26

ASSET-BASED PERSONALIZED LEARNING

Jaclyn Ocumpaugh, Rod D. Roscoe, Ryan S. Baker, Stephen Hutt, and Stephen J. Aguilar

Introduction

Focusing on students' strengths can sometimes feel counterintuitive in education, where the common goals of "remediating" or "adding" to students' existing knowledge or skills often implicitly categorizes every student as deficient in some way. Theoretical frameworks for constructing and co-constructing knowledge often emphasize the need for identifying student strengths (Freire, 1970; Friere & Macedo, 1995; Moll et al., 1992; Sobel, 2004); yet, the designs of adaptive systems have often not facilitated these efforts even in the face of increasing calls for personalization (Ocumpaugh et al., 2024).

In our recent work on designing asset-based intelligent educational technologies, we have argued that assets can take many forms. Indeed, the research literature on asset-based approaches – typically situated outside of the communities studying adaptive systems – often stresses students' cultural knowledge and lived experience. Both of these expansive topics are difficult to fully describe via rich ethnographic methods, let alone with the kinds of data (i.e., quantitative and decontextualized) that have been historically available through educational technologies.

Nonetheless, considerations of students' experiences, prior knowledge, and existing skills relevant to their learning situations have influenced previous work in adaptive systems. Examples of these efforts include systems that improved the representativeness of non-player characters or pedagogical agents who interact with the students (Finkelstein et al., 2013b; Metcalf et al., 2023). Similarly, other systems have leveraged concrete knowledge from students' home or family life to create culturally relevant learning opportunities. For instance, Worsley and Bar-El (2022) used culturally important textile skills to make computing processes easier to understand. As the field has worked to increase the personalization of adaptive systems, calls for better understanding culture have become more common (Baker et al., 2019), and the field is poised for a paradigm shift toward more inclusive technology (Roscoe et al., 2022) that can better recognize a larger range of student assets.

As the work in this handbook has shown, personalization is also an expansive topic. And, in parallel with other educational research strands, personalization also sometimes adopts a "find and fix" mentality. However, a diverse body of scholarship demonstrates that student achievement is stronger and more enduring when students' existing strengths, cultures, and resources are embraced in ways that support opportunities for growth (e.g., Flint & Jaggers, 2021;

DOI: 10.4324/9781032719467-33

BK-TandF-BERNACKI_9781032719481-250571-Chp26.indd 437 9/16/25 12:01 PM

Montañez, 2023; Verdín, 2021; Wolfram et al., 1999). In this chapter, we explore how the frameworks of our handbook coauthors – including the extensible model proposed in Chapter 3 – might empower further understanding or application of the asset-based principles we recently proposed (Ocumpaugh et al., 2024). Specifically, we will adopt a reciprocal approach that (a) uses the work of our coauthors to reflect on the underlying assumptions implicit in these principles and (b) uses our asset-based principles to examine further opportunities for personalization across settings.

Asset-Based Approaches to Teaching and Learning

Asset-based paradigms have a long history in education research. Those who advocate such approaches advise educators to emphasize the knowledge, capabilities, resources, interests, and experiences that students *already* have, which can stem from diverse formal educational experiences, community and cultural experiences, or family and personal life (Esteban-Guitart et al., 2014; Moll, 1992; Verdín, 2021). Within these approaches, educators are encouraged to explicitly connect new material to the student's funds of knowledge (FOK; Esteban-Guitart & Moll, 2014). Although their nomenclature varies, theories of culturally relevant pedagogy (Ladson-Billings, 1995), culturally responsive pedagogy (Rychly & Graves, 2012), and culturally sustaining pedagogy (Paris, 2012) all highlight the importance of learners' strengths and agency (for more details, see Pruitt-Britton, this volume).

Importantly, asset-based approaches do not ignore that students need or benefit from gaining new knowledge, building new skills, or overcoming misconceptions. Instead, asset-based approaches often acknowledge the systemic differences that sometimes limit opportunities for students from historically marginalized groups: "deficits" reside in the systems rather than the students. This mindset recognizes that many "opportunity gaps" result from mismatches between the lived experiences of students compared to the designers and architects of educational systems (e.g., Gutiérrez, 2008; Rodriguez, 1998). Asset-based teaching and learning also highlight the strength and resilience of students who have persisted or even thrived under such conditions (Gorski, 2017).

A key premise of this chapter is that asset-based approaches are well aligned to personalized learning. Specifically, these approaches suggest that we connect to existing student schemas (e.g., Saxe, 1988) and reference their linguistic, cultural, and place-based knowledge to bridge to new material. As discussed in Ocumpaugh et al. (2024), there is now a substantial body of research demonstrating the effectiveness of this approach across wide-ranging learning domains and student demographics (e.g., Adger et al., 2014; Byrd et al., 2023; Civil et al., 2019; Edmonds-Wathen et al., 2019; Finkelstein et al., 2013a, 2013b; Rioux & Ewing, 2022; Shapiro & MacDonald, 2017; Spycher et al., 2020; Wolfram et al., 1999).

These approaches discourage teachers (and developers of online learning systems) from assuming that everyone in a given demographic category has identical needs, goals, or preferences (Ladson-Billings, 2021; Paris & Alim, 2014). In fact, authors of a substantial body of research argue that we should be doing more to identify meaningful differences among our students (Carpenter Ford, 2013; Charity-Hudley & Mallinson, 2011; Wheeler, 2016). Drawing upon localized, community knowledge can facilitate new ways of engaging with the material that bridge the disconnects that sometimes occur between abstract knowledge (e.g., math) and students' everyday lives. Moreover, these frameworks are established to mitigate stereotyped thinking about "deficient" populations (Boser et al., 2014; Dedeoglu & Lamme, 2011; Ferguson, 2003; Guskey, 1982; Howard, 2003), which can lead to unfairly low expectations from teachers (Sharma, 2018) or worse (Walkey et al., 2013).

BK-TandF-BERNACKI_9781032719481-250571-Chp26.indd 438 9/16/25 12:01 PM

However, asset-based approaches suggest that we should *extend* and *expand* supports for learning rather than eliminating effective uses of corrective feedback (Davis & Museus, 2019; Stewart et al., 2024). Instead, asset-based approaches emphasize how diverse strengths, skills, and resources can be used to facilitate learning. These efforts are compatible with many learning environments that incorporate artificial intelligence in education (i.e., AIED) tools that have already been developed, where identifying prior knowledge has been a long-term effort (e.g., Allen et al., 2015; Corlatescu et al., 2024; Cosyn et al., 2021; Kim & McCarthy, 2021; McCarthy & McNamara, 2022; Shute, 2011), along with efforts to detect different types of problem-solving strategies (Aleven et al., 2016). Importantly, student assets may be more intangible than prior knowledge. For example, students who appear unmotivated to learn a given topic for their own purposes might nonetheless value how that knowledge could benefit others. Leveraging these pro-social values and agency can be an important method for drawing upon students' strengths (see Asher & Harackiewicz, this volume). Many of the best-performing teachers are particularly adept at understanding and leveraging how students' knowledge and skills intersect with their values and other resources. However, these can be challenging pedagogical skills for some teachers to develop, and developing learning systems that can detect and act upon the myriad ways in which such intangible assets may emerge is not trivial either. That said, there has already been considerable study of how to detect many such assets in online learning systems. Contemporary systems have been developed to identify and leverage students' strategies for self-regulated learning (Zhang et al., 2022), inquiry (Wang et al., 2023), and invention (Chase et al., 2019) – all of which serve as existing assets that can be leveraged to develop further assets. Finally, intelligent educational systems have also been created to personalize content based on learners' own interests and goals (Walkington & Bernacki, 2019; Walkington et al., this volume). In addition to highlighting the foundations for asset-based approaches that are already evident in AIED work, which should underscore the feasibility of implementing Ocumpaugh et al.'s (2024) asset-based principles, we seek to emphasize the compatibility of these principles with personalized learning. Specifically, we argue in this chapter that building on students' strengths is critical to addressing the opportunity gaps (Gorski, 2017), as that is what effective learning design has always done (Ladson-Billings, 1995).

Asset-Based Principles for the Design of Intelligent Educational Technology

Our principles for asset-based AIED weave together scholarship from several areas of study, and are guided by the goal of enriching the assessment used in AIED. Typically, AIED systems have adopted "expert model" approaches where student knowledge and progress are measured as a divergence or "subtraction" from a single, idealized model of performance (Arslan & Tenison, this volume; Woolf, 2010). Such designs can be highly amenable to personalization methods (e.g., providing personalized content to help students achieve mastery) but are often not used in asset-based ways. As some of this handbook's other chapters have noted, efforts to individualize students can create deficit labels that become difficult for students to overcome (Emery et al., this volume).

In our prior work (Ocumpaugh et al., 2024), we proposed five principles for asset-based AIED design:

Principle 1: Conceptualize and define learner assets expansively.
Principle 2: Detect assets that students possess or can access.
Principle 3: Leverage existing learner assets using system features and functions.

BK-TandF-BERNACKI_9781032719481-250571-Chp26.indd 439 9/16/25 12:01 PM

Principle 4: Develop new assets using system features and functions.
Principle 5: Make assets visible and appreciated for all stakeholders.

In reviewing the work presented in this handbook, we see strong compatibility with many of these principles, along with potential for strengthening and deepening our understanding of the best ways to facilitate asset-based approaches to learning.

In accord with Principle 1 (i.e., Conceptualize and define learner assets expansively), we observed that our coauthors have emphasized the importance of *prior knowledge* (Arslan & Tenison, Chapter 6; Fancsali & Ritter, Chapter 15; McCarthy, Chapter 16) and a wide range of learner characteristics (Bernacki & Walkington, Chapter 3 ; Plass & Froehlich, Chapter 1), such as the places that learners perceive as home (Schocker & Aumen, Chapter 17). Noted learner characteristics also encompassed *sociocultural variables* (e.g., Daltry et al., Chapter 6; Ober et al., Chapter 24; Pruitt-Britton, Chapter 11; Schocker & Aumen, Chapter 17), *identity* (Cross Francis et al., Chapter 21), *lived experiences* (Ober et al., Chapter 24), *relationships* (Cross Francis et al., Chapter 21; Ober et al., Chapter 24), and *contexts* (e.g., Daltry et al., Chapter 25). Scholars and handbook chapter authors also emphasized how student *engagement*, *cognition*, *emotion*, *motivation*, and *interest* can all serve as assets to be leveraged for learning (e.g., Daltry et al., Chapter 25). They also highlighted the importance of *autonomy* (Zong & Patall, Chapter 9), while arguing that students' choices must be meaningful to students (e.g., Schocker & Aumen, Chapter 17). Notably, discussions of students' *cultural values* – and particularly cultures that value relationships (Hamilton & Tanchuk, Chapter 22) – raised important questions about how adaptive systems might best meet the needs of diverse learners.

Identifying assets remains an important goal. A large body of research outside of the AIED community has sought to measure sociocultural factors that influence student engagement, and it is worth thinking about what these might include and how they might influence students' interactions with the school system. For example, students in the United States from a non-English speaking background may be entitled to a large number of supports when attending a traditional, monolingual school (see Haas & Gort, 2009). However, in large part, the supports intended to compensate for the monolingual setting are designed to help learners adapt to their new environment – as opposed to embracing or supporting their existing language(s) or culture(s) (Schultz, 2016). In addition to language differences, we may also observe cultural differences surrounding interest in particular topics, beliefs about right and wrong, expectations about students' roles in the classroom and external world, and exposure to different kinds of media, people, and opportunities. To the extent that we wish to improve students' relationships with learning and their schools, it will be important to measure these factors. Survey measures of student belonging (Duran et al., 2020) and community cultural wealth (Sablan, 2019) are one approach, but researchers should also consider new ways of assessing these characteristics and outcomes such as interactive scenarios supported by generative AI (e.g., student use of AI to personalize math stories; Walkington et al., Chapter 7).

Several chapter authors argue that the humanity of our students is greater than the sum of their parts (e.g., Emery et al., Chapter 10). This perspective is perhaps best articulated by Hamilton & Tanchuk (Chapter 22), which criticizes atomistic approaches to educational goals and measurement as well as the assumption that full, individualistic autonomy is a universal value. Concerns about approaches that fragment learners into specific characteristics are echoed by Emery et al. (Chapter 10); they discuss individualized education programs, which provide important educational services but also explicitly label student deficits in ways that can persist their whole lives. Likewise, Zong and Patall (Chapter 9) emphasize that asking some students to make choices without recommendations from trusted community members (e.g., family,

BK-TandF-BERNACKI_9781032719481-250571-Chp26.indd 440 9/16/25 12:01 PM

friends, teachers, and mentors whom learners have close positive relationships with) may undermine necessary feelings of relatedness. These unintended negative outcomes may be stronger for learners from cultures that emphasize more interdependent and collectivistic values. It is important to critically examine such concerns as assets are being identified, as even well intentioned designs may have unintended negative consequences.

In Principle 2 (Detect assets that students possess or can access), we argue that simply acknowledging that assets exist is insufficient. Our learning systems must also *detect* or assess those assets. McCarthy (Chapter 16) suggests that this task might be accomplished via measures that enable prediction of knowledge and reading skills. iSTART already partially performs this task; the system detects when students may be connecting to prior knowledge, but it does not yet know how to detect what that knowledge is. Ober and et al. (Chapter 24) remind us that many teachers also struggle to understand students' prior knowledge. We also believe that researchers working in this space should also carefully consider the social model of disability that is highlighted as an often-implicit lens during instructional design (Emery et al., Chapter 10). As we consider reinventing learning spaces, designing these spaces to detect neurodivergent assets could significantly help provide equitable learning opportunities to more students.

Although many of the behavioral "detectors" in AIED systems are deficit-based (e.g., tracking off-task behaviors, gaming the system, mind-wandering, and abuse of help and hint tools), the community has also produced many asset-based detectors. For example, scholars have sought to identify constructs such as *conscientiousness* and *productive persistence* (Kai et al., 2018; Moore & Shute, 2017; Ventura & Shute, 2013, Baker et al., 2024) and *creativity* (Shute & Rahimi, 2021; Skalicky et al., 2017) that enable us to describe our learners more completely and positively. Related efforts are underway in the learner modeling research (e.g., Winne, 2021), which includes efforts to model cognitive constructs like *working memory* (Chang et al., 2013; Cojean & Martin, 2022) and *response time* (Mettler et al., 2011). Moreover, we should consider the degree to which certain detectors that seem deficit-based could be reframed to better reflect students' assets. For example, detectors of help avoidance (Aleven et al., 2006; Baker et al., 2013) may reflect a strong sense of autonomy or self-efficacy that is desirable to maintain. When warranted, reframing these instances as "productive failure" or "ambition" could help us to better understand these behaviors.

In Principle 3 (Leverage existing learner assets using system features and functions), we argue that learning systems should leverage existing learner assets using system features and functions. McCarthy et al. (Chapter 16) suggests that process-related data collected in online systems could be used for these purposes (Ocumpaugh et al., 2024). Likewise, Zong and Patall (Chapter 9) discuss self-determination theory and operationalize the effort to leverage students' strengths by providing students with choices tailored to their existing strengths. Ober et al. (Chapter 24) build on these ideas of agency and choice and suggest that designers and teachers can leverage collaboration while providing opportunities for shared power and respect. Meanwhile, Schocker and Aumen (Chapter 17) remind us that teacher involvement and self-reflection are critical to culturally sustaining pedagogy. Working outside of a framework for designing online learning, the authors of this chapter emphasize students' need to connect to the learning environment most relevant to them – their own communities – an important goal that could become more feasible as our technologies continue to improve.

Although we are unaware of personalization in intelligent learning systems that allows for local, place-based connections to individual students, there are an expanding number of efforts to leverage existing learner assets. For example, efforts have been underway to broaden the pedagogical approaches used to teach, with an increasing number of learning games that may provide new, richer contexts for learning. These include games with diverse non-player

BK-TandF-BERNACKI_9781032719481-250571-Chp26.indd 441 9/16/25 12:01 PM

characters (Cole, 2018; Finkelstein et al., 2013b; Metcalf et al., 2023) and diverse geographic locations and settings (Ballagas et al., 2008; Ćosović & Brkić, 2019; Holden & Sykes, 2011; Huizenga et al., 2009; Wang, 2021), for topics across a range of learning domains.

Moreover, researchers continue to work with an aim to recognize a wider range of student problem-solving approaches within both educational games and intelligent tutoring systems. For example, Gobert et al. (2013) have developed methods and models for detecting when students grasp the ideas of experimentation but may be employing strategies that differ from classical "expert" methods. Holmes and colleagues (2014) have similarly crafted models of a range of invention strategies, and Nasiar and colleagues (2023) have developed an approach to identify when students create a novel strategy. Crossley et al. (2014) modeled different approaches to successful writing. Meanwhile, other researchers have explored how diverse paths through an open-ended science game can be associated with 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 – seems likely to enrich the AIED toolkit.

Although existing student assets should be embraced and celebrated, intelligent learning systems should also *use system features to develop new assets* (Principle 4). Whether coaching teachers (Cross Francis et al., Chapter 21; Ober et al., Chapter 24) or providing instruction to students (e.g., early learners; see Veng et al., Chapter 19 and those in higher education; see Imundo et al., Chapter 20), there is widespread agreement that we should nurture the development of new skills and knowledge. Interestingly, however, there is not always a discussion of the kinds of skills and community-related values that emerge across chapters. For example, collaboration (as considered by Ober et al., Chapter 24) is sometimes a feature of online learning systems, though it may sometimes be more of a means to an end (to improve learning of other skills) rather than a learning goal itself. Likewise, the development of empathy is not often discussed in the learning analytics community, nor are skills surrounding civic engagement (Schocker & Aumen, Chapter 17), though both reflect important cultural practices that can also be used to improve learning. These potential oversights may warrant reflection within the field, alongside Hamilton & Tanchuk's (Chapter 22) advice to provide a more holistic approach to conceptualizing students.

Rather than focusing on ways to "fix" gaps in students' knowledge – a framing that may overlook or undervalue their existing resources – the field might achieve greater impact by emphasizing the variety of ways that students can grow during their acquisition of knowledge. Leveraging the assets of students whose cultural backgrounds are often overlooked (Principle 3) could provide opportunities for role reversals, wherein the students who typically receive help are given more opportunities to provide it. Research demonstrates that learning by teaching can lead to deeper learning (Duran, 2017; Roscoe, 2007, 2014) and that students can benefit from receiving assessments from their peers (e.g., Patchan et al., 2016). However, this is not a "zero-sum game"; learning by teaching (Duran, 2017) and peer assessment (Patchan et al., 2016) also provides productive challenges and learning opportunities for students' whose cultural background is typically privileged in the classroom, which is aligned with goals with broadening knowledge for all learners.

Finally, our principles include *making assets visible and appreciated for all stakeholders* (Principle 5), which is echoed in Arslan and Tenison's (Chapter 6) call to report the assets highlighted in other chapters' and calls to expand the assets that are defined and detected (see discussions of Principles 1 and 2 for examples). As Schocker and Aumen (Chapter 17) argue, expanding the kinds of assets that our field highlights will demonstrate their value to students and legitimize them to others who are charged to assessment, and we echo Ober et al.'s (Chapter 24)

BK-TandF-BERNACKI_9781032719481-250571-Chp26.indd 442 9/16/25 12:01 PM

call to integrate culturally responsive assessment tools (e.g., Walker et al., 2023) into our field's practices.

In particular, it is important to consider Emery et al.'s (Chapter 10) concerns about labeling students in ways that may permanently associate them with specific abilities – or the perceived lack of ability. Specifically, constructs like working memory (Chang et al., 2013; Cojean & Martin, 2022) and response time (Mettler et al., 2011) – which can sometimes help teachers and researchers to better understand why students might struggle – can be used to determine when the system can better support the student. However, as Ocumpaugh et al. (2017) argue, caution is important when putting these types of information into dashboards or otherwise presenting them to stakeholders in ways that might cause them to permanently think about a specific student in a specific fashion. Detecting these types of constructs is not the issue; how it is used by the learning system determines whether the system is deficit-focused or asset-focused.

Data visualizations and dashboards should also be designed so that they present and can be used to nurture student assets. Wise et al. (2021) have argued that we should incorporate "blank box dashboards" that transparently reveal which learner characteristics and assessments that learning systems are *unable* to measure. Such concerns have also been noted by scholars who develop open learner models (OLMs; see reviews in Bull & Kay, 2010; Bull, 2020), which display the contents of learner models to the learners themselves. OLMs can invite and empower learners to inspect, transform, or otherwise interact with those models (Bull & Kay, 2007; Dimitrova et al., 1999), and this can scaffold learners' reflection and self-regulated learning (Hooshyar et al., 2020; Winne, 2021). Many OLMs have addressed the same deficits as prior AIED work, but Bull (2020) has argued that OLMs can also be developed to highly and nurture learners' strengths and knowledge growth (e.g., employing positive representations such as growing trees or other cartoons to represent student knowledge). Similarly, Bull et al. (2016) implemented word clouds to capture both students' strengths and weaknesses – a seemingly minor shift in emphasis that enables designs to frame assets over deficits. Students using OLMs have self-reported that these visualizations indeed contributed to their appreciation of their own strengths as well as weaknesses (Bull et al., 2007).

In addition to borrowing from the data visualization techniques used with OLMs, the field should also consider leveraging dialog patterns and interaction between students and OLMs to orient students toward productive, asset-based reflections. Given recent and significant advances in AI, this strategy could also allow us to broaden the kinds of knowledge, skills, and other resources that are reported when we assess students (see Lan, t Chapter 14). By gaining deeper insights into students' existing resources, we can also help educators and students align their learning goals with their existing values.

Conclusion

As we have discussed, research shows that emphasizing both existing and emerging assets creates valuable opportunities for deeper student engagement and learning. Effective personalization involves extending efforts to characterize, detect, and leverage existing assets alongside efforts to support the development of new ones. In this section, we build on the flexibility of the extensible model (Bernacki & Walkington, Chapter 3) to highlight our asset-based approach.

As Figure 26.1 shows, it is possible to explicitly (re)define and (re)imagine a large range of learner characteristics as potential assets. These include prior knowledge, which has long shown a reciprocal relationship with learning and motivation. Therefore, expanding the scope and definitions of prior knowledge to more deeply represent the rich experiences and backgrounds

BK-TandF-BERNACKI_9781032719481-250571-Chp26.indd 443 9/16/25 12:01 PM

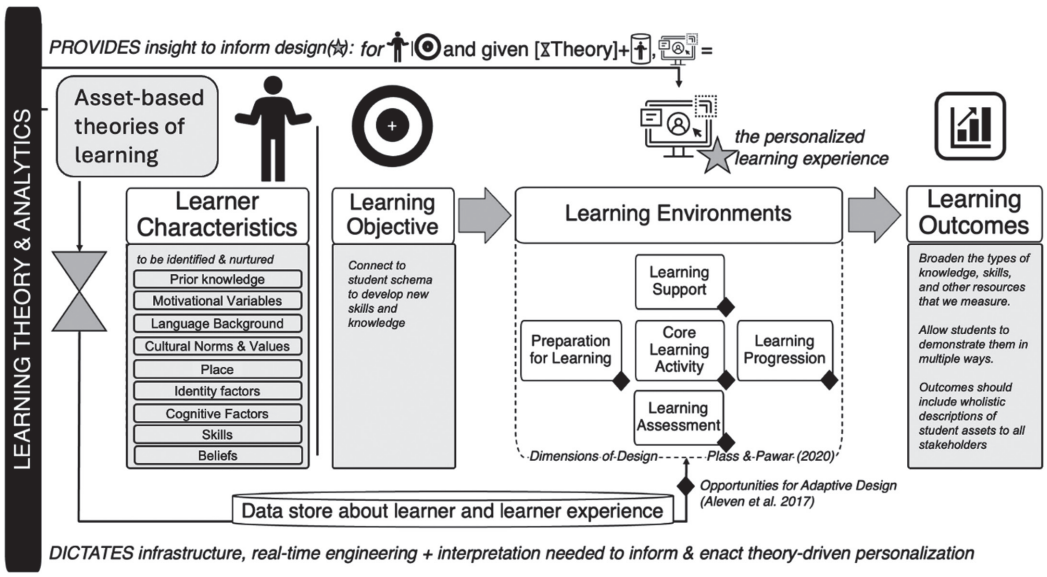


Figure 26.1 Asset-based learning and the extensible model.

that students bring to a learning context should be a critical priority in the design of any learning system (see Arslan & Tenison, Chapter 6).

Expanding the detection of prior knowledge and skills will likely involve improving the representation of other characteristics, such as students' language background, place, and cultural norms and values. All of these factors are deeply intertwined. These constructs can also interact with constructs like student identity – or how students define themselves as a learner – both within and beyond the classroom. Our goal should be to create learning systems that allow students to embrace productive learner identities (e.g., Kolb & Kolb, 2009; Wortham, 2006). Leveraging these characteristics also has the potential to help students to see how their prior knowledge connects to new learning opportunities while also nurturing motivational dispositions (e.g., self-efficacy and interest) that are known to promote learning.

In some cases, broadening the ways in which we characterize particular learners may incorporate information that can be readily interpreted as deficient in nature. For example, detecting that a student exhibits "lower working memory" (as operationalized by one or more measures) might be important for providing mnemonic support and strategies. Likewise, the experience of many forms of anxiety, such as math anxiety and test anxiety, is known to hinder learning (Barroso et al., 2021); the same is true for low interest (Renninger & Hidi, 2020) and low self-efficacy (Hodges, 2008). An asset-based system can still leverage this knowledge to support the learner through the learning process while also – when possible – helping them to develop their own self-regulation skills. This approach might include in-the-moment interventions to lower the frustration of anxious students (Andres et al., 2022), as well as asynchronous messages that could support the student's ability to regulate these emotions without prompting. In other words, some consideration of areas where students need support can still be part of an approach that attempts to build more on student strengths.

A reasonable heuristic is to consider how *any* detectable construct should be modeled and used in connection to students' schemas, and for developing new knowledge, skills, and opportunities for holistic growth. However, the benefits of asset-based approaches are not limited

BK-TandF-BERNACKI_9781032719481-250571-Chp26.indd 444 9/16/25 12:01 PM

to connecting to learner schemas. There are also benefits to reporting students' assets and holistic growth. For example, it is probably not optimal to design reports that lead to students being critiqued for expending less time practicing skills or studying topics for which they have proficiency, if they are expending considerable effort to improve in a topic on which they are less advanced. Educational data reporting systems – whether dashboards, data visualizations, or some other format – should use available data to provide as comprehensive a picture as possible, and they should also leverage the kinds of student feedback used in OLMs to fill in the gaps. We should also consider Wise et al.'s (2021) approach, which transparently reminds students and stakeholders that there are many things that systems are not measuring. These reporting systems should also follow best practices in data visualization for not over-representing the accuracy of any model, particularly when sensitive measures are involved (see discussion in Ocumpaugh et al., 2017).

Ultimately, we feel that a consideration of assets is complementary to Bernacki and Walkington's model. In order to more effectively leverage student assets within personalized learning, two steps will be necessary. First, learning systems must measure students' knowledge, skills, and dispositions more comprehensively and transparently. Then, they must use this information – both directly within a personalized learning system, and by providing better information on assets to teachers for their use in differentiating, individualizing, or personalizing learning. By doing so, we can develop learning systems that personalize effectively for a broader range of learners.

References

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

Aleven, V., Mclaren, B., Roll, I., & Koedinger, K. (2006). Toward meta-cognitive tutoring: A model of help seeking with a cognitive tutor. *International Journal of Artificial Intelligence in Education*, *16*(2), 101–128.

Aleven, V., Roll, I., McLaren, B. M., & Koedinger, K. R. (2016). Help helps, but only so much: Research on help seeking with intelligent tutoring systems. *International Journal of Artificial Intelligence in Education*, *26*, 205–223.

Allen, L. K., Snow, E. L., & McNamara, D. S. (2015, March). Are you reading my mind? Modeling students' reading comprehension skills with Natural Language Processing techniques. In *Proceedings of the fifth international conference on learning analytics and knowledge* (pp. 246–254). ACM.

Andres, J. A. L., Hutt, S., Ocumpaugh, J., Baker, R. S., Nasiar, N., & Porter, C. (2022). How anxiety affects affect: a quantitative ethnographic investigation using affect detectors and data-targeted interviews. In B. Wasson, S. Zörgö (Eds.), *Advances in quantitative ethnography: Third international conference, ICQE 2021, Virtual Event, November 6–11, 2021, Proceedings 3* (pp. 268–283). Springer International Publishing.

Baker, R. S., Corbett, d, & Gowda, A. T. (2013). Generalizing automated detection of the robustness of student learning in an intelligent tutor for genetics. *Journal of Educational Psychology*, *105*(4), 946–956.

Baker, R. S., Hutt, S., Bosch, N., Ocumpaugh, J., Biswas, G., Paquette, L., ... & Munshi, A. (2024). Detector-driven classroom interviewing: Focusing qualitative researcher time by selecting cases in situ. *Educational* Technology Research and Development, *72*(5), 2841–2863. https://doi.org/10.1007/s11423-023-10324-y

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.

Ballagas, R., Kuntze, A., & Walz, S. P. (2008, May). Gaming tourism: Lessons from evaluating rexplorer, a pervasive game for tourists. In J. Indulska, D. J. Patterson, T. Rodden, M. Ott (Eds.), *International conference on pervasive computing* (pp. 244–261). Springer Berlin Heidelberg.

Barroso, C., Ganley, C. M., McGraw, A. L., Geer, E. A., Hart, S. A., & Daucourt, M. C. (2021). A meta-analysis of the relation between math anxiety and math achievement. *Psychological Bulletin*, *147*(2), 134–168.

BK-TandF-BERNACKI_9781032719481-250571-Chp26.indd 445 9/16/25 12:01 PM

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

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

Bull, S., Ginon, B., Boscolo, C., & Johnson, M. (2016, April). Introduction of learning visualisations and metacognitive support in a persuadable open learner model. In LAK '16: Proceedings of the 6th international conference on learning analytics & knowledge (pp. 30–39). ACM. https://doi.org/10.1145/2883851.2883853

Bull, S., & Kay, J. (2007). Student models that invite the learner in: The SMILI: Open learner modelling framework. *International Journal of Artificial Intelligence in Education*, *17*(2), 89–120.

Bull, S., Mabbott, A., & Abu Issa, A. S. (2007). UMPTEEN: Named and anonymous learner model access for instructors and peers. *International Journal of Artificial Intelligence in Education*, *17*(3), 227–253.

Byrd, A. S., Huang, Y. T., & Edwards, J. (2023). The impact of dialect differences on spoken language comprehension. *Applied Psycholinguistics*, *44*(4), 610–633. https://doi.org/10.1017/S0142 71642.30002 43

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.

Chang, T. W., El-Bishouty, M. M., & Graf, S. (2013, July). An approach for detecting students' working memory capacity from their behavior in learning systems. In *2013 IEEE 13th international conference on advanced learning technologies* (pp. 82–86). IEEE.

Charity, H., & Mallinson, C. (2011). *Understanding English language in US schools*. Teachers College Press.

Charity Hudley, A. H., & Mallinson, C. (2018). Introduction: Language and social justice in higher education. *Journal of English Linguistics*, *46*(3), 175–185.

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(2), 283–316. https://doi.org/10.1007/s40593-019-00178-y

Civil, M., Hunter, R., & Crespo, S. (2019). Mathematics teachers committed to equity: A review of teaching practices. *International Handbook of Mathematics Teacher Education*, *1*, 243–273.

Cojean, S., & Martin, N. (2022). Adaptive learning technology based on working memory capacity. In *Proceedings of the annual meeting of the cognitive science society* (Vol. 44, No. 44). Cognitive Science Society.

Cole, A. (2018). Categories of representation: Improving the discussion and depiction of diversity. *TEXT*, *22*(Special 53), 1–13.

Corlatescu, D. G., Watanabe, M., Ruseti, S., Dascalu, M., & McNamara, D. S. (2024). The automated model of comprehension version 4.0–Validation studies and integration of ChatGPT. *Computers in Human Behavior*, *154*, 108154.

Ćosović, M., & Brkić, B. R. (2019). Game-based learning in museums—Cultural heritage applications. *Information*, *11*(1), 22.

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.

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

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).

Dedeoglu, H., & Lamme, L. L. (2011). Selected demographics, attitudes, and beliefs about diversity of preservice teachers. *Education and Urban Society*, *43*(4), 468–485.

Dimitrova, V., Self, J., & Brna, P. (1999). The interactive maintenance of open learner models. *Artificial Intelligence in Education*, *50*, 405–412.

Dudley-Marling, C. (2015). The resilience of deficit thinking. *Journal of Teaching and Learning*, *10*(1). https://doi.org/10.22329/jtl.v10i1.4171

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.

BK-TandF-BERNACKI_9781032719481-250571-Chp26.indd 446 9/16/25 12:01 PM

Duran, D. (2017). Learning-by-teaching. Evidence and implications as a pedagogical mechanism. *Innovations in Education and Teaching International*, *54*(5), 476–484.
Eckert, R. C., & Rowley, A. J. (2013). Audism: A theory and practice of audiocentric privilege. *Humanity & Society*, *37*(2), 101–130.
Edmonds-Wathen, C., Owens, K., & Bino, V. (2019). Identifying vernacular language to use in mathematics teaching. *Language and Education*, *33*(1), 1–17.
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.
Ferguson, R. F. (2003). Teachers' perceptions and expectations and the Black-White test score gap. *Urban Education*, *38*(4), 460–507.
Finkelstein, S., Ogan, A., Vaughn, C., & Cassell, J. (2013a). Alex: A virtual peer that identifies student dialect. In M. Kravcik, B. Krogstie, A. Moore, V. Pammer, L. Pannese, M. Prilla, W. Reinhardt & T. D. Ullmann (Eds.), *Proc. workshop on culturally-aware technology enhanced learning in conjunction with EC-TEL*.
Finkelstein, S., Yarzebinski, E., Vaughn, C., Ogan, A., & Cassell, J. (2013b). The effects of culturally congruent educational technologies on student achievement. In H. C. Lane, K. Yacef, J. Mostow, P. Pavlik (Eds.), *Artificial intelligence in education: 16th international conference, AIED 2013, Memphis, TN, USA, July 9–13, 2013. Proceedings 16* (pp. 493–502). Springer Berlin Heidelberg.
Flint, A. S., & Jaggers, W. (2021). You matter here: The impact of asset-based pedagogies on learning. *Theory Into Practice*, *60*(3), 254–264.
Freire, P. (1970). Pedagogy of the oppressed (MB Ramos, Trans.). Continuum, 2007.
Freire, P., & Macedo, D. (1995). A dialogue: Culture, language, and race. *Harvard Educational Review*, *65*(3), 377–403.
Gobert, J. D., Sao Pedro, M., Raziuddin, J., & Baker, R. S. (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.
Gorski, P. C. (2017). *Reaching and teaching students in poverty: Strategies for erasing the opportunity gap*. Teachers College Press.
Guskey, T. R. (1982). Differences in teachers' perceptions of personal control of positive versus negative student learning outcomes. *Contemporary Educational Psychology*, *7*(1), 70–80.
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.
Haas, E., & Gort, M. (2009). Demanding more: Legal standards and best practices for English language learners. *Bilingual Research Journal*, *32*(2), 115–135.
Hodges, C. B. (2008). Self-efficacy in the context of online learning environments: A review of the literature and directions for research. *Performance Improvement Quarterly*, *20*(3–4), 7–25.
Holden, C. L., & Sykes, J. M. (2011). Leveraging mobile games for place-based language learning. *International Journal of Game-Based Learning (IJGBL)*, *1*(2), 1–18.
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.
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.
Howard, T. C. (2003). Culturally relevant pedagogy: Ingredients for critical teacher reflection. *Theory into Practice*, *42*(3), 195–202.
Huizenga, J., Admiraal, W., Akkerman, S., & Dam, G. T. (2009). Mobile game-based learning in secondary education: Engagement, motivation and learning in a mobile city game. *Journal of Computer Assisted Learning*, *25*(4), 332–344.
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.
Kim, M. K., & McCarthy, K. S. (2021). Improving summary writing through formative feedback in a technology-enhanced learning environment. *Journal of Computer Assisted Learning*, *37*(3), 684–704.
Kolb, A., & Kolb, D. (2009). On becoming a learner: The concept of learning identity. In D. Bamford-Rees, B. Doyle, B. Klein-Collins, & J. Wertheim (Eds.), *Learning never ends: Essays on adult learning inspired by the life and work of David O. Justice* (pp. 5–13). CAEL Forum and News.

BK-TandF-BERNACKI_9781032719481-250571-Chp26.indd 447 9/16/25 12:01 PM

Ladson-Billings, G. (1995). Toward a theory of culturally relevant pedagogy. *American Educational Research Journal*, *32*(3), 465–491.

Ladson-Billings, G. (2021, July). Three decades of culturally relevant, responsive, & sustaining pedagogy: What lies ahead?. In *The Educational Forum* (Vol. 85, No. 4, pp. 351–354). Routledge.

Ladson-Billings, G. (1995). But that's just good teaching! The case for culturally relevant pedagogy. *Theory into Practice*, *34*(3), 159–165.

Lawson, A. (2014). Learner identities in the context of undergraduates: A case study. *Educational Research*, *56*(3), 343–356.

McCarthy, K. S., Allen, L. K., & Hinze, S. R. (2020, June). Predicting reading comprehension from constructed responses: Explanatory retrievals as stealth assessment. In *International conference on artificial intelligence in education* (pp. 197–202). Springer International Publishing.

Metcalf, S. J., Gagnon, D., & Slater, S. (2023). Shifts in student attitudes and beliefs about science through extended play in an immersive science game. In M. L. Bourguet, J. M. Krüger, D. Pedrosa, A. Dengel, A. Peña-Rios, J. Richter (Eds.), *International conference on immersive learning* (pp. 330–342). Springer Nature Switzerland.

Mettler, E., Massey, C., & Kellman, P. (2011). Improving adaptive learning technology through the use of response times. In *Proceedings of the annual meeting of the cognitive science society* (Vol. 33, No. 33). Cognitive Science Society.

Moll, L. C. (1992). Bilingual classroom studies and community analysis: Some recent trends. *Educational Researcher*, *21*(2), 20–24.

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* (pp. 355–368). Springer.

Nasiar, N., Zambrano, A. F., Ocumpaugh, J., Hutt, S., Goslen, A., Rowe, J., & Mott, B. (2023, June). It's good to explore: Investigating silver pathways and the role of frustration during game-based learning. In N. Matsuda, V. Dimitrova, O. C. Santos (Eds.), *International conference on artificial intelligence in education* (pp. 497–503). Springer Nature Switzerland.

Ocumpaugh, J., Baker, R. S., San Pedro, M. O., Hawn, M. A., Heffernan, C., Heffernan, N., & Slater, S. A. (2017, March). Guidance counselor reports of the ASSISTments college prediction model (ACPM). In *Proceedings of the 7th international learning analytics & knowledge conference* (pp. 479–488).

Ocumpaugh, J., Roscoe, R. D., Baker, R. S., Hutt, S., & Aguilar, S. J. (2024). Toward asset-based instruction and assessment in artificial intelligence in education. *International Journal of Artificial Intelligence in Education*, *34*(4), 1559–1598. https://doi.org/10.1007/s40593-023-00382-x

Paris, D. (2012). Culturally sustaining pedagogy: A needed change in stance, terminology, and practice. *Educational Researcher*, *41*(3), 93–97.

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.

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.

Renninger, K. A., & Hidi, S. E. (2020). To level the playing field, develop interest. *Policy Insights from the Behavioral and Brain Sciences*, *7*(1), 10–18.

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.

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), 195216. https://doi.org/10.1615/JWomenMinorScienEng.v4.i2-3.80

Roscoe, R. D. (2014). Self-monitoring and knowledge-building in learning by teaching. *Instructional Science*, *42*, 327–351.

Roscoe, R. D., & Chi, M. T. (2007). Understanding tutor learning: Knowledge-building and knowledge-telling in peer tutors' explanations and questions. *Review of Educational Research*, *77*(4), 534–574.

BK-TandF-BERNACKI_9781032719481-250571-Chp26.indd 448 9/16/25 12:01 PM

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. McClaren, A. H Alavi (Eds.), *Artificial intelligence in STEM education* (pp. 359–374). CRC Press.

Rychly, L., & Graves, E. (2012). Teacher characteristics for culturally responsive pedagogy. *Multicultural Perspectives*, *14*(1), 44–49.

Sablan, J. R. (2019). Can you really measure that? Combining critical race theory and quantitative methods. *American Educational Research Journal*, *56*(1), 178–203.

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

Schultz, L. (2016). Resisting assimilation: Deliberate acculturation by the American English language learner. *Multicultural Perspectives*, *18*(2), 103–107.

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

Sharma, M. (2018). Seeping deficit thinking assumptions maintain the neoliberal education agenda: Exploring three conceptual frameworks of deficit thinking in inner-city schools. *Education and Urban Society*, *50*(2), 136–154.

Shute, V. J. (2011). Stealth assessment in computer-based games to support learning. *Computer Games and Instruction*, *55*(2), 503–524.

Shute, V. J., & Rahimi, S. (2021). Stealth assessment of creativity in a physics video game. *Computers in Human Behavior*, *116*, 106647.

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.

Sobel, D. (2004). Place-based education: Connecting classrooms and communities. *Education for Meaning and Social Justice*, *17*(3), 63–64.

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

Stewart, A., Mills, C., & Hutt, S. (2024). Marrying asset-and deficit-based approaches: A data feminist perspective in learning analytics. In *CEUR workshop proceedings* (Vol. 3667, pp. 292–294). CEUR-WS.

Ventura, M., & Shute, V. (2013). The validity of a game-based assessment of persistence. *Computers in Human Behavior*, *29*(6), 2568–2572.

Verdín, D. (2021). The power of interest: Minoritized women's interest in engineering fosters persistence beliefs beyond belongingness and engineering identity. *International Journal of STEM Education*, *8*(1), 33.

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*, *2023*(1), 1–24.

Walkey, F. H., McClure, J., Meyer, L. H., & Weir, K. F. (2013). Low expectations equal no expectations: Aspirations, motivation, and achievement in secondary school. *Contemporary Educational Psychology*, *38*(4), 306–315.

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.

Wang, T., Zhang, L., Xie, Z., & Liu, J. (2023). [IS THIS IT?] How does mathematical modeling competency affect the creativity of middle school students? The roles of curiosity and guided inquiry teaching. *Frontiers in Psychology*, *13*, 1044580.

Wang, X. (2021). The Effect of Mobile Serious Games on Learning Intangible Cultural Heritage [Unpublished doctoral dissertation or master's thesis]. (Doctoral dissertation, University of York.

Wheeler, R. (2016). "So much research, so little change": Teaching standard English in African American classrooms. *Annual Review of Linguistics*, *2*(1), 367–390.

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

Wolfram, W., Adger, C. T., & Christian, D. (1999). *Dialects in schools and communities.* Routledge.

Woolf, B. P. (2010). *Building intelligent interactive tutors: Student-centered strategies for revolutionizing e-learning.* Morgan Kaufmann.

BK-TandF-BERNACKI_9781032719481-250571-Chp26.indd 449 9/16/25 12:01 PM

Worsley, M., & Bar-El, D. (2022). Inclusive making: Designing tools and experiences to promote accessibility and redefine making. *Computer Science Education*, *32*(2), 155–187.

Wortham, S. (2006). *Learning identity. The joint emergence of social identification and academic learning*. Cambridge UP.

Zambrano, A. F., Barany, A., Ocumpaugh, J., Nasiar, N., Hutt, S., Goslen, A., & Mott, B. (2023, October). Cracking the code of learning gains: Using ordered network analysis to understand the influence of prior knowledge. In G. Arastoopour Irgens, S. Knight (Eds.), *International conference on quantitative ethnography* (pp. 18–33). Springer Nature Switzerland.

Zhang, T., Taub, M., & Chen, Z. (2022, March). A multi-level trace clustering analysis scheme for measuring students' self-regulated learning behavior in a mastery-based online learning environment. In *LAK22: 12th international learning analytics and knowledge conference* (pp. 197–207).

BK-TandF-BERNACKI_9781032719481-250571-Chp26.indd 450 9/16/25 12:01 PM