges from how these models are sometimes undermined or rejected in classrooms. Researchers have observed that teachers are sometimes uncomfortable with AIED systems' recommendations and insistence on perseverance. Some systems may require frustrated students to struggle on the same topic for substantial periods of time; teachers then override or disable the systems' mastery learning so their students can progress (Ritter et al., 2016). To our knowledge, research has not yet systematically studied *why* teachers make these choices, and there is ongoing debate about whether these decisions lead to better learning outcomes for students (Ritter et al., 2016; Sales & Pane, 2019). Although sometimes framed as a problem of "implementation fidelity" (implicitly characterizing teachers' use of these systems as deficient), it may first be worth trying to better understand what information and insights (e.g., about the learners) teachers rely on when deciding to intervene, modify, or abandon the mastery model.

The above summary of mastery and misconception models raises questions about how such approaches could be reimagined in an asset-based manner. One strategy might be to expand expert models to incorporate more and diverse assets into the characterization of expert performance. Similarly, one might develop multiple models of desired skills and competencies. In many domains, there may be several distinct ways to attain success (e.g., correctly solve a problem) or to demonstrate competence. A multiple model system could first assess which model best captures students' current knowledge and skills, and then adapt subsequent instruction to learners' individual pathway(s), an approach considered in early AIED systems (Greer & Koehn, 1995).

Relatedly, several systems have extended mastery learning to approaches that go beyond fixed curricula (i.e., all students proceed through the same topics in the same order). This adaptive approach explicitly selects and sequences content based on expectations of student knowledge. ALEKS—the first widely-scaled system to adopt this method—developed a graph of skills and their prerequisites (Cosyn et al., 2021). Students complete a set of assessments to position them on the graph, and then are directed to domain content that they "do not know" but for which they possess all of the prerequisites. Research suggests that this adaptive sequencing approach improves performance on learning tasks (Zou et al., 2019) and overall learning outcomes (Mojarad et al., 2021). Such modifications may better account for students' capabilities and further improve efficacy, but they nonetheless retain deficit-based assumptions since the expert model(s) still establish thresholds that learners must meet or fail to meet.

A subtly different alternative might be to develop models that explicitly map learners' *existing* knowledge, skills, and opportunities for growth, building on the expertise that learners have already developed from their lives outside of school (e.g. Crowley & Jacobs, 2003). For example, scholars who study misconceptions have sometimes discussed the *alternative conceptions,* which reflect developmentally normal understandings that may be functional for students' everyday lives even if they do not align to normative or "expert" conceptions (Gilbert & Watts, 1983). This approach is not without criticism (see concerns summarized in Maskiewicz & Lineback, 2013), but recognizing how alternative conceptions can serve as functional assets may be beneficial for understanding how and whether these conceptions need to change. If these conceptions have meaning and value that aligns with other aspects of learners' lives (e.g., family and religious traditions), students may resist efforts to refute or "fix" them, instead interpreting that effort as an assault on their identity (Truong et al., 2018; Barnes et al., 2021).

To be clear, asset-based learning pedagogies do not advocate an "anything goes" approach, where any alternative conception is considered acceptable. Within the community on culturally-responsive pedagogy, this is seen as a trivialization of the asset-based perspective (Sleeter, 2012). Instead, a more nuanced view recognizes the role that certain misconceptions can serve in bridging student understanding. This approach takes into account students' starting places and trajectories rather than simply identifying and eliminating misconceptions (Maskiewicz & Lineback, 2013). Work in this community also considers the cultural factors that influence the ordering of prerequisite skills for different learners (e.g., O'Shaughnessy et al.'s (2023) findings on the influence of number systems on mathematical sense making processes). Overall, this paradigm suggests that it may be important to look at whether students' trajectories through learning systems—particularly more open-ended systems—lead to growth, rather than whether or not a student has completed the material in the way an expert might have (see for example, Nasiar et al., 2023; Zambrano et al., 2023).

Altogether, an asset-based approach toward mastery and misconceptions may reconsider instruction as "steering," "guiding," or "reconciling" alternative conceptions rather than as "repairing" misconceptions. In practice, the instructional goal may still be to help students attain canonical knowledge and skills, but it may be more effective to achieve this goal if instruction is guided by deeper appreciation of students' starting place, values, and resources.

2.2 Metacognition and Self-Regulated Learning (SRL) Detection

Overlay and misconception models tend to emphasize conceptual knowledge and skill acquisition, which may be captured through students' products (e.g., answers and solutions) and procedures (e.g., intermediate products and solution steps). Other recent classes of AIED systems have delved more deeply into students' learning *processes*—the ways they approach learning and studying. For instance, several AIED systems have sought to support better metacognitive engagement (Arroyo et al., 2014; McNamara & Shapiro, 2005) or to facilitate self-regulated learning (SRL) (Roll et al., 2011; Roscoe & Craig, 2022). In brief, metacognition broadly refers to cognitive evaluations (e.g., judging accuracy, relevance, and confidence) applied to one's own thoughts, feelings, and behaviors (Hacker, 1998). SRL refers to iterative cycles of learning wherein learners metacognitively plan learning activities, implement strategies, assess themselves and their performance, and then adapt to improve future work (Winne, 2021a). Metacognition—particularly in the context of SRL—has been well-documented as a key component of successful learning (Winne, 2017).

To assess or scaffold learners' metacognitive engagement and SRL, AIED systems necessarily need to detect and track the occurrence of relevant behaviors. Specifically, SRL models gather data on learners' actions and interactions within the system, and certain patterns are then taken as indicators of metacognitive activities or skills (e.g., voluntarily requesting a quiz as a form of self-monitoring) (Roscoe et al., 2013; Azevedo et al., 2012; Zhang et al., 2022). Within these paradigms, deficit-based approaches are predominant – approaches describe learners as "lacking" SRL skills and strategies (Miller & Bernacki, 2019), using "shallow" strategies (Roscoe et al., 2013), or being "inaccurate" or "miscalibrated" in their metacognitive judgments (Mudrick et al., 2019). Subsequent tutorials or feedback are then focused on addressing strategy gaps or otherwise remediating students (Roll et al., 2011; Roscoe & Craig, 2022). This approach has generated numerous successes (Roll et al., 2011; Azevedo et al., 2022), but it is worth asking what *also* might be enabled or supported via asset-based framing.

In articulating an asset-based approach to SRL models, it is worth noting that metacognition and self-regulation are often described as powerful *domain-general* resources that support performance on many or most tasks (Karabenick & Zusho, 2015). Even when learners "lack" existing domain-specific knowledge or skills, self-monitoring and regulation can be harnessed to develop understanding or attain success. Thus, comprehension monitoring, predictions of knowing, metamotivation, and similar processes might be seen as powerful *assets* that learners may bring to diverse learning settings even when other resources are less available. As noted above, we already possess AI-driven techniques and tools to detect these metacognitive processes, but we could do better with acknowledging and leveraging existing skills instead of focusing solely on "missing" skills.

AIED systems might highlight and communicate students' SRL assets in several ways. For instance, dashboards might signal to teachers when students successfully use any self-regulatory strategy. Such communication would empower teachers to understand what different students are capable of and perhaps recommend how the same strategies could be applied broadly (i.e., skill transfer). Teachers might also use this information to further develop these strategies: if a student is already familiar with predicting their own learning, then perhaps other kinds of predictive or anticipatory strategies (e.g., planning) might be accessible. Finally, teachers might promote peer learning and help-giving by inviting students to demonstrate or mentor SRL strategies for their classmate, building appreciation for both demonstrating and sharing assets.

AI-driven feedback can also be provided directly to learners. Systems that detect SRL strategies can encourage students to be more aware and intentional about strategy use, such as by signaling or "naming" the observed strategies. Students can also be reminded of successful strategies that they have used in the past or in other tasks, and which might be relevant to a current problem. In this manner, AIED systems may raise students' awareness of their own assets and the applicability of those assets, which might in turn strengthen their metacognitive knowledge and self-efficacy.

2.3 Affect and Engagement Detection Models

Over the last fifteen years, a number of AIED systems have attempted to go beyond the cognitive domain by tracking and responding to student affect and engagement (D'Mello et al., 2010; DeFalco et al., 2018; Xia et al., 2020; Li et al., 2021). Affect refers to learners' subjective attitudes and emotions related to learning and learning environments (e.g., feeling happy about passing a difficult test; Efklides et al., 2017). Engagement is a multifaceted construct that comprises emotional, behavioral, cognitive, and agentic components (Feng et al., 2013; Sinatra et al., 2015; Smallwood & Schooler, 2015). Many educators and scholars have argued that integration of all of these components is important (or even required) for effective learning. Consequently, the capacity for AIED systems to be "affect-aware" and "engagement-aware" has been an active goal of recent work (D'Mello et al., 2017). Indeed, systems that can respond to negative affect and disengagement have been successful at improving learning outcomes (D'Mello et al., 2010; DeFalco et al., 2018; Xia et al., 2020; Li et al., 2021).

As with detecting knowledge, skills, or strategies, engagement-aware AIED depends on tracking behaviors or other cues (in real-time) that may be indicative of students' emotions and other aspects of engagement. Learner states can be solicited via self-report—students can be prompted to indicate their moods and attitudes throughout the learning experience. However, it is often worthwhile to avoid disrupting learners with repeated probes, and thus unobtrusive, automated detection is necessary. For example, learners might display a very slow rate of interacting with system features (e.g., long pauses between solution steps) that might indicate distraction, boredom, or confusion (Pardos et al., 2014; Mills et al., 2020). In combination with other cues (e.g., frequently accessing browser tabs outside of a web-based tutor), systems might hone in on the most likely interpretations (e.g., distraction). Given the complexities and contextual factors inherent in engagement (Schooler et al., 2011; Smallwood & Schooler, 2015; Sinatra et al., 2015; Heddy et al., 2017), scholars have attempted to leverage a range of sensor-based technologies (e.g., facial feature tracking, eye tracking, and posture sensors) and sensor-free methods to detect engagement. For example, eye tracking tools may examine whether students are attending to the computer screen (Mills et al., 2020) and galvanic skin response (GSR) measures can track whether learners are in a heightened state of arousal (e.g., anxiety or excitement) (AlZoubi et al., 2012). Sensor-free methods have been developed to detect affect and engagement-related behaviors and cues without the need for biometric equipment, such as identifying off-task behavior or gaming the system based on patterns of human-computer interactions (e.g., Pardos et al., 2014; Paquette & Baker, 2019).

Affect and engagement modeling can readily be used to implement a deficit-based approach. When detection emphasizes "lack" of motivation or "disengagement," learners are once again framed as "missing" important resources rather than credited for what they do possess. Perhaps similarly, when students express "negative" affect, they may be faulted for experiencing emotions that are valid reactions to tasks or content (e.g., frustration and boredom). Deficit-based framing is further built into paradigms for intervention. Once (dis)engagement has been detected, verbal or visual cues might try to reclaim "lapsed" attention (Pham & Wang, 2015, 2017), or repeat information that was "missed" while students were disengaged (Hutt et al., 2021). Similarly, when students are observed to be gaming the system, AIED systems might either display visualizations to communicate why students should not game (Xia et al., 2020) or change the system's incentive structure (Li et al., 2021).

As with metacognitive and self-regulation strategies, affect and engagement also have high potential for capturing students' assets. For instance, higher levels of curiosity and enjoyment have been associated with increased effort, persistence, and strategy use (Linnenbrink & Pintrich, 2002). Thus, holding a strong personal interest in a topic may be a resource to draw upon even when prior knowledge is "low" or repeated "failures" have occurred. Other motivational factors such as achievement goals might serve a similar function (Church et al., 2001; Priniski et al., 2019; Hecht et al., 2021). In addition, learners' patterns might also be presented or communicated in ways that emphasize positive, agentic actions (e.g., proportion of time spent on-task) rather than problems (e.g., proportion of time spent off-task). By emphasizing what students *are* positively doing, rather than what they are not doing, it may reinforce that students have control and can make (perhaps different) decisions about their behaviors.

3.0 An Asset-Based Vision for the Future of Artificial Intelligence in Education

A fundamental task for education—and the AIED community—is to characterize learners. Learners are multidimensional, with differences that span knowledge, skills, misconceptions, strategies, metacognition, emotions, engagement, interests, values, and more. In order to adopt asset-based approaches, learning should be characterized in multifaceted ways that consider both the learner and their context (see also scholarship on intersectionality; Else-Quest & Hyde, 2016; Sibbett, 2020; Von Esch et al., 2020; Davis et al., 2023). While deficit-based approaches (e.g., detecting students' needs and obstacles) have provided useful mechanisms for supporting students, we argue that these characterizations are incomplete and potentially problematic, as they may focus teachers' (and students') attention solely on what students do not know or cannot achieve. Instead, we argue that the AIED community should seek to appreciate, build on, and advance the cognitive, metacognitive, affective, social, and cultural resources students bring to learning, regardless of whether these resources are formally (e.g., learned in school) or informally (e.g., practiced at home) obtained.

To elucidate the opportunities for learners that an asset-based approach can bring, and illustrate the steps needed to realize that potential, we put forward five principles which could guide future AIED innovation. In order to achieve AIED systems that allow learners, educators and other stakeholders to fully leverage learner assets, and produce greater successes across a diverse range of students and a wide range of learning contexts, we argue that AIED developers and researchers should:

1. *Conceptualize and define learner assets expansively*.
2. *Detect assets that students possess or have access to*.
3. *Leverage learner assets using system features and functions*.
4. *Provide opportunities to develop new assets using system features and functions*.
5. *Make assets visible for learners, educators, and other stakeholders*.

We argue that these principles can be applied across a range of modeling approaches in AIED systems—even those which are most rooted in deficit-based frameworks (i.e., mastery and misconception models). We articulate potential opportunities for incorporating asset-based approaches into AIED, many of which cut across principles, in the remainder of this section.

3.1 Principle 1: Conceptualize and Define Learner Assets Expansively

Research on asset based approaches emphasizes the resources students bring from their home and community, including those related to their cultural and linguistic practices (e.g., McSwan, 2020). It is clear that the AIED community could also draw on many other learner resources, including cognitive and metacognitive strategies, motivational beliefs and goals, emotions and emotional regulation, and interests that might arise from school-based resources, social networks, recreational activities, and even work places. Thus, our first principle for designing asset-based AIED is that these systems should *conceptualize and define learner assets expansively.*

Within the AIED community, it is crucial that we work to define, identify and comprehend the strengths students bring to the table. We encourage the field to explore the ways in which culturally mediated resources, which Rodriguez and colleagues (2004) describes as "symbols, thoughts, cognitive processes and social contexts derived from an individual's culture" can be engaged in order to improve learning. This differs from the common practice of simply identifying and fixing shortcomings in their knowledge base. Along with developing methods to incorporate students' existing knowledge into the AIED system, we should also focus more on learning environments outside the AIED system that are known to influence education. While work has already suggested that the research community should be more mindful of *who* we are studying (Paquette et al., 2020), we suggest that it may be beneficial to broaden this effort to also examine the ways that we categorize students' lived experience (e.g., Belitz et al., 2022).

Doing so may also include broadening the number of data sources used (e.g., teacher evaluations, classroom data, surveys, and other self-evaluations). For example, CueThink—which provides middle school math instruction—has integrated detectors of student behaviors with surveys of metacognitive awareness, game-based measures of executive functioning, and language data from student reflection probes to better understand math learning (Zhang et al., 2022; Andres et al., 2023). Meanwhile, a large body of research outside of the AIED community has sought to measure sociocultural factors that influence student engagement. Incorporating data sources that tackle these issues could be beneficial. For instance, Duran and colleagues' (2020) survey on students' sense of belonging or Sablan's (2019) survey of community cultural wealth can provide valuable insights. These resources could assist teachers, researchers, and other stakeholders in better understand the students' learning context. Simultaneously, they could reveal a broader spectrum of students' strengths, which can serve as a foundation for further development. These methods could complement other novel self-report tools that are emerging in the AIED literature, including Walkington and Bernacki's (2014) efforts to capture important factors outside of students' formal educational experiences (e.g., their cultural, familial, and recreation experiences). In the longer term, it may be worth thinking about how AIED systems can be made more open-ended in ways that enable us to learn more about the assets students bring to a learning experience, including assets that AIED system developers may not have initially considered at all.

3.2 Principle 2: Detect Assets that Students Possess or Have Access to

Acknowledging that students have a wide range of assets is important, but the system must also be able to *detect the assets that students possess or have access to* (Principle 2). If we limit the metrics we detect to narrow definitions of learning and performance, we lose information that is important to defining the well-being and growth of the learner, which may be foundational to the very learning goals we hope to achieve.

As noted in the discussion of Principle 1, context and information that informs our understanding of student assets can be obtained through self-report. Another approach is to capture student assets by building on the already expansive list of learner models (see reviews in Normadhi et al., 2019; Abyaa et al., 2019), and to use those in conjunction with real-time detection techniques. The field has already demonstrated its ability to identify a variety of factors beyond just domain knowledge, such as affective states, self-regulation, and other metacognitive elements. Moreover, the development of these detectors has taken into account student assets, identifying constructs like conscientiousness and persistence (Ventura & Shute, 2013; Moore & Shute, 2017; Kai et al., 2018) and creativity (Skalicky et al., 2017; Shute & Rahimi, 2021), which fall more clearly under the category of assets. Given that the majority of detectors are framed in a deficit style, more attention to detecting student assets would be of benefit to the field.

Even when deficits are detected, it is possible to address them in an asset-based manner, particularly if learning systems work to find the ways in which students' needs are not being met. Again, the concern is not that deficits are being detected. All learners—by definition—have room for growth. Instead, the concern is that only deficits are being acknowledged—even when the apparent shortfalls also reflect significant strengths. For example, "wheel spinning" (Beck & Gong, 2013), where a student persists without achieving the learning goal, has been framed negatively but suggests praiseworthy levels of tenacity and determination on the part of the student. Productive persistence and unproductive persistence often differ in terms of the strategies students use (Kai et al., 2018), suggesting that it may be possible to build on student assets to make persistence productive. In other cases, it may be possible that the learner needs other kinds of scaffolding (e.g., greater practice on prerequisite skills). Regardless, wheel-spinning does not indicate that the student has a deficit; it indicates that the student is not being well-served by the current learning system.

As a field we should seek to reframe other student performance constructs in ways that support recognition of student assets. For example, if working memory (Chang et al., 2013; Cojean & Martin, 2022) and response time (Mettler et al., 2011) —two constructs incorporated in learner models to better understand why students might struggle—are detected, they can be used to determine when the system can better support the student. This suggests that detecting a construct is not the issue; how it is used by the learning system determines whether the system is deficit-focused or asset-focused. As such, constructs that can be used in a deficit fashion should be cautiously presented in dashboards or data visualization in order to prevent students from being labeled as deficient in these constructs (see discussion in Ocumpaugh et al., 2017). To summarize more strongly, we argue that pedagogies are not deficit-based when they find places where students need support. They are deficit based when they *only* find areas where students are deficient.

3.3 Principle 3: Leveraging Existing Learner Assets Using System Features and Functions

Following from Principles 1 and 2, which recommend defining and detecting a broader range of assets, our third principle for designing asset-based AIED recommends that we *use system functions to leverage these learner assets*. AIED systems have already been successful at building students' knowledge assets, but these efforts have emphasized student deficits.

Increasing the number of pedagogical and student problem-solving approaches that AIED systems model and encourage could help us to meet these goals. For example, Hunt et al., (2022) suggests that one reason students with learning disabilities benefit from open-ended problem solving is that educators often underestimate the extent (and type) of their prior knowledge. In other words, even teachers who are in daily contact with their students can struggle to fully identify and leverage students' assets. Today, AIED systems are able to offer various levels of open-endedness (Fournier-Viger et al., 2010) that could be used to develop more equitable learning opportunities.

In fact, researchers have already begun to model a wide range of variation in student learning approaches. For instance, Gobert et al., (2013) has developed models that can detect when a student understands the concept of experimentation but is using a different strategy than the most straightforward, expert approach. Holmes and colleagues (2014) have developed models of strategies for invention and Nasiar and colleagues (2023) have built models that can identify when a student invents a new strategy. Crossley et al., (2014) has modeled different approaches to successful writing. Meanwhile, other researchers have looked at how a variety of different paths through an open-ended science game might relate to student learning (Nasiar et al., 2023; Zambrano et al., 2023). Expanding these efforts to deliberately identify how these differences represent student assets—whether they stem from cultural differences, past educational experiences, or neurodiversity—could only improve the AIED toolkit.

3.4. Principle 4: Developing New Assets Using System Features and Functions

Our fourth principle is that AIED systems should *use system features and functions to build student assets*. Many of the constructs we have already discussed, including the variation in student learning approaches discussed in Principle 3, could be used towards this goal. Similarly, tools that support self-regulated learning (e.g., Roll et al., 2011; Azevedo et al., 2022; Roscoe & Craig, 2022) can empower learners to develop their own assets with greater agency and independence. The central idea of Principle 4 is that we emphasize the variety of ways that all students can obtain *more* knowledge, *more* techniques, and *more* tools to work with rather than merely "fixing" their current knowledge, and ignoring or dismissing their existing resources.

As with previous principles, broadening learning content to reflect a wider range of cultural backgrounds, while requiring effort, could also help us to better serve all students. By leveraging the assets of students whose cultural backgrounds are often overlooked (Principle 3), such efforts would benefit those students. This is not a zero-sum game either: such enhancements would also provide new opportunities for students whose backgrounds are typically privileged, to make new connections and learn new skills and strategies. Integrating content from more diverse students might also provide opportunities for classroom role reversals, where students who typically need help now practice delivering it. Research demonstrates that learning by teaching can lead to deeper learning (Duran, 2017), and that students can benefit from receiving assessments from their peers (e.g., Patchan et al., 2016). Therefore, adding content that reverses the typical helper-helpee relationships in the classroom could improve learning opportunities for both groups.

3.5 Principle 5: Assets Must be Visible and Appreciated for Learners, Educators, and Other Stakeholders

Principle 5, in tandem with the others we have proposed, states that *AIED systems should make learner assets visible and appreciated for learners, educators and other stakeholders*. This principle encompasses everything from including the home and cultural assets of our learners when presenting domain knowledge to be acquired, to re-designing the data visualizations and dashboards used to communicate about the learner.

Recognizing student assets can have multiple benefits. Incorporating culturally responsive domain knowledge helps students to understand how their new knowledge and skills connect to their existing knowledge and skills. However, there are other effects as well. Specifically, recognizing students' assets in formal settings can improve their self-efficacy and strengthen their relationship with formal academic institutions, because this visibility demonstrates that their home knowledge *belongs* in the learning domain (Wolfram et al., 1999; Brown, 2006; Listman et al., 2011; Crumb et al., 2023). As such, we should ensure that the content of our learning systems more directly reflects the cultural and linguistic assets that students bring with them to the classroom, and we should also seek to encourage learners, teachers, and other stakeholders to explore the ways in which students' home cultures can be leveraged to better support the students.

Data visualizations and dashboards, whether student, teacher, or school leader-facing, should also consider the ways in which we can capture and nurture student assets. While there has been an increased interest in making education data driven, there are numerous cautions about designing without taking the data literacy of the audience into consideration (Ancker & Kaufman, 2007; Ocumpaugh et al., 2015; Mansoor & Harrison, 2018; Chang & Luo, 2021; Franconeri et al., 2021; Christensen et al., 2022; Panavas et al., 2022). Given concerns that data-driven reform can increase the use of deficit labels for students (Bertrand & Marsh, 2021), we would recommend that the AIED community build on the emerging literature on culturally responsive data literacy (Mandinach, 2022). For reports for teachers in particular, this may mean moving beyond highly popular (though not universal) traffic-light reporting schemes, despite their usefulness in many cases (Arnold & Pistilli, 2012; Krumm et al., 2014). While traffic-light dashboards have the benefit of connecting to a wide-reaching cultural metaphor (Gerofsky, 2011; Ocumpaugh et al., 2017), they may encourage those who read them to think of students in three buckets (red=low knowledge assets/high-risk, green=high knowledge assets/low-risk, and yellow=students on the cusp) (Mandinach & Schildkamp, 2021). In general, numerous learning systems already possess dashboards that track student performance or help teachers diagnose learners or instructional needs. These tools might be easily reimagined to highlight student resources and successes, rather than deficits.

These considerations can also be applied to the open learner models that have been studied within the AIED community (see reviews in Bull & Kay, 2010; Bull, 2020). Open learner models visualize the contents of learner models to students in ways they can interpret, and often invite the learner to edit, modify, or engage in dialogue with those models (Dimitrova et al., 1999; Bull & Kay, 2007). As such, open learner models can play an important role in scaffolding learners' reflection and self-regulation of their learning (Hooshyar et al., 2020; Winne, 2021b). Thus far, many open learner models have focused on the same deficits as much of the rest of the AIED community's work. However, as noted in Bull's (2020) review, open learner models can also be designed in ways that emphasize learners' strengths or growth of knowledge. Students using open learner models have indeed explicitly stated that these models helped them see their strengths as well as weaknesses (Bull, Mabbott, & Abu-Issa, 2007). In that review, Bull notes that many open learner models use positive representations such as growing trees or other cartoons that represent student knowledge. While these representations still present information about what students do not know (with the goal of eliminating those deficits), they do so in a positive fashion that represents growth towards assets rather than focusing on what is lacking. Similarly, (Bull et al., 2016) uses word clouds to represent both students' strengths and weaknesses – a small shift in emphasis would enable such a design to emphasize assets over deficits. Overall, the open learner model community's work demonstrates steps towards an asset-based framework, and it may be relatively easy to shift the communication in open learner models to focus on assets. In particular, it may be possible to use the process of dialogue and interaction between a student and an open learner model to focus a student towards reflecting on their assets.

In designing both dashboards and open learner models, careful attention needs to be paid to how students are labeled. There is clear evidence that applying a label to a student (e.g., high performing) affects both their own self-conceptions and the other people's expectations of their capability (see discussions in O'Donnell & Sireci ,2022; Walker et al., 2023; and Bertrand & Marsh, 2021). Labels have the power to create or justify categories that were previously non-existent or not seen as meaningful by the student or teacher (Altenhof & Roberts, 2021; Johnson & Papafragou, 2016; Fairchild et al., 2018), both for good and for ill. These effects can persist far beyond their utility. Labels related to student skills in one domain have the potential to anchor interpretations of future student data, even when the skills are not related (Krämer & Zimmermann, 2022). It is therefore important to remember that these proficiency labels—while often useful—can encourage a range of cognitive biases. If poorly selected, these labels may prevent both high and low achieving students from receiving appropriate support (e.g., the issue of halo effects, Malouf et al., 2014; Sanrey et al., 2021). As the field works to develop in-the-moment-feedback and reporting systems for a variety of audiences, it will become important to build upon the research in both motivation and culturally-sustaining pedagogies to nudge stakeholders in ways that help to facilitate asset-based approaches.

4.0 Conclusions

Researchers who advocate for asset-based approaches, such as those working with the funds of knowledge framework, have long contended that educators should deliberately leverage students' cultural and linguistic resources (Moll et al., 1992; Llopart & Esteban-Guitart, 2018). This advice is grounded in cognitive theories of learning that suggest that students' learning is more effective when it connects to students' existing knowledge. It draws on findings that demonstrate the importance of visibly incorporating the resources that students bring to the learning environment, as a method of communicating the educational relevance of those resources to students and otherwise promoting a sense of competence (Celedón-Pattichis et al., 2018). This advice is also highly compatible with the goals of personalization that inform our research community, and as we have pointed out, the field has already made efforts to detect constructs that might be considered assets.

Naturally, when there is room for learning and growth, it is tempting to categorize a deficit. Note, though, that even students who are categorized as high-achieving in deficit-based frameworks still have room for learning and growth. For example, a system should not characterize a 4th grader who is working on 5th grade math as "deficient" when they haven't mastered new 5th grade material. Instead, it should acknowledge space to grow and opportunity to build upon the array of skills and knowledge they have already acquired. One of the central ideas we are proposing is that systems should afford the same opportunities to all students—particularly those who have not typically been characterized as high-achieving—by building systems that are better at detecting and using assets that have historically been less recognized and leveraged. We acknowledge that there may be times when systems cannot do so—in fact, that currently appears to be the norm. However, when systems are unable to appropriately support students and build on their assets, this must be acknowledge as a failure of the system rather than as a failure of the student. Wise et al.'s (2021) discussion of so-called blank-box dashboards, which explicitly point users to constructs the system is unable to measure, might serve as one possible method of doing so.

This paper seeks to encourage the AIED community to take deliberate steps toward a more asset-based approach. The past two decades of research and practice have demonstrated that deficit-oriented AIED approaches have utility, but many areas of education research suggest that we should be cautious about defining students exclusively on what they lack. Therefore, we argue that the *next* decade of research should more actively integrate asset-based approaches alongside existing successful approaches. This encouragement falls within the recent calls for a greater focus on equity in AIED (Holstein & Doroudi, 2022; Riazy et al., 2021; Roscoe et al., 2022), which include the importance of considering demographics (Paquette et al., 2020; Sabnis et al., 2022) and the limitations of our own approaches (e.g., Wise et al., 2021; Karumbaiah & Brooks 2021). In many ways, it echoes previous calls for the field to consider culturally-responsive designs (Vatrapu, 2011), and it is compatible with increasing efforts within the AIED community to incorporate research paradigms that align with asset-based approaches (e.g., Steiner et al., 2015; Baker, 2016; Eppard et al., 2021; Baker et al., 2019; Patterson et al., 2023; Nasiar et al., 2023; Aguilar, 2018; Uttamchandani & Quick, 2022; Holstein et al., 2019; Hutt et al., 2021; Kizilcec et al., 2023; Li et al., 2023; Kang & Furtak, 2021; Mayfield et al., 2019; Viberg et al., 2023; Jivet et al., 2022). In other words, the seeds for developing asset-based technologies are already present in the both the AIED literature and the learning technology community more broadly (Gauthier et al., 2022; Christensen & Knezek, 2022; Raza et al., 2021; Datnow et al., 2018).

Specifically, we argue that we should take an expansive approach to defining, detecting, leveraging and building student assets—and that we do so in ways that are visible to both the learner and the other stakeholders in each educational context. Efforts to achieve the principles we have proposed may require more close-knit research collaborations with diverse students and teachers. These collaborations could help to better understand the cultural differences that emerge when students are interacting with technology (e.g., Blanchard & Mizoguchi, 2008; Karumbaiah et al., 2021; Casano & Rodrigo, 2022) and to ensure that teachers are prepared to use that technology and formative assessments we are designing (Datnow et al., 2018; Rodrigo, 2023).

In addition to making more deliberate efforts to consider students funds of knowledge when we design AIED systems, we also advocate following through on McCarthy et al.'s (2022) suggestion to build on work that points toward solutions. We already see a strong foundation for asset-based approaches present within the existing research and detector development, particularly if we are deliberate in how we use these to present formative assessments and feedback (Ocumpaugh et al., 2017). We hope that this paper can point our community toward deliberate reflection on the processes that might lead toward deficit-based labels (Bertrand & Marsh, 2021), and we hope that we can be successful in finding innovative ways to collaborate with communities (Kalwar et al., 2013) to ensure that both design and implementation recognizes, leverages, and develops the assets of all learners.

5.0 Acknowledgements: The authors would like to acknowledge the following funders: AERDF/EF+Math grant "Making learning visible: scalable, multisystem detection of self-regulation related to EF" for Jaclyn Ocumpaugh, Stephen Hutt, and Ryan Baker; Gates Foundation #INV-006123 for funding Rod Roscoe, and the University of Southern California's *James H Zumberge Faculty Research & Innovation Fund* for funding Stephen Aguilar. The statements made in this article represent our own opinions and do not necessarily represent the opinions of our funders. We would also like to acknowledge our anonymous reviewers for their careful and thoughtful reviews.

6.0 References

Abyaa, A., Khalidi Idrissi, M., & Bennani, S. (2019). Learner modelling: systematic review of the literature from the last 5 years. *Educational Technology Research & Development*, *67*, 1105-1143. https://doi.org/10.1007/s11423-018-09644-1

Adger, C. T., Wolfram, W., & Christian, D. (2014). *Dialects in schools and communities*. Routledge. https://doi.org/10.4324/9781410616180

Aguilar, S. J. (2018). Learning analytics: At the nexus of big data, digital innovation, and social justice in education. *TechTrends*, *62*, 37-45. https://doi.org/10.1007/s11528-017-0226-9

Agsuilar, S. J., Galperin, H., Baek, C., & Gonzalez, E. (2020). *When school comes home: How low-income families are adapting to distance learning*. USC Rossier School of Education & USC Annenberg School for Communication and Journalism. https://doi.org/10.35542/osf.io/su8wk

Aguilar, S. J., Galperin, H., Baek, C., & Gonzalez, E. (2022). Live instruction predicts engagement in K–12 remote learning. *Educational Researcher*, *51*(1), 81-84. https://doi.org/10.3102/0013189X211056884

Al-Shanfari, L., Demmans Epp, C., Baber, C. (2017). Evaluating the effect of uncertainty visualisation in open learner models on students' metacognitive skills. In: André, E., Baker, R., Hu, X., Rodrigo, M., du Boulay, B. (eds) *Artificial Intelligence in Education. AIED 2017. Lecture Notes in Computer Science*, vol 10331. Springer, Cham. https://doi.org/10.1007/978-3-319-61425-0_2

Aleven, V., McLaren, B. M., Sewall, J., Van Velsen, M., Popescu, O., Demi, S., Ringenberg, M., & Koedinger, K. R. (2016). Example-tracing tutors: Intelligent tutor development for non-programmers. *International Journal of Artificial Intelligence in Education*, *26*, 224-269. https://doi.org/10.1007/s40593-015-0088-2

Aleven, V., Rowe, J., Huang, Y., & Mitrovic, A. (2023). Domain modeling for AIED systems with connections to modeling student knowledge: A review. *Handbook of Artificial Intelligence in Education*, 127-169.Alim, H. S., & Paris, D. (2017). What is culturally sustaining pedagogy and why does it matter. *Culturally sustaining pedagogies: Teaching and learning for justice in a changing world*, *1*, 24.Stockman, I. J. (2010). A review of developmental and applied language research on African American children: From a deficit to difference perspective on dialect differences. Language, Speech, & Hearing Services in Schools, (41)23-38.

Altenhof, A. M., & Roberts, G. (2021). Labels, Even Arbitrary Ones, Facilitate Categorization. In *Proceedings of the Annual Meeting of the Cognitive Science Society* (Vol. 43, No. 43).

AlZoubi, O., D'Mello, S. K., & Calvo, R. A. (2012). Detecting naturalistic expressions of nonbasic affect using physiological signals. *IEEE Transactions on affective computing, 3*(3), 298-310. https://doi.org/10.1109/T-AFFC.2012.4

Ancker, J. S., & Kaufman, D. (2007). Rethinking health numeracy: a multidisciplinary literature review. *Journal of the American Medical Informatics Association, 14*(6), 713-721. https://doi.org/10.1197/jamia.M2464

Andres, J.M.A.L., Baker, R.S., Hutt, S.J., Mills, C., Zhang, J., Rhodes, S., DePiro, A. (2023) Anxiety, achievement, and self-regulated learning in CueThink. *Proceedings of the International Society of the Learning Sciences*.

Arnold, K. E., & Pistilli, M. D. (2012, April). Course signals at Purdue: Using learning analytics to increase student success. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 267-270). https://doi.org/10.1145/2330601.2330666

Arroyo, I., Woolf, B. P., Burelson, W., Muldner, K., Rai, D., & Tai, M. (2014). A multimedia adaptive tutoring system for mathematics that addresses cognition, metacognition and affect. *International Journal of Artificial Intelligence in Education*, *24*, 387-426. https://doi.org/10.1007/s40593-014-0023-y

Au, K., & Jordan, C. (1981). Teaching reading to Hawaiian children: Finding a culturally appropriate solution. In H. Trueba, G. Guthrie, & K. Au (Eds.), *Culture and the bilingual classroom: Studies in classroom ethnography* (pp. 139-152). Rowley, MA: Newbury.

Au K. H. (2003). *Literacy instruction in multicultural settings*. New York, NY: Harcourt Brace.

Azevedo, R., Behnagh, R. F., Duffy, M., Harley, J. M., & Trevors, G. (2012). Metacognition and self-regulated learning in student-centered learning environments. In *Theoretical foundations of learning environments* (pp. 171-197). Routledge.

Azevedo, R., Bouchet, F., Duffy, M., Harley, J., Taub, M., Trevors, G., Cloude, E., Dever, D., Wiedbusch, M., Wortha, F., & Cerezo, R. (2022). Lessons learned and future directions of MetaTutor: Leveraging multichannel data to scaffold self-regulated learning with an intelligent tutoring system. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.813632 Bacon, C. K. (2017). Dichotomies, dialects, and deficits: Confronting the "Standard English" myth in literacy and teacher education. *Literacy Research: Theory, Method, and Practice*, *66*(1), 341-357.

Baker, R. (2016). Using learning analytics in personalized learning. In M. Murphy, S. Redding, & J. Twyman (Eds.), *Handbook on personalized learning for states, districts, and schools*, 165-174.

Baker, R. S., & Hawn, A. (2022). Algorithmic bias in education. *International Journal of Artificial Intelligence in Education*, 1-41. https://doi.org/10.1007/s40593-021-00285-9

Baker, R., Scruggs, R., Pavlik, P.I., McLaren, B.M., Liu, Z. (in press) How well do contemporary knowledge tracing algorithms predict the knowledge carried out of a digital learning game? To appear in *Educational Technology Research & Development*.

Baker, R. S., Ogan, A. E., Madaio, M., & Walker, E. (2019). Culture in computer-based learning systems: Challenges and opportunities. *Computer-based Learning in Context, 1*(1), 1–13. https://doi.org/10.5281/zenodo.4057223

Baker-Bell, A. (2020). Dismantling anti-black linguistic racism in English language arts classrooms: Toward an anti-racist black language pedagogy. *Theory Into Practice, 59*(1), 8-21. https://doi.org/10.1080/00405841.2019.1665415

Baker-Bell, A. (2020). *Linguistic justice: Black language, literacy, identity, and pedagogy*. Routledge.

Barnes, M. E., Supriya, K., Zheng, Y., Roberts, J. A., & Brownell, S. E. (2021). A new measure of students' perceived conflict between evolution and religion (PCoRE) is a stronger predictor of evolution acceptance than understanding or religiosity. *CBE—Life Sciences Education*, *20*(3), ar42. https://doi.org/10.1187/cbe.21-02-0024

Beck, J. E., Gong, Y. (2013). Wheel-Spinning: Students who fail to master a skill. In: Lane, H.C., Yacef, K., Mostow, J., Pavlik, P. (eds) *Artificial Intelligence in Education. AIED 2013. Lecture Notes in Computer Science*(), vol 7926. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-39112-5_44

Belitz, C., Ocumpaugh, J., Ritter, S., Baker, R.S., Fancsali, S.E., Bosch, N. (2022) Constructing categories: Moving beyond protected classes in algorithmic fairness. *Journal of the Association for Information Science and Technology*, *74* (6), 663-668. https://doi.org/10.1002/asi.24643

Bennett, R. E. (2011). Formative assessment: A critical review. *Assessment in Education: Principles, Policy & Practice*, *18*(1), 5-25. https://doi.org/10.1080/0969594X.2010.513678

Bertrand, M., & Marsh, J. (2021). How data-driven reform can drive deficit thinking. *Phi Delta Kappan*, *102*(8), 35-39. https://doi.org/10.1177/00317217211013936

Bishop R., Berryman M., Cavanagh T., Teddy L. (2009). Te Kotahitanga: Addressing educational disparities facing Māori students in New Zealand. *Teaching and Teacher Education*, 25, 734-742.

Blanchard, E. G., & Mizoguchi, R. (2008). Designing culturally-aware tutoring systems: towards an upper ontology of culture. In *CATS 2008: Workshop on Culturally-Aware Tutoring Systems*, 23-34.

Boser, U., Wilhelm, M., & Hanna, R. (2014). The power of the Pygmalion effect: Teachers' expectations strongly predict college completion. *Center for American Progress*.

Brayboy B. M. J., Castagno A. E. (2009). Self-determination through self-education: Culturally responsive schooling for Indigenous students in the U.S.A. *Teaching Education*, 20(1), 31-53.

Brown, D. W. (2006). Micro-level teaching strategies for linguistically diverse learners. *Linguistics and Education, 17*(2), 175-195. https://doi.org/10.1016/j.linged.2006.08.001

Brown, J. S., & Burton, R. R. (1978). Diagnostic models for procedural bugs in basic mathematical skills. *Cognitive Science*, *2*(2), 155-192.

Byrd, A. S., Huang, Y. T., & Edwards, J. (2023). The impact of dialect differences on spoken language comprehension. *Applied Psycholinguistics*, 1-24. https://doi.org/10.1017/S0142716423000243

Bull, S. (2020). There are open learner models about!. *IEEE Transactions on Learning Technologies*, *13*(2), 425-448.

Bull, S., & Kay, J. (2010). Open learner models. In *Advances in intelligent tutoring systems* (pp. 301-322). Berlin, Heidelberg: Springer Berlin Heidelberg.
Bull, S., Mabbott, A., Abu-Issa, A. (2007) UMPTEEN: named and anonymous learner model access for instructors and peers. *International Journal of Artificial Intelligence and Education, 17* (3), 227–253.
Burt, W. M., & Stapleton, L. M. (2010). Connotative meanings of student performance labels used in standard setting. *Educational Measurement: Issues and Practice*, *29*(4), 28-38.
Cammarota J., Romero A. (2009). The Social Justice Education Project: A critically compassionate intellectualism for Chicana/o students. In Ayers W., Quinn T., Stovall D. (Eds.), *Handbook for social justice education* (pp. 465-476). New York, NY: Lawrence Erlbaum.
Cannon, J. E., & Luckner, J. L. (2016). Increasing cultural and linguistic diversity in deaf education teacher preparation programs. *American Annals of the Deaf*, *161*(1), 89-103. https://doi.org/10.1353/aad.2016.0014
Carpenter Ford, A. (2013). "Verbal ping pong" as culturally congruent communication: Maximizing African American students' access and engagement as socially just teaching. *Equity & Excellence in Education*, 46(3), 371-386. https://doi.org/10.1080/10665684.2013.806852
Carr, B., & Goldstein, I. P. (1977). Overlays: A theory of modelling for computer aided instruction. Massachusetts Inst of Tech Cambridge Artificial Intelligence Lab.
Casano, J. D. L., Rodrigo, M. M. T. (2022). A comparative assessment of US and PH learner traversals and in-game observations within Minecraft. In M. M. Rodrigo, N. Matsuda, A. I. Cristea, & V. Dimitrova (Eds.) *Artificial Intelligence in Education. Posters and Late Breaking Results, Workshops and Tutorials, Industry and Innovation Tracks, Practitioners' and Doctoral Consortium. AIED 2022. Lecture Notes in Computer Science*, vol 13356, 267-270. Springer, Cham. https://doi.org/10.1007/978-3-031-11647-6_49
Celedón-Pattichis, S., Borden, L. L., Pape, S. J., Clements, D. H., Peters, S. A., Males, J. R., Chapman, O., & Leonard, J. (2018). Asset-based approaches to equitable mathematics education research and practice. *Journal for Research in Mathematics Education*, *49*(4), 373-389. https://doi.org/10.5951/jresematheduc.49.4.0373
Chang, C. J., & Luo, Y. (2021). Data visualization and cognitive biases in audits. *Managerial Auditing Journal*, *36*(1), 1-16. https://doi.org/10.1108/MAJ-08-2017-1637
Chang, T. W., El-Bishouty, M. M., & Graf, S. (2013). An approach for detecting students' working memory capacity from their behavior in learning systems. In *Proceedings of the 13th International Conference on Advanced Learning Technologies* (pp. 82-86). IEEE. https://doi.org/10.1109/ICALT.2013.29
Chapman, A., & McHatton, P.A. (2022). It helps to know Spanish: A multicultural approach by tapping into Latinx learners' native language to learn science. In: Atwater, M.M. (eds) *International Handbook of Research on Multicultural Science Education*. Springer International Handbooks of Education. Springer, Cham. https://doi.org/10.1007/978-3-030-83122-6_4
Chase, C. C., Connolly, H., Lamnina, M., & Aleven, V. (2019). Problematizing helps! A classroom study of computer-based guidance for invention activities. *International Journal of Artificial Intelligence in Education*, *29*, 283-316. https://doi.org/10.1007/s40593-019-00178-y
Chi, M. T. (2005). Commonsense conceptions of emergent processes: Why some misconceptions are robust. *Journal of the Learning Sciences*, *14*(2), 161-199. https://doi.org/10.1207/s15327809jls1402_1
Chou, P. I., Su, M. H., & Wang, Y. T. (2018). Transforming teacher preparation for culturally responsive teaching in Taiwan. *Teaching and Teacher Education, 75*, 116-127. https://doi.org/10.1016/j.tate.2018.06.013
Christensen, R., & Knezek, G. (2022). Impacting culturally responsive teaching strategies by decreasing bias through simulation experiences. *Excellence and Innovation in Learning and Teaching-Open Access*, *7*(2). https://doi.org/10.3280/exioa2-2022oa15077
Christensen, T., Rose, A. M., Rose, J. M., & Sanderson, K. A. (2022). Effects of data visualizations on jurors' judgments. *Behavioral Research in Accounting*, *34*(1), 23-41. https://doi.org/10.2308/BRIA-2021-005
Church, M. A., Elliot, A. J., & Gable, S. L. (2001). Perceptions of classroom environment, achievement goals, and achievement outcomes. *Journal of Educational Psychology*, *93*(1), 43. https://doi.org/10.1037/0022-0663.93.1.43
Civil, M., Hunter, R., & Crespo, S. (2019). Mathematics teachers committed to equity: A review of teaching practices. In *International handbook of mathematics teacher education: Volume 1* (pp. 243–273). Leiden: Brill Sense. https://doi.org/10.1163/9789004418875_010
Cleveland, R., Chambers, J., Mainus, C., Powell, N., Skepple, R., Tyler, T., & Wood, A. (2012). School culture, equity, and student academic performance in a rural Appalachian school. *Kentucky Journal of Excellence in College Teaching and Learning*, *9*(1), 4.
Cojean, S., & Martin, N. (2022). Adaptive learning technology based on working memory capacity. In *Cogsci 2022 - Cognitive Science Society*, Jul 2022, Toronto, France. https://hal.science/hal-03712903

Corbett, A. (2001). Cognitive computer tutors: Solving the two-sigma problem. In: M. Bauer, P. J. Gmytrasiewicz, J. Vassileva, (Eds.) *User Modeling 2001. UM 2001. Lecture Notes in Computer Science()*, vol 2109. Springer, Berlin, Heidelberg. https://doi.org/10.1007/3-540-44566-8_14

Corbett, A. T., & Anderson, J. R. (1995). Knowledge tracing: Modeling the acquisition of procedural knowledge. *User modeling and user-adapted interaction, 4*, 253-278. https://doi.org/10.1007/BF01099821

Cosyn, E., Uzun, H., Doble, C., & Matayoshi, J. (2021). A practical perspective on knowledge space theory: ALEKS and its data. *Journal of Mathematical Psychology*, *101*, 102512. https://doi.org/10.1016/j.jmp.2021.102512

Cramer, H., Garcia-Gathright, J., Springer, A., & Reddy, S. (2018). Assessing and addressing algorithmic bias in practice. *Interactions*, *25*(6), 58-63. https://doi.org/10.1145/3278156

Crowley, K., & Jacobs, M. (2003). Building islands of expertise in everyday family activity. In Learning conversations in museums (pp. 337-360). Routledge._

Crossley, S. A., Roscoe, R., & McNamara, D. S. (2014). What is successful writing? An investigation into the multiple ways writers can write successful essays. *Written Communication*, *31*(2), 184-214. https://doi.org/10.1177/0741088314526354

Crumb, L., Chambers, C., Azano, A., Hands, A., Cuthrell, K., & Avent, M. (2023). Rural cultural wealth: dismantling deficit ideologies of rurality. *Journal for Multicultural Education*, *17*(2), 125-138. https://doi.org/10.1108/JME-06-2022-0076

Curtin, E. M. (2006). Lessons on effective teaching from middle school ESL students. *Middle School Journal*, 37(3), 38-45. https://doi.org/10.1080/00940771.2006.11461534

D'Mello, S., Dieterle, E., & Duckworth, A. (2017). Advanced, analytic, automated (AAA) measurement of engagement during learning. *Educational psychologist*, *52*(2), 104-123. https://doi.org/10.1080/00461520.2017.1281747

D'Mello, S., Lehman, B., Sullins, J., Daigle, R., Combs, R., Vogt, K., Perkins, L., & Graesser, A. (2010). A time for emoting: When affect-sensitivity is and isn't effective at promoting deep learning. In *Proceedings of the 10th International Conference on Intelligent Tutoring Systems* (pp. 245-254). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-13388-6_29

Datnow, A., Choi, B., Park, V., & John, E. S. (2018). Teacher talk about student ability and achievement in the era of data-driven decision making. *Teachers College Record*, *120*(4), 1-34. https://doi.org/10.1177/016146811812000408

Davis, D. J., Olive, J. L., & Brunn-Bevel, R. J. (Eds.). (2023). *Intersectionality in educational research*. Taylor & Francis. https://doi.org/10.1353/rhe.2019.0039

Davis, L. P., & Museus, S. D. (2019). What is deficit thinking? An analysis of conceptualizations of deficit thinking and implications for scholarly research. *NCID Currents*, *1*(1). 117-129. http://doi.org/10.3998/currents.17387731.0001.110

Dedeoglu H., Lamme L. L. (2011). Selected demographics, attitudes, and beliefs about diversity of preservice teachers. *Education & Urban Society*, *43*, 468–485. https://doi.org/10.1177/0013124510380718

DeFalco, J.A., Rowe, J.P., Paquette, L., Georgoulas-Sherry, V., Brawner, K., Mott, B.W., Baker, R.S., Lester, J.C. (2018) Detecting and addressing frustration in a serious game for military training. *International Journal of Artificial Intelligence and Education*, *28*(2), 152-193. https://doi.org/10.1007/s40593-017-0152-1

del Rosario Basterra, M., Trumbull, E., & Solano-Flores, G. (Eds.). (2011). *Cultural Validity in Assessment: Addressing Linguistic and Cultural Diversity*. Routledge.

Dimitrova, V., Self, J., & Brna, P. (1999). The interactive maintenance of open learner models. In *Artificial intelligence in education* (Vol. 50, pp. 405-412).

Diwan, C., Srinivasa, S., Suri, G., Agarwal, S., & Ram, P. (2023). AI-based learning content generation and learning pathway augmentation to increase learner engagement. *Computers and Education: Artificial Intelligence*, *4*, 100-110. https://doi.org/10.1016/j.caeai.2022.100110

Doroudi, S. (2020). Mastery learning heuristics and their hidden models. In *Artificial Intelligence in Education: 21st International Conference, AIED 2020, Ifrane, Morocco, July 6–10, 2020, Proceedings, Part II 21* (pp. 86-91). Springer International Publishing. https://doi.org/10.1007/978-3-030-52240-7_16

Dudley-Marling, C. (2015). The resilience of deficit thinking. *Journal of Teaching and Learning*, *10*(1).

Dumas, D., Alexander, P. A., & Grossnickle, E. M. (2013). Relational reasoning and its manifestations in the educational context: A systematic review of the literature. *Educational Psychology Review*, *25*, 391-427. https://doi.org/10.1007/s10648-013-9224-4

Duran, D. (2017). Learning-by-teaching. Evidence and implications as a pedagogical mechanism. *Innovations in Education and Teaching International*, *54*(5), 476-484. https://doi.org/10.1080/14703297.2016.1156011

Duran, A., Dahl, L. S., Stipeck, C., & Mayhew, M. J. (2020). A critical quantitative analysis of students' sense of belonging: Perspectives on race, generation status, and collegiate environments. *Journal of College Student Development*, *61*(2), 133-153. https://doi.org/10.1353/csd.2020.0014

Edmonds-Wathen, C. (2013). Frame of reference in Iwaidja: Towards a culturally responsive early years mathematics program (Doctoral dissertation, RMIT University). Retrieved from https://researchrepository.rmit.edu.au/view/delivery/61RMIT_INST/12247487360001341/1324840873000134 1 Egan, K. L., Schneider, M. C., & Ferrara, S. (2012). Performance level descriptors: History, practice, and a proposed framework. In *Setting performance standards* (pp. 79-106). Routledge.

Ellis, C. (2013). Broadening the scope and increasing the usefulness of learning analytics: The case for assessment analytics. *British Journal of Educational Technology*, *44*(4), 662-664. https://doi.org/10.1111/bjet.12028

Else-Quest, N. M., & Hyde, J. S. (2016). Intersectionality in quantitative psychological research: I. Theoretical and epistemological issues. Psychology of Women Quarterly, *40*(2), 155-170. https://doi.org/10.1177/0361684316629797

Eppard, J., Kaviani, A., Bowles, M., & Johnson, J. (2021). EdTech culturation: Integrating a culturally relevant pedagogy into educational technology. *Electronic Journal of e-Learning*, *19*(6), 516-530. https://doi.org/10.34190/ejel.19.6.2065

Esteban-Guitart, M., Lalueza, J. L., Zhang-Yu, C., & Llopart, M. (2019). Sustaining students' cultures and identities. A qualitative study based on the funds of knowledge and identity approaches. *Sustainability*, *11*(12), 3400. https://doi.org/10.3390/su11123400

Esteban-Guitart, M., & Moll, L. C. (2014). Funds of identity: A new concept based on the funds of knowledge approach. *Culture & Psychology*, *20*(1), 31-48. https://doi.org/10.1177/1354067X13515934 Fairchild, S., Mathis, A., & Papafragou, A. (2018). Linguistic cues are privileged over non-linguistic cues in young children's categorization. *Cognitive Development*, *48*, 167-175.

Feng, M., Heffernan, N., Collins, K., Heffernan, C., & Murphy, R. F. (2023). Implementing and evaluating ASSISTments online math homework support at large scale over two years: Findings and lessons learned. In *International Conference on Artificial Intelligence in Education* (pp. 28-40). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-36272-9_3

Feng, S., D'Mello, S. K., & Graesser, A. C. (2013). Mind wandering while reading easy and difficult texts. *Psychonomic Bulletin & Review*, *20*(3), 586–592. https://doi.org/10.3758/s13423-012-0367-y

Ferguson, R. F. (2003). Teachers' perceptions and expectations and the Black-White test score gap. *Urban Education*, *38*(4), 460-507. https://doi.org/10.1177/0042085903038004006

Finkelstein, S., Yarzebinski, E., Vaughn, C., Ogan, A., & Cassell, J. (2013). The effects of culturally congruent educational technologies on student achievement. *Proceedings of the 16th International Conference on Artificial Intelligence in Education*, 493-502. https://doi.org/10.1007/978-3-642-39112-5_50

Fitzgerald, L., Hunter, J., & Hunter, R. (2021). Shifting teacher practices in relation to grouping: Gap gazing or strengths focused approaches. *Mathematics Teacher Education & Development*, 23(3), 97-110.

Flint, A. S., & Jaggers, W. (2021). You matter here: The impact of asset-based pedagogies on learning. *Theory Into Practice*, *60*(3), 254-264. https://doi.org/10.1080/00405841.2021.1911483

Flood, J., Lapp, D., & Heath, S. B. (2004). Bridging home and school literacies: Models for culturally responsive teaching, a case for African-American English. In *Handbook of research on teaching literacy through the communicative and visual arts* (pp. 365-375). Routledge. https://doi.org/10.4324/9781410611161-39

Flores, A. (2007). Examining disparities in mathematics education: Achievement gap or opportunity gap?. *The High School Journal*, *91*(1), 29-42. https://doi.org/10.1353/hsj.2007.0022

Fournier-Viger, P., Nkambou, R., & Nguifo, E. M. (2010). Building intelligent tutoring systems for ill-defined domains. *Advances in Intelligent Tutoring Systems*, 81-101. https://doi.org/10.1007/978-3-642-14363-2_5

Franconeri, S. L., Padilla, L. M., Shah, P., Zacks, J. M., & Hullman, J. (2021). The science of visual data communication: What works. *Psychological Science in the Public Interest*, *22*(3), 110-161. https://doi.org/10.1177/15291006211051956

Fuson, K. C., Smith, S. T., & Cicero, A. M. L. (1997). Supporting Latino first graders' ten-structured thinking in urban classrooms. *Journal for Research in Mathematics Education*, *28*(6), 738-766. https://doi.org/10.5951/jresematheduc.28.6.0738

García, O. (2009). *Bilingual education in the 21st century: A Global Perspective.* Wiley-Blackwell.

Gauthier, A., Rizvi, S., Cukurova, M., & Mavrikis, M. (2022). Is it time we get real? A systematic review of the potential of data-driven technologies to address teachers' implicit biases. *Frontiers in Artificial Intelligence*, *5*. https://doi.org/10.3389/frai.2022.994967

Gerofsky, S. 2011. Ancestral genres of mathematical graphs. *For the Learning of Mathematics*, 31(1), 14-19

Gilbert, J. K., & Watts, D. M. (1983). Concepts, misconceptions and alternative conceptions: Changing perspectives in science education. *Studies in Science Education*, 10(1), 61-98. https://doi.org/10.1080/03057268308559905

Gobert, J. D. (2023). Inq-ITS: Creating rigorous assessment and real-time support of science learning. *XRDS: Crossroads, The ACM Magazine for Students*, *29*(3), 36-40. https://doi.org/10.1145/3589647

Gobert, J.D., Sao Pedro, M., Raziuddin, J., Baker, R. (2013) From log files to assessment metrics: Measuring students' science inquiry skills using educational data mining. *Journal of the Learning Sciences*, *22*(4), 521-563. https://doi.org/10.1080/10508406.2013.837391

Gorski, P. C. (2017). *Reaching and teaching students in poverty: Strategies for erasing the opportunity gap*. Teachers College Press.

Greenberg, J.B. (1989). Funds of knowledge: Historical constitution, social distribution, and transmission. Paper presented at the annual meetings of the Society for Applied Anthropology, Santa Fe, NM.

Greer, J., & Koehn, G. M. (1995). The peculiarities of plan recognition for intelligent tutoring systems. In *IJCAI* 95, 54-59.

Griesen, M., Georges, C., Hornung, C., Sonnleitner, P., & Schlitz, C. (2021). Learning mathematics with shackles: How lower reading comprehension in the language of mathematics instruction accounts for lower mathematics achievement in speakers of different home languages. *Acta Psychologica*, *221*. https://doi.org/10.1016/j.actpsy.2021.103456

Grundwag, C., Nordfors, D., & Yirmiya N. (2017) "Coolabilities"—Enhanced abilities in disabling conditions. Whitepaper.

Guskey, T. R. (1982). The effects of change in instructional effectiveness on the relationship of teacher expectations and student achievement. *Journal of Educational Research*, *75*, 345-348. https://doi.org/10.1080/00220671.1982.10885407

Gutiérrez, K. D., & Rogoff, B. (2003). Cultural ways of learning: Individual traits or repertoires of practice. *Educational Researcher*, *32*(5), 19-25. https://doi.org/10.3102/0013189X032005019

Gutiérrez, R. (2008). Research commentary: A gap-gazing fetish in mathematics education? Problematizing research on the achievement gap. *Journal for Research in Mathematics Education*, *39*(4), 357-364. https://doi.org/10.5951/jresematheduc.39.4.0357

Hacker, D. J. (1998). Definitions and empirical foundations. In *Metacognition in Educational Theory and Practice* (pp. 15-38). Routledge.

Hall, W. C. (2017). What you don't know can hurt you: The risk of language deprivation by impairing sign language development in deaf children. *Maternal and child health journal*, *21*(5), 961-965.

Hecht, C. A., Grande, M. R., & Harackiewicz, J. M. (2021). The role of utility value in promoting interest development. *Motivation science*, *7*(1), 1. https://doi.org/10.1037/mot0000182

Heddy, B. C., Sinatra, G. M., Seli, H., Taasoobshirazi, G., & Mukhopadhyay, A. (2017). Making learning meaningful: facilitating interest development and transfer in at-risk college students. *Educational Psychology*, *37*(5), 565–581. https://doi.org/10.1080/01443410.2016.1150420

Hendricks, A. E., & Adlof, S. M. (2017). Language assessment with children who speak nonmainstream dialects: Examining the effects of scoring modifications in norm-referenced assessment. *Language, Speech, and Hearing Services in Schools*, 48(3), 168-182. https://doi.org/10.1044/2017_LSHSS-16-0060

Hilliard, A. (1992). Behavioral style, culture, and teaching and learning. *The Journal of Negro Education*, *61*, 370-377. https://doi.org/10.2307/2295254

Hirashima, T., Shinohara, T., Yamada, A., Hayashi, Y., & Horiguchi, T. (2017). Effects of error-based simulation as a counterexample for correcting MIF misconception. In E. André, R. Baker, X. Hu, M. Rodrigo, B. du Boulay (Eds.), *Artificial Intelligence in Education: 18th International Conference*. Springer International Publishing. https://doi.org/10.1007/978-3-319-61425-0_8

Holmes, N. G., Day, J., Park, A. H., Bonn, D. A., & Roll, I. (2014). Making the failure more productive: scaffolding the invention process to improve inquiry behaviors and outcomes in invention activities. *Instructional Science*, *42*, 523-538. https://doi.org/10.1007/s11251-013-9300-7

Holstein, K., Aleven, V., & Rummel, N. (2020). A conceptual framework for human–AI hybrid adaptivity in education. In *Artificial Intelligence in Education: 21st International Conference, AIED 2020, Ifrane, Morocco, July 6–10, 2020, Proceedings, Part I 21* (pp. 240-254). Springer International Publishing. https://doi.org/10.1007/978-3-030-52237-7_20

Holstein, K., & Doroudi, S. (2022). Equity and artificial intelligence in education. In *The ethics of artificial intelligence in education* (pp. 151-173). Routledge.

Holstein, K., Wortman Vaughan, J., Daumé III, H., Dudik, M., & Wallach, H. (2019, May). Improving fairness in machine learning systems: What do industry practitioners need?. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (pp. 1-16). https://doi.org/10.1145/3290605.3300830

Hooshyar, D., Pedaste, M., Saks, K., Leijen, Ä., Bardone, E., & Wang, M. (2020). Open learner models in supporting self-regulated learning in higher education: A systematic literature review. *Computers & Education, 154*, 103878.

Houser, N. O., & Chevalier, M. (1995). Multicultural self-development in the preservice classroom: Equity education for the dominant culture. *Equity & Excellence in Education*, *28*(3), 5-13. https://doi.org/10.1080/1066568950280302

Howard, T. C. (2003). Culturally relevant pedagogy: Ingredients for critical teacher reflection. *Theory into Practice*, *42*(3), 195-202. https://doi.org/10.1207/s15430421tip4203_5

Howard, T. C. (2019). *Why race and culture matter in schools: Closing the achievement gap in America's classrooms*. Teachers College Press.

Huang, X., Craig, S. D., Xie, J., Graesser, A., & Hu, X. (2016). Intelligent tutoring systems work as a math gap reducer in 6th grade after-school program. *Learning and Individual Differences*, *47*, 258-265. https://doi.org/10.1016/j.lindif.2016.01.012

Humphries, T. (2013). Schooling in American Sign Language: A paradigm shift from a deficit model to a bilingual model in deaf education. *Berkeley Review of Education*, *4*(1).

Hunt, J., Taub, M., Marino, M., Duarte, A., Bentley, B., Holman, K., & Banzon, A. (2022). Enhancing engagement and fraction concept knowledge with a universally designed game based curriculum. *Learning Disabilities: A Contemporary Journal, 20*(1), 77-95.

Hutt, S., Wong, A., Papoutsaki, A., Baker, R.S., Gold, J.I, & Mills, C. (2023). Webcam-based eye tracking to detect mind wandering and comprehension errors. *Behavior Research Methods* (2023). https://doi.org/10.3758/s13428-022-02040-x

Hutt, S., Krasich, K., Brockmole, J. R., & D'Mello, S. K. (2021). Breaking out of the lab: Mitigating mind wandering with gaze-based attention-aware technology in classrooms. *ACM SIGCHI: Computer-Human Interaction* (pp1-14). https://doi.org/10.1145/3411764.3445269

Hutt, S., Ocumpaugh, J., Ma, J., Andres, A. L., Bosch, N., Paquette, L., Biswas, G., & Baker, R. S. (2021). Investigating SMART models of self-regulation and their impact on learning. *Proceedings of the 14th International Educational Data Mining Society* (pp. 580-587).

Ijtihadie, R. M., Hidayanto, B. C., Affandi, A., Chisaki, Y., & Usagawa, T. (2012). Dynamic content synchronization between learning management systems over limited bandwidth network. *Human-Centric Computing and Information Sciences*, *2*, 1-16. https://doi.org/10.1186/2192-1962-2-17

Jablansky, S., Alexander, P. A., Dumas, D., & Compton, V. (2020). The development of relational reasoning in primary and secondary school students: a longitudinal investigation in technology education. *International journal of technology and design education*, 30, 973-993. https://doi.org/10.1007/s10798-019-09529-1

Jackson, G. T., Boonthum-Denecke, C., & McNamara, D. S. (2012). A comparison of gains between educational games and a traditional ITS. In *Proceedings of the Twenty-Fifth International Florida Artificial Intelligence Research Society Conference.* 444-449.

Jivet, I., Viberg, O., & Scheffel, M. (2022). Culturally aware learning analytics. In *Proceedings of the 12th International Conference on Learning Analytics and Knowledge* (pp. 186-188).

Johanson, M., & Papafragou, A. (2016). The influence of labels and facts on children's and adults' categorization. Journal of Experimental Child Psychology, 144, 130-151.

Johnson, D. C., Johnson, E. J., & Hetrick, D. (2020). Normalization of language deficit ideology for a new generation of minoritized US youth. *Social Semiotics*, *30*(4), 591-606.

Johnson, J., Shope, S., & Roush, J. (2009). Toward a responsive model for educational leadership in rural Appalachia: Merging theory and practice. *International Journal of Educational Leadership Preparation*, *4*(2), n2.

Jones, A., & Bomash, I. (2018). Validating mastery learning: assessing the impact of adaptive learning objective mastery in Knewton Alta. In *Proceedings of the 19th International Conference of Artificial Intelligence in Education* (pp. 433-437). Springer International Publishing. https://doi.org/10.1007/978-3-319-93846-2_81

Kai, S., Almeda, M.V., Baker, R.S., Heffernan, C., Heffernan, N. (2018) Decision tree modeling of wheel-spinning and productive persistence in skill builders. *Journal of Educational Data Mining*, *10*(1), 36-71. https://doi.org/10.5281/zenodo.3344810

Kalwar, S. K., Heikkinen, K., & Porras, J. (2013). Quantifying cultural attributes for understanding human behavior on the internet. In *Online Communities and Social Computing: 5th International conference, OCSC 2013, Held* *as Part of HCI International 2013, Las Vegas, NV, USA, July 21-26, 2013. Proceedings 5* (pp. 40-49). Springer Berlin Heidelberg.

Kang, J., Baker, R., Feng, Z., Na, C., Granville, P., & Feldon, D.F. (2022) Detecting threshold concepts through Bayesian knowledge tracing: Examining research skill development in biological sciences at the doctoral level. *Instructional Science, 50*(3), 475-497. https://doi.org/10.1007/s11251-022-09578-5

Kang, H., & Furtak, E. M. (2021). Learning theory, classroom assessment, and equity. *Educational Measurement: Issues and Practice*, *40*(3), 73-82. https://doi.org/10.1111/emip.12423

Karabenick, S. A., & Zusho, A. (2015). Examining approaches to research on self-regulated learning: conceptual and methodological considerations. *Metacognition and Learning*, *10*, 151-163. https://doi.org/10.1007/s11409-015-9137-3

Karumbaiah, S., & Brooks, J. (2021). How colonial continuities underlie algorithmic injustices in education. In *Conference on Research in Equitable and Sustained Participation in Engineering, Computing, and Technology (RESPECT)* (pp. 1-6). IEEE. https://doi.org/10.1109/RESPECT51740.2021.9620605

Karumbaiah, S., Ocumpaugh, J., & Baker, R. S. (2021). Context matters: Differing implications of motivation and help-seeking in educational technology. *International Journal of Artificial Intelligence in Education*, 32, 685-724. https://doi.org/10.1007/s40593-021-00272-0

Kizilcec, R. F., & Lee, H. (2022). Algorithmic fairness in education. In *The Ethics of Artificial Intelligence in Education* (pp. 174-202). Routledge.

Kizilcec, R. F., Mason, J., McCarthy, K. S., Rodrigo, M. M. T., & Rose, C. P. (2023). Using technology to foster equitable access and diverse learning communities. *Rapid Community Report Series*. Digital Promise and the International Society of the Learning Sciences. https://repository.isls.org//handle/1/8002

Koedinger, K. R., McLaughlin, E. A., & Heffernan, N. T. (2010). A quasi-experimental evaluation of an on-line formative assessment and tutoring system. *Journal of Educational Computing Research*, *43*(4), 489-510. https://doi.org/10.2190/EC.43.4.d

Krämer, S., & Zimmermann, F. (2022). Students with emotional and behavioral disorder and teachers' stereotypes–effects on teacher judgments. *The Journal of Experimental Education*, *91*(3), 450-471.

Krumm, A. E., Waddington, R. J., Teasley, S. D., & Lonn, S. (2014). A learning management system-based early warning system for academic advising in undergraduate engineering. *Learning analytics: From research to practice*, 103-119. https://doi.org/10.1007/978-1-4614-3305-7_6

Kulik, J. A., & Fletcher, J. D. (2016). Effectiveness of intelligent tutoring systems: a meta-analytic review. *Review of Educational Research*, *86*(1), 42-78. https://doi.org/10.3102/0034654315581420

Kumar, R., Ai, H., Beuth, J. L., & Rosé, C. P. (2010). Socially capable conversational tutors can be effective in collaborative learning situations. *Proceedings of the International Conference on Intelligent Tutoring Systems* (pp. 156-164). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-13388-6_20

Labov W. (1970). The logic of non-standard English. In Williams F. (Ed.), *Language and poverty*. Chicago, IL: Rand McNally. https://doi.org/10.1016/B978-0-12-754850-0.50014-3

Ladson-Billings, G. (1995). Toward a theory of culturally relevant pedagogy. *American Educational Research Journal*, *32*(3), 465-491. https://doi.org/10.3102/00028312032003465

Ladson-Billings, G. (2021). Critical race theory—What it is not!. In M. Lynn & A. D. Dixson (Eds.), *Handbook of critical race theory in education* (pp. 32-43). Routledge.

Langley, P., & Ohlsson, S. (1984). Automated cognitive modeling. In *Proceedings of the 4th AAAI Conference on Artificial Intelligence* (pp. 193-197).

Lee, C. (1994). African-centered pedagogy: Complexities and possibilities. In M. J. Shujaa (Ed.), *Too much schooling, too little education* (pp. 295-318). Trenton, NJ: Africa World Press.

Li, Y., Nwogu, J., Buddemeyer, A., Solyst, J., Lee, J., Walker, E., Ogan, A., & Stewart, A. E. (2023). "I Want to Be Unique From Other Robots": Positioning Girls as Co-creators of Social Robots in Culturally-Responsive Computing Education. *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (pp. 1-14). https://doi.org/10.1145/3544548.3581272

Li, Y., Zou, X., Ma, Z., Baker, R.S. (2022) A multi-pronged redesign to reduce gaming the system. *Proceedings of the 23rd International Conference on Artificial Intelligence in Education*, 334-337. https://doi.org/10.1007/978-3-031-11647-6_64

Liang, J., Hare, R., Chang, T., Xu, F., Tang, Y., Wang, F. Y., Peng, S. & Lei, M. (2022). Student modeling and analysis in adaptive instructional systems. *IEEE Access*, *10*, 59359-59372. https://doi.org/10.1109/ACCESS.2022.3178744

Lin, A. M. (2020). From deficit-based teaching to asset-based teaching in higher education in BANA countries: Cutting through 'either-or'binaries with a heteroglossic plurilingual lens. *Language, Culture & Curriculum*, *33*(2), 203-212. https://doi.org/10.1080/07908318.2020.1723927

Linnenbrink, E. A., & Pintrich, P. R. (2002). Achievement goal theory and affect: An asymmetrical bidirectional model. *Educational Psychologist*, *37*(2), Article 2. https://doi.org/10.1207/S15326985EP3702_2

Lipsky, D. K., & Gartner, A. (1989). Overcoming school failure: A vision for the future. *Proceedings of the Academy of Political Science*, 37(2), 149-158.

Listman, J., Rogers, K. D., & Hauser, P. C. (2011). Community cultural wealth and deaf adolescents' resilience. In *Resilience in deaf children: Adaptation through emerging adulthood* (pp. 279-297). New York, NY: Springer New York. https://doi.org/10.1007/978-1-4419-7796-0_11

Llopart, M., & Esteban-Guitart, M. (2018). Funds of knowledge in 21st century societies: Inclusive educational practices for under-represented students. A literature review. *Journal of Curriculum Studies*, 50(2), 145-161. https://doi.org/10.1080/00220272.2016.1247913

Lovett, M. C. (1998). Cognitive task analysis in service of intelligent tutoring system design: A case study in statistics. In *Intelligent Tutoring Systems: 4th International Conference* (pp. 234-243). Springer Berlin Heidelberg. https://doi.org/10.1007/3-540-68716-5_29

Lu, L. (2022). Exploring Singlish as a pedagogical resource in the ELT classroom: Implementing bidialectal pedagogy in Singapore. *TESOL Quarterly,* 57(2), 323-350. https://doi.org/10.1002/tesq.3148

Mandinach, E. B. (2022). Culturally responsive data literacy: An emerging and important construct. In *Companion Proceedings of the Web Conference 2022 (WWW '22)*. Association for Computing Machinery, 402. https://doi.org/10.1145/3487553.3527180

Mandinach, E. B., & Schildkamp, K. (2021). Misconceptions about data-based decision making in education: An exploration of the literature. *Studies in Educational Evaluation*, *69*, 100842. https://doi.org/10.1016/j.stueduc.2020.100842

Mansoor, H., & Harrison, L. (2018). Data visualization literacy and visualization biases: Cases for merging parallel threads. In Ellis, G. (eds) *Cognitive biases in visualizations*, 87-96. Springer, Cham. https://doi.org/10.1007/978-3-319-95831-6_7 Malouff, J. M., Stein, S. J., Bothma, L. N., Coulter, K., & Emmerton, A. J. (2014). Preventing halo bias in grading the work of university students. *Cogent Psychology*, *1*(1), 988937.

Maskiewicz, A. C., & Lineback, J. E. (2013). Misconceptions are "so yesterday!". *CBE—Life Sciences Education*, *12*(3), 352-356. https://doi.org/10.1187/cbe.13-01-0014

Mayfield, E., Madaio, M., Prabhumoye, S., Gerritsen, D., McLaughlin, B., Dixon-Román, E., & Black, A. W. (2019). Equity beyond bias in language technologies for education. In *Proceedings of the 14th Workshop on Innovative Use of NLP for Building Educational Applications* (pp. 444-460). http://dx.doi.org/10.18653/v1/W19-4446

McCarthy, K. S., Crossley, S. A., Meyers, K., Boser, U., Allen, L. K., Chaudhri, V. K., Collins-Thompson, K., D'Mello, S., De Choudhury, M., Garg, K., Goel, A., Gosha, K., Heffernan, N., Hooper, M. A., Hyman, E., Jarratt, D. C., Khalil, D., Kizilcec, R. F., Litman, D., Malatinszky, A., Marks, K., McNamara, D. S., Menko, R., Palermo, C., Porcaro, D., Roscoe, R. D., Shapiro, S., Thai, K. P., Trumbore, A. M., White, C., Wong, R., Yang, D., & Zampieri, M. (2022). Toward more effective and equitable learning: Identifying barriers and solutions for the future of online education. *Technology, Mind, & Behavior*, *3*(1), 1-15. https://doi.org/10.1037/tmb0000063

McLaren, B. M., Adams, D. M., Mayer, R. E., & Forlizzi, J. (2017). A computer-based game that promotes mathematics learning more than a conventional approach. *International Journal of Game-Based Learning*, *7*(1), 36-56. http://doi.org/10.4018/IJGBL.2017010103

McNamara, D. S., & Shapiro, A. M. (2005). Multimedia and hypermedia solutions for promoting metacognitive engagement, coherence, and learning. *Journal of Educational Computing Research*, *33*(1), 1-29. https://doi.org/10.2190/7N6R-PCJL-UMHK-RYPJ

Mejia, J. A., Arana, M., Roberto, M., & Reyes, N. (2020, June). ¿ Por qué no los dos? The importance of translanguaging in bridging language, literacy, and engineering. In *Proceedings of the 2020 American Society for Engineering Education (ASEE) Annual Conference*. https://doi.org/10.18260/1-2--33961

Mettler, E., Massey, C. M., & Kellman, P. J. (2011). Improving adaptive learning technology through the use of response times. In *Proceedings of the 33rd Cognitive Science Society Annual Meeting*, 2532-2537.

Miller, C. J., & Bernacki, M. L. (2019). Training preparatory mathematics students to be high ability self-regulators: Comparative and case-study analyses of impact on learning behavior and achievement. *High Ability Studies*, *30*(1-2), 167-197. https://doi.org/10.1080/13598139.2019.1568829

Mills, C., Gregg, J., Bixler, R., & D'Mello, S. K. (2020). Eye-Mind reader: an intelligent reading interface that promotes long-term comprehension by detecting and responding to mind wandering. *Human-Computer Interaction*, *36*(4), 306-332. https://doi.org/10.1080/07370024.2020.1716762

Mohatt, G. & Erikson, F. (1981). Cultural differences in teaching styles in an Odawa school: A sociolinguistic approach. In H. Trueba, P. Guthrie & K. Au, (Eds.), *Culture and the bilingual classroom: Studies in classroom ethnography*. Rowley, Massachusetts: Newbury House.

Mojarad, S., Baker, R. S., Essa, A., Stalzer, S. (2021) Replicating studying adaptive learning efficacy using propensity score matching and inverse probability of treatment weighting. *Journal of Interactive Learning Research*, *32* (3), 169-203.

Moll, L. C. (Ed.). (1992). *Vygotsky and education: Instructional implications and applications of sociohistorical psychology*. Cambridge University Press. https://doi.org/10.1017/CBO9781139173674.016

Moll, L. C., Amanti, C., Neff, D., & Gonzalez, N. (1992). Funds of knowledge for teaching: Using a qualitative approach to connect homes and classrooms. *Theory into Practice*, 31(2), 132–141. https://doi.org/10.1080/00405849209543534

Montañez, S. R. (2023). Advancing equity through research: The importance of asset-based approaches and methods. *Journal of Applied Developmental Psychology*, 86, 101540. https://doi.org/10.1016/j.appdev.2023.101540

Moore, G. R., & Shute, V. J. (2017). Improving learning through stealth assessment of conscientiousness. *Handbook on Digital Learning for K-12 Schools*, 355-368. https://doi.org/10.1007/978-3-319-33808-8_21

Moussavi, R., Gobert, J., & Sao Pedro, M. S. (2016). The effect of scaffolding on the immediate transfer of students' data interpretation skills within science topics. *Proceedings of the International Society of the Learning Sciences* (pp. 1002-1005). Singapore. https://doi.dx.org/10.22318/icls2016.157

Mudrick, N. V., Azevedo, R., & Taub, M. (2019). Integrating metacognitive judgments and eye movements using sequential pattern mining to understand processes underlying multimedia learning. *Computers in Human Behavior*, *96*, 223-234. https://doi.org/10.1016/j.chb.2018.06.028

Murrell, P. (1993). Afrocentric immersion: Academic and personal development of African American males in public schools. In T. Perry & J. Fraser (Eds.), *Freedom's plow: Teaching in the multicultural classroom* (pp. 231-259). New York: Routledge.

Nasiar, N., Baker, R. S., Zou, Y., Zhang, J., & Hutt, S. (2023, June). Modeling problem-solving strategy invention (PSSI) behavior in an online math environment. In *International Conference on Artificial Intelligence in Education* (pp. 453-459). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-36336-8_70

Nasiar, N., Zambrano, A.F., Ocumpaugh, J., Hutt, S., Goslen, A., Rowe, J., Lester, J., Henderson, N., Wiebe, E., Boyer, K., Mott., B. (2023). It's good to explore: Investigating silver pathways and the role of frustration during game-based learning. International Conference on Artificial Intelligence in Education.

Normadhi, N. B. A., Shuib, L., Nasir, H. N. M., Bimba, A., Idris, N., & Balakrishnan, V. (2019). Identification of personal traits in adaptive learning environment: Systematic literature review. *Computers & Education*, *130*, 168–190. https://doi.org/10.1016/j.compedu.2018.11.005

Nye, B. D. (2015). Intelligent tutoring systems by and for the developing world: A review of trends and approaches for educational technology in a global context. *International Journal of Artificial Intelligence in Education*, *25*, 177-203. https://doi.org/10.1007/s40593-014-0028-6

Ocumpaugh, J., Baker, R.S., Rodrigo, M.M.T. (2015) Baker Rodrigo Ocumpaugh monitoring protocol (BROMP) 2.0 technical and training manual. Technical Report. New York, NY: Teachers College, Columbia University. Manila, Philippines: Ateneo Laboratory for the Learning Sciences.

Ocumpaugh, J., Baker, R., Slater, S., San Pedro, M.O., Heffernan, N, Heffernan, C., Hawn, A. (2017) Guidance counselor reports of the Assistments college prediction model (ACPM). *Proceedings of the International Conference on Learning Analytics and Knowledge*, 479-488. https://doi.org/10.1145/3027385.3027435

O'Donnell, F., & Sireci, S. G. (2022). Language matters: teacher and parent perceptions of achievement labels from educational tests. *Educational Assessment*, *27*(1), 1-26.

Ogan, A., Yarzebinski, E., De Roock, R., Dumdumaya, C., Banawan, M., & Rodrigo, M. M. (2017). Proficiency and preference using local language with a teachable agent. In *Artificial Intelligence in Education: 18th International Conference, AIED 2017, Wuhan, China, June 28–July 1, 2017, Proceedings 18* (pp. 548-552). Springer International Publishing. https://doi.org/10.1007/978-3-319-61425-0_61

O'Shaughnessy, D. M., Cruz Cordero, T., Mollica, F., Boni, I., Jara-Ettinger, J., Gibson, E., & Piantadosi, S. T. (2023). Diverse mathematical knowledge among indigenous Amazonians. *Proceedings of the National Academy of Sciences*, *120*(35), e2215999120.

Panavas, L., Worth, A. E., Crnovrsanin, T., Sathyamurthi, T., Cordes, S., Borkin, M. A., & Dunne, C. (2022, April). Juvenile graphical perception: A comparison between children and adults. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (pp. 1-14). https://doi.org/10.1145/3491102.3501893

Pane, J. F., Griffin, B. A., McCaffrey, D. F., & Karam, R. (2014). Effectiveness of cognitive tutor algebra I at scale. *Educational Evaluation and Policy Analysis*, *36*(2), 127-144. https://doi.org/10.3102/0162373713507480

Paquette, L., & Baker, R. S. (2019). Comparing machine learning to knowledge engineering for student behavior modeling: a case study in gaming the system. *Interactive Learning Environments*, *27*(5-6), 585-597. https://doi.org/10.1080/10494820.2019.1610450

Paquette, L., Ocumpaugh, J., Li, Z., Andres, J.M.A.L., Baker, R.S. (2020) Who's learning? Using demographics in EDM research. *Journal of Educational Data Mining*, *12*(3), 1-30. https://doi.org/10.5281/zenodo.4143612

Pardos, Z.A., Baker, R.S., San Pedro, M.O.C.Z., Gowda, S.M., Gowda, S.M. (2014) Affective states and state tests: Investigating how affect and engagement during the school year predict end of year learning outcomes. *Journal of Learning Analytics*, *1*(1), 107-128. https://doi.org/10.18608/jla.2014.11.6

Paris, D. (2012). Culturally sustaining pedagogy: A needed change in stance, terminology, and practice. *Educational Researcher*, *41*(3), 93-97 https://doi.org/10.3102/0013189X12441244

Paris, D., & Alim, H. S. (2014). What are we seeking to sustain through culturally sustaining pedagogy? A loving critique forward. *Harvard educational review*, *84*(1), 85-100. https://doi.org/10.17763/haer.84.1.982l873k2ht16m77

Patchan, M. M., Schunn, C. D., & Correnti, R. J. (2016). The nature of feedback: How peer feedback features affect students' implementation rate and quality of revisions. *Journal of Educational Psychology*, *108*(8), 1098. https:// doi.org/10.1037/edu0000103

Patterson, C., York, E., Maxham, D., Molina, R., & Mabrey, P. (2023). Applying a responsible innovation framework in developing an equitable early alert system: A case study. *Journal of Learning Analytics*, *10*(1), 24-36. https://doi.org/10.18608/jla.2023.7795

Pedersen, H., Gard, D., Soukup, M., & Huston, M. (2021). The role of teachers who are Deaf/hard of hearing in the field of Deaf/hard of hearing education. *Review of Disability Studies: An International Journal*, *17*(3).

Penetito W., Hindle R., Hynds A., Savage C., Kus L. (2011). The impact of culturally responsive pedagogies on students and families. In Sleeter C. E. (Ed.), *Professional development for culturally responsive and relationship-based pedagogy*. New York, NY: Peter Lang. (pp. 139-162)

Pham, P., & Wang, J. (2015). AttentiveLearner: improving mobile MOOC learning via implicit heart rate tracking. In C. Conati, N. Heffernan, A. Mitrovic, & M. F. Verdejo (Eds.), *Artificial Intelligence in Education* (pp. 367–376). Springer. https://doi.org/10.1007/978-3-319-19773-9_37

Pham, P., & Wang, J. (2017). AttentiveLearner2: A multimodal approach for improving MOOC learning on mobile devices. *Proceedings of the International Conference on Artificial Intelligence in Education*, 561–564. https://doi.org/10.1007/978-3-319-61425-0_64

Piaget, J. (1926). *The language and thought of the child*. New York: Harcourt Brace Jovanovich.

Priniski, S. J., Rosenzweig, E. Q., Canning, E. A., Hecht, C. A., Tibbetts, Y., Hyde, J. S., & Harackiewicz, J. M. (2019). The benefits of combining value for the self and others in utility-value interventions. *Journal of Educational Psychology*, *111*(8), 1478. https:// doi.org/10.1037/edu0000343

Raza, A., Penuel, W. R., Allen, A. R., Sumner, T., & Jacobs, J. K. (2021). "Making it culturally relevant": A visual learning analytics system supporting teachers to reflect on classroom equity. In *Proceedings of the 15th International Conference of the Learning Sciences-ICLS*. International Society of the Learning Sciences, 442-449. https://doi.dx.org/10.22318/icls2021.442

Reeve, J. (2013). How students create motivationally supportive learning environments for themselves: The concept of agentic engagement. *Journal of Educational Psychology*, *105*(3), 579. https://doi.org/10.1037/a0032690

Reynolds, S., & Johnson, J. (2014). Pillars of support: A functional asset-based framework for ABE learners. *Journal of Research & Practice for Adult Literacy, Secondary & Basic Education, 3*(3), 36-49.

Riazy, S., Simbeck, K., & Schreck, V. (2021). Systematic literature review of fairness in learning analytics and application of insights in a case study. In *Computer Supported Education: 12th International Conference*, CSEDU 2020, Virtual Event, May 2–4, 2020, Revised Selected Papers 12 (pp. 430-449). Springer International Publishing. https://doi.org/10.1007/978-3-030-86439-2_22

Rickford, J. R., Sweetland, J., & Rickford, A. E. (2004). African American English and other vernaculars in education: A topic-coded bibliography. *Journal of English Linguistics*, *32*(3), 230–320. https://doi.org/10.1177/0075424204268226

Rioux, J., & Ewing, B. (2022). Contextualising Aboriginal faunal stories with the Linnaean taxonomy: Culturally responsive pedagogy in zoology. *Australian Journal of Indigenous Education (Online), 51*(1), 1-16. https://www.doi.org/10.55146/ajie.2022.7

Ritter, S., Yudelson, M., Fancsali, S. E., & Berman, S. R. (2016). How mastery learning works at scale. *Proceedings of the 3rd (2016) ACM Conference on Learning@ Scale* (pp. 71-79). https://doi.org/10.1145/2876034.2876039

Rocha, J., Castillo-Lavergne, C. M., & Yancy, C. W. (2022). Affirming and nurturing students' cultural wealth to enhance self-efficacy: Examination of urban high school students' lived experiences in a STEM-Medicine pipeline program. *Urban Education, 0*(0). https://doi.org/10.1177/00420859211073

Rodrigo, M. M. T. (2023). Is the AIED conundrum a first-world problem?. *International Journal of Artificial Intelligence in Education*, 1-7. https://doi.org/10.1007/s40593-023-00345-2

Rodriguez, A. J. (1998). Busting open the meritocracy myth: Rethinking equity and student achievement in science education. *Journal of Women and Minorities in Science and Engineering*, *4*(2&3). http://doi.org/10.1615/JWomenMinorScienEng.v4.i2-3.80

Rodriguez, J. L., Jones, E. B., Pang, V. O., & Park, C. D. (2004). Promoting academic achievement and identity development among diverse high school students. *The High School Journal*, *87*(3), 44-53. https://doi.org/10.1353/hsj.2004.0002

Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. *International Journal of Artificial Intelligence in Education*, *26*(2), 582-599. https://doi.org/10.1007/s40593-016-0110-3

Roll, I., Aleven, V., McLaren, B. M., & Koedinger, K. R. (2011). Improving students' help-seeking skills using metacognitive feedback in an intelligent tutoring system. *Learning & Instruction*, *21*(2), 267-280. https://doi.org/10.1016/j.learninstruc.2010.07.004

Roschelle, J., Cheng, B. H., Hodkowski, N., Neisler, J., & Haldar, L. (2020). Evaluation of an Online Tutoring Program in Elementary Mathematics. *Digital Promise*. https://doi.org/10.51388/20.500.12265/94

Roscoe, R. D. (2022). Please join me/us/them on my/our/their journey to justice in STEM. *Discourse Processes, 59*(5-6), 345-360. https://doi.org/10.1080/0163853X.2022.2050084

Roscoe, R. D. (2023). Building inclusive and equitable artificial intelligence for education. *XRDS: Crossroads, The ACM Magazine for Students, 29*(3), 22-25. https://doi.org/10.1145/3589637

Roscoe, R. D., & Craig, S. D. (2022). A heuristic assessment framework for the design of self-regulated learning technologies. *Journal of Formative Design in Learning*, *6*, 77-94. https://doi.org/10.1007/s41686-022-00070-4

Roscoe, R. D., Salehi, S., Nixon, N., Worsley, M., Piech, C., & Luckin, R. (2022). Inclusion and equity as a paradigm shift for artificial intelligence in education. In F. Ouyang, P. Jiao, B. M. McLaren, & A. H. Alavi (Eds.), *Artificial intelligence in STEM education: The paradigmatic shifts in research, education, and technology* (pp. 359-373). Boca Raton, FL: CRC Press. https://doi.org/10.1201/9781003181187

Roscoe, R. D., Segedy, J. R., Sulcer, B., Jeong, H., & Biswas, G. (2013). Shallow strategy development in a teachable agent environment designed to support self-regulated learning. *Computers & Education*, *62*, 286-297. https://doi.org/10.1016/j.compedu.2012.11.008

Rowe, E., Almeda, M. V., Asbell-Clarke, J., Scruggs, R., Baker, R., Bardar, E., & Gasca, S. (2021). Assessing implicit computational thinking in Zoombinis puzzle gameplay. *Computers in Human Behavior*, *120*. https://doi.org/10.1016/j.chb.2021.106707

Rychly, L., & Graves, E. (2012). Teacher characteristics for culturally responsive pedagogy. *Multicultural Perspectives*, *14*(1), 44-49. https://doi.org/10.1080/15210960.2012.646853

Sa'd, S. H. T., & Eames, O. Q. (2021). A classroom survey of language teachers' discriminatory practices against students: causes, consequences and keys. *Center for Educational Policy Studies Journal*, *11*(1), 91-114. https://doi.org/10.26529/cepsj.541

Sablan, J. R. (2019). Can you really measure that? Combining critical race theory and quantitative methods. *American Educational Research Journal*, *56*(1), 178-203. https://doi.org/10.3102/0002831218798325

Sabnis, S., Yu, R., & Kizilcec, R. F. (2022). Large-scale student data reveal sociodemographic gaps in procrastination behavior. In *Proceedings of the 9th ACM Conference on Learning@ Scale* (pp. 133-141). https://doi.org/10.1145/3491140.3528285

Sales, A. C., & Pane, J. F. (2019). The role of mastery learning in an intelligent tutoring system: Principal stratification on a latent variable. *The Annals of Applied Statistics*, *13*(1), 420-443. https://doi.org/10.1214/18-AOAS1196

Sanrey, C., Bressoux, P., Lima, L., & Pansu, P. (2021). A new method for studying the halo effect in teachers' judgement and its antecedents: Bringing out the role of certainty. *British journal of educational psychology*, *91*(2), 658-675.

Sarra, G., & Ewing, B. (2014). Indigenous students transitioning to school: responses to pre-foundational mathematics. *SpringerPlus, 3*, 1-9. https://doi.org/10.1186/2193-1801-3-685

Savage C., Hindle R., Meyer L. H., Hynds A., Penetito W., Sleeter C. E. (2011). Culturally responsive pedagogies in the classroom: Indigenous student experiences across the curriculum. *Asia-Pacific Journal of Teacher Education*, 39, 183-198.

Saxe, G. B. (1988). Candy selling and math learning. *Educational researcher*, *17*(6), 14-21.

Schleppegrell, M. J. (2004). *The language of schooling: A functional linguistics perspective*. Routledge. https://doi.org/10.4324/9781410610317

Schooler, J. W., Smallwood, J., Christoff, K., Handy, T. C., Reichle, E. D., & Sayette, M. A. (2011). Meta-awareness, perceptual decoupling and the wandering mind. *Trends in Cognitive Sciences*, *15*(7), 319–326. https://doi.org/10.1016/j.tics.2011.05.006

Selwyn, N. (2020). Re-imagining 'Learning Analytics'… a case for starting again?. *The Internet and Higher Education*, *46*, 100745.

Shapiro, S., & MacDonald, M. (2017). From deficit to asset: Locating discursive resistance in a refugee-background student's written and oral narrative. *Journal of Language, Identity & Education, 16*(2), 80–93. https://doi.org/10.1080/15348458.2016.1277725

Shermis, M. D., & Hamner, B. (2013). Contrasting state-of-the-art automated scoring of essays. In *Handbook of automated essay evaluation* (pp. 335-368). Routledge.

Shute, V. J., & Rahimi, S. (2021). Stealth assessment of creativity in a physics video game. Computers in Human Behavior, 116, 1-13. https://doi.org/10.1016/j.chb.2020.106647

Sibbett, L. (2020). Intersectionality in US educational research. *Oxford Research Encyclopedia of Education*, 1-42. https://doi.org/10.1093/acrefore/9780190264093.013.403

Sinatra, G. M., Heddy, B. C., & Lombardi, D. (2015). The challenges of defining and measuring student engagement in science. *Educational Psychologist*, *50*(1). https://doi.org/10.1080/00461520.2014.1002924

Skalicky, S., Crossley, S. A., McNamara, D. S., & Muldner, K. (2017). Identifying creativity during problem solving using linguistic features. *Creativity Research Journal*, *29*(4), 343-353. https://doi.org/10.1080/10400419.2017.1376490

Smallwood, J., & Schooler, J. W. (2015). The science of mind wandering: Empirically navigating the stream of consciousness. *Annual Review of Psychology*, *66*, 487–518. https://doi.org/10.1146/annurev-psych-010814-015331

Smit, R. (2012). Towards a clearer understanding of student disadvantage in higher education: Problematising deficit thinking. *Higher Education Research & Development*, *31*(3), 369-380. https://doi.org/10.1080/07294360.2011.634383

Solano-Flores, G. and Li, M. (2006). The use of generalizability (G) theory in the testing of linguistic minorities. *Educational Measurement: Issues and Practice, 25*(1), 13-22. https://doi.org/10.1111/j.1745-3992.2006.00048.x

Spiro, R. J., Bruce, B. C., & Brewer, W. F. (Eds.). (2017). *Theoretical issues in reading comprehension: Perspectives from cognitive psychology, linguistics, artificial intelligence and education* (Vol. 11). Routledge.

Spycher, P., Girard, V., & Moua, B. (2020). Culturally sustaining disciplinary language and literacy instruction for Hmong-American children. *Theory into Practice, 59*(1), 89-98. https://doi.org/10.1080/00405841.2019.1665410

Steiner, C. M., Kickmeier-Rust, M. D., & Albert, D. (2015). Making sense of game-based user data: Learning analytics in applied games. In *IADIS International Conference e-Learning 2015* (pp. 195-198). IADIS Press.

Swisher, K. (1990). Cooperative learning and the education of American Indian/Alaskan Native students: A review of the literature and suggestions for implementation. *Journal of American Indian Education*, 29(2), 36-43.

Ting, C. Y., & Chong, Y. K. (2006). Conceptual change modeling using dynamic Bayesian network. *Proceedings of Intelligent Tutoring Systems: 8th International Conference*, ITS 2006, Jhongli, Taiwan, June 26-30, 2006. (pp. 95-103). Springer Berlin Heidelberg. https://doi.org/10.1007/11774303_10

Truong, J. M., Barnes, M. E., & Brownell, S. E. (2018). Can six minutes of culturally competent evolution education reduce students' level of perceived conflict between evolution and religion?. *The American Biology Teacher*, *80*(2), 106-115. https://doi.org/10.1525/abt.2018.80.2.106

Uttamchandani, S., & Quick, J. (2022). An introduction to fairness, absence of bias, and equity in learning analytics. *Handbook of Learning Analytics*, 205-212

Valencia Mazzanti, C., & Karsli-Calamak, E. (2022). "Kind of interrupting": Teachers of young children understanding mathematics learning and linguistic diversity. *International Journal of Qualitative Studies in Education, 35*(2), 210-227. https://doi.org/10.1080/09518398.2020.1829740

VanLehn, K. (1988). Student modeling. *Foundations of intelligent tutoring systems*, *55*, 78.

VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist*, *46*(4), 197-221. https://doi.org/10.1080/00461520.2011.611369

Vatrapu, R. (2011). Cultural considerations in learning analytics. In *Proceedings of the 1st International Conference on Learning Analytics and Knowledge* (pp. 127-133). https://doi.org/10.1145/2090116.2090136

Ventura, M., & Shute, V. (2013). The validity of a game-based assessment of persistence. *Computers in Human Behavior*, *29*(6), 2568-2572. https://doi.org/10.1016/j.chb.2013.06.033

Verdín, D., Smith, J. M., & Lucena, J. (2021). Funds of knowledge as pre-college experiences that promote minoritized students' interest, self-efficacy beliefs, and choice of majoring in engineering. *Journal of Pre-College Engineering Education Research* (J-PEER), *11*(1). https://doi.org/10.7771/2157-9288.1281

Viberg, O., Jivet, I., & Scheffel, M. (2023). Designing culturally aware learning analytics: A value sensitive perspective. In *Practicable Learning Analytics* (pp. 177-192). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-27646-0_10

Von Esch, K. S., Motha, S., & Kubota, R. (2020). Race and language teaching. *Language Teaching, 53*(4), 391-421. https://doi.org/10.1017/S0261444820000269

Waitoller, F. R., & King Thorius, K. A. (2016). Cross-pollinating culturally sustaining pedagogy and universal design for learning: Toward an inclusive pedagogy that accounts for dis/ability. *Harvard Educational Review*, *86*(3), 366-389. https://doi.org/10.17763/1943-5045-86.3.366

Walker, M. E., Olivera-Aguilar, M., Lehman, B., Laitusis, C., Guzman-Orth, D., & Gholson, M. (2023). Culturally Responsive Assessment: Provisional Principles. *ETS Research Report Series*.

Walkington, C., & Bernacki, M. L. (2014). Motivating students by "personalizing" learning around individual interests: A consideration of theory, design, and implementation issues. *Motivational Interventions, 18*, 139-176. https://doi.org/10.1108/S0749-742320140000018004

Walkington, C., & Bernacki, M. L. (2019). Personalizing algebra to students' individual interests in an intelligent tutoring system: Moderators of impact. *International Journal of Artificial Intelligence in Education*, *29*, 58-88. https://doi.org/10.1007/s40593-018-0168-1

Wang, K. D., Cock, J. M., Käser, T., & Bumbacher, E. (2023). A systematic review of empirical studies using log data from open-ended learning environments to measure science and engineering practices. *British Journal of Educational Technology*, *54*(1), 192-221. https://doi.org/10.1111/bjet.13289

Warschauer, M. (2012). The digital divide and social inclusion. *Americas Quarterly*, *6*(2), 131-135.

Watahomigie L. J., McCarty T. (1994). Bilingual/bicultural education at Peach Springs: A Hualapai way of schooling. *Peabody Journal of Education*, 69, 26-42.

Wheeler, R. (2016). "So much research, so little change": Teaching standard English in African American classrooms. *Annual Review of Linguistics*, *2*, 367-390. https://doi.org/10.1146/annurev-linguistics-011415-040434

Winne, P. H. (2017). Cognition and metacognition within self-regulated learning. In *Handbook of self-regulation of learning and performance* (pp. 36-48). Routledge. https://doi.org/10.4324/9781315697048-3

Winne, P. H. (2021a). Cognition, metacognition, and self-regulated learning. In *Oxford Research Encyclopedia of Education*. https://doi.org/10.1093/acrefore/9780190264093.013.1528

Winne, P. H. (2021b). Open learner models working in symbiosis with self-regulating learners: A research agenda. *International Journal of Artificial Intelligence in Education, 31*(3), 446-459.

Wise, A. F., Knight, S., & Ochoa, X. (2021). What makes learning analytics research matter. *Journal of Learning Analytics*, *8*(3), 1-9. https://doi.org/10.18608/jla.2021.7647

Wise, A. F., Sarmiento, J. P., & Boothe Jr, M. (2021, April). Subversive learning analytics. In *LAK21: 11th international learning analytics and knowledge conference* (pp. 639-645).

Wolfram, W. (1999). "Dialect awareness programs in the school and community." *Language Alive in the Classroom, 8*(3), 47-66.

Wolfram, W., Adger, C. T., & Christian, D. (1999). *Dialects in schools and communities*. Routledge. https://doi.org/10.4324/9781410601148

Xia, M., Asano, Y., Williams, J. J., Qu, H., & Ma, X. (2020). Using information visualization to promote students' reflection on" gaming the system" in online learning. *Proceedings of the Seventh ACM Conference on Learning@ Scale* (pp. 37-49). https://doi.org/10.1145/3386527.3405924

Xu, W., & Ouyang, F. (2022). The application of AI technologies in STEM education: A systematic review from 2011 to 2021. *International Journal of STEM Education*, *9*(1), 1-20. https://doi.org/10.1186/s40594-022-00377-5

Yang, J., & Zhang, B. (2019). Artificial intelligence in intelligent tutoring robots: A systematic review and design guidelines. *Applied Sciences*, 9(10), 2078. https://doi.org/10.3390/app9102078

Young, J. L., Young, J. R., & Capraro, R. M. (2018). Gazing past the gaps: A growth-based assessment of the mathematics achievement of Black girls. *The Urban Review*, *50*(1), 156-176. https://doi.org/10.1007/s11256-017-0434-9

Zambrano, A.F., Barany, A., Ocumpaugh, J., Nasiar, N., Hutt, S., Goslen, A., Rowe, J., Lester, J., Wiebe, E., Mott, B. (2023). Cracking the code of learning gains: Using Ordered Network Analysis to Understand the Influence of Prior Knowledge. In International Conference on Quantitative Ethnography.

Zhang, J. (1991). Integration of abductive and deductive inference diagnosis model and its application in intelligent tutoring system. Doctoral Dissertation, Old Dominion University.

Zhang, J., Andres, J.M.A.L., Hutt, S., Baker, R.S., Ocumpaugh, J., Nasiar, N., Mills, C., Brooks, J., Sethuraman, S., Young, T. (2022) Using machine learning to detect SMART model cognitive operations in mathematical problem-solving process. *Journal of Educational Data Mining*, *14* (3), 76-108. https://doi.org/10.5281/zenodo.7304763

Declarations

Work on this paper was sponsored in part by research grants from AERDF/EF+Math grant “Making learning visible: scalable, multisystem detection of self-regulation related to EF”; Gates Foundation #INV-006123, and the University of Southern California’s *James H Zumberge Faculty Research & Innovation Fund*. The authors have no financial or non-financial conflicts of interest to disclose.