Using Technology to Address Individual Differences in Learning

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Problem Definition

Each individual possesses a unique pattern of mental abilities to process vast amounts of information, motivation levels for performing various tasks, visuospatial skills to navigate spaces and comprehend visual stimuli, and numerous other sets of aptitudes and traits that vary in their degree of stability over time. Recognizing that people think and learn differently, educators strive to design learning experiences and integrate technology to support a wide range of students with important differences in perception, attention, cognition, affect, motivation, self-regulation, and so on. Individual differences in learning are defined as skills, aptitudes, preferences, and traits that serve as a source of variability among learners and influence learning experiences and learners' ability to accomplish learning outcomes (Jonassen & Grabowski, 1993). Individual differences in learning are manifested in a variety of ways. Learners may express preferences for learning with different media (e.g., text, images) and modalities (e.g., auditory, visual, kinesthetic; Plass, Kalyuga, & Leutner, 2010). Learning is also moderated by cognitive differences such as processing speed, attention span, working memory capacity, inhibitory control (Zelazo, 2015), and a host of noncognitive variables such as interest, self-efficacy, goal orientation, and so on (Belland, Kim, & Hannafin, 2013). Motivational, cognitive, and affective variables are interconnected in many intricate ways to create each individual's subjective experience of learning (Ainley, 2006), which makes the study of individual differences, as well as design, development, and application of appropriate educational technologies, more difficult.

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M. J. Bishop et al. (eds.), *Handbook of Research in Educational Communications and Technology*, https://doi.org/10.1007/978-3-030-36119-8_6

Research on individual differences in learning has a long history (Cronbach & Snow, 1977; Eysenck, 1969). However, using technology to support learning for all students remains an elusive goal. Issues with lack of student motivation and engagement, frustration and boredom, and compromised learning in technology-supported environments continue to be pervasive and are often attributed to our inability to adapt instruction to reflect the differences among learners (Aleven, McLaughlin, Glenn, & Koedinger, 2017; Hung, 2011). A recent study exploring the technology decisions for inclusive middle-school science instruction revealed that while teachers did consider instructional technologies for inclusive science classrooms, students' learning differences were not among the factors that influenced teachers' technology selections (Rutt, Mumba, Chabalengula, & Ochs, 2017). Given these concerns, the problem addressed in this chapter is the need to conduct more research and development to capitalize on the affordances of twenty-first-century technology as well as the new and emerging assessment methods that measure dynamics of individual differences to design learning environments that account for variation among learners relative to motivation, affect, and cognition.

Historical Overview

A number of learning theories and instructional design models have emphasized the notion that learning relies on students' cognition, affect, and motivation. In 1902, John Dewey called for a reform in curriculum design that moves away from the inflexible, one-size-fits-all curricula to instructional programs that are sensitive to children's needs and interests (Dewey, 1964). Across the globe, Soviet psychologist Lev Vygotsky developed the concept of the zone of proximal development, or the difference between what learners can and cannot do without the help of a more knowledgeable other, and introduced the idea of instructional scaffolding or changing the level of support to accommodate the cognitive potential of the child (Vygotsky, 1987). The study of scaffolding, and particularly adaptive scaffolding, remains a prominent trend in educational research and practice (Belland, Walker, Kim, & Lefler, 2017).

An important development in individual differences research occurred in 1957 when Lee J. Cronbach reported on the outcomes of correlational research to relate individual differences and learning gains on different experimental treatments (Cronbach, 1957). This work helped lay the foundation for what is now known as aptitude-treatment interactions (ATI; Cronbach & Snow, 1969). A pervasive finding in ATI research has been that selection of effective instructional treatment depends on learners' knowledge in the domain (Cronbach & Snow, 1977). This finding has been incorporated in instructional design models such as Gagne's Nine Events of Instruction where one of the early design steps is "Stimulate recall of prior knowledge" (Gagne, 1985), in the student knowledge-informed use of instructional texts (McNamara, Kintsch, Songer, & Kintsch, 1996), and, more recently, in the design of learning technologies that adapt to student knowledge of the domain (e.g., Arroyo et al., 2014; VanLehn et al., 2000).

Current Perspectives

The resurgence of interest in individual differences in the 1950s and 1960s reflected an increased interest of psychologists in the study of cognition that is often referred to as the cognitive revolution in psychology (Baars, 1986). From a cognitive perspective, learning with technology requires effective processing of information presented to the learner using various media or modalities. Thus, much of the cognitivist research in educational technology has focused on the cognitive load imposed by various technology-supported learning materials. Within this line of inquiry, it is assumed that poor learning outcomes are due to the ineffective design of learning materials (e.g., when images and text are not semantically related). Cognitive load is discussed primarily as a consequence of the design of the learning materials, and differences in individual learner characteristics that may impact cognition are typically not addressed (Plass et al., 2010; Wiley, Sanchez, & Jaeger, 2014). A notable exception is research on the expertise reversal effect that discusses the design of learning materials relative to differences between expert and novice learners (Kalyuga, 2007). Specifically, students with high prior knowledge have been found to experience increased extraneous cognitive load when presented with instructional scaffolds for the material they had already internalized, whereas low prior knowledge students experienced decreased extraneous load and exhibited learning gains when presented with instructional scaffolding.

A complementary approach that puts learners and their characteristics front and center focuses on the effects of individual differences in learning with technology. Unlike scholarship exploring the properties of learning materials, an individual differences approach addresses the moderating effects of individual differences among learners that represent a spectrum of motivational, affective, and cognitive variables that we have long known exist and influence learning (Eysenck, 1969). The extent of variation among individuals across all the cognitive, motivational, and affective dimensions is incredibly vast. However, scholars do agree on a number of assumptions about differences among individuals and their learning (Jonassen & Grabowski, 1993):

- Individual differences in learning show systematic variation in the population.
- Individual differences in learning have pervasive effects on cognition, emotion, motivation, and behavior.
- Individual differences in learning affect the learner's ability to perform learning tasks and accomplish learning outcomes

The types of individual learner differences have been described in many different frameworks. For example, Jonassen and Grabowski's (1993) taxonomy of individual differences in learning distinguishes between cognitive abilities (cognitive controls, cognitive styles, and learning styles), personality styles, and prior knowledge. Some of the types of individual differences such as learning styles are still being debated (Kirschner & van Merrienboer, 2013; Pashler, McDaniel, Rohrer, & Bjork, 2009), whereas other variables such as prior knowledge, working memory capacity, motivation, and emotional arousal have been shown to be valid and relevant concepts that reflect variability among learners and serve to inform theories of learning and the practice of teaching (Akshoomoff et al., 2013).

Today, there is increased recognition that learning is influenced by affect and motivation (D'Mello & Graesser, 2011), and so a number of taxonomies have been devised to describe variations among learners relative to the motivation and emotions they experience during learning. For instance, Pekrun (2010) discusses achievement emotions, topic emotions, social emotions, and epistemic emotions that moderate learning and cognition. Ryan and Deci's (2004) self-determination theory provides a useful taxonomy of learner motivation and motivation regulation that describes learner motivation along a continuum from amotivation to extrinsic motivation (external regulation, introjected regulation, identified regulation, and integrated regulation) to intrinsic motivation with self-determined, intrinsic regulation. These taxonomies serve as logical tools that inform the study of individual differences in learning and inform the design of affective, motivational, and cognitive scaffolding.

Individual Differences as States and Processes

To facilitate the discussion of cognitive, affective, and motivational differences in learning, it may be useful to examine them along a continuum from the relatively stable and constant *states* to the highly dynamic and volatile *processes*. Prior knowledge, metacognitive awareness, reading ability, visuospatial abilities, and working memory capacity are all examples of states that remain comparatively constant over time. On the other hand, a key characteristic of processes is that they fluctuate during the learning task. For instance, boredom, frustration, cognitive load, stress, and strategy choice are dynamic processes that constantly change, reflecting situational and task dynamics such as relevance, difficulty of content, and design of instructional scaffolding. As is the case with many educational and psychological variables, however, true dichotomies (such as the above distinction between states and processes) are rare. While we believe this categorization helps with analyzing the causes and effects of individual differences in learning, it is also understood that (a) there may be great variability within both states and processes relative to their stability and volatility (e.g., an active social sciences researcher's knowledge of statistics may develop much more dynamically compared to her or his knowledge of geometry), and (b) states and processes are highly interactive (e.g., prior knowledge influences cognitive load and cognitive load impacts the development of new knowledge; Kalyuga, 2007).

An important implication of discussing individual differences as states versus processes is measurement. Due to their relative stability, states such as prior knowledge, metacognitive skills, or reading ability usually only need to be assessed once, using pre-task measures such as tests of prior knowledge or metacognitive awareness instruments (e.g., Schraw & Dennison, 1994). However, because process variables such as cognitive load or affective responses fluctuate during the learning task, continuous online assessments during the task are needed to inform individualization of learning (Sinatra, Heddy, & Lombardi, 2015).

Promising Directions

Advances in the assessment of individual differences in learning and recent technological innovations in dynamic web and mobile application development have resulted in the design of systems that adapt to individual differences at both the state level and the process level (e.g., Aleven et al., 2017; D'Mello, Dieterle, & Duckworth, 2017).

Addressing State-Level Differences

State-level individual differences in learning such as prior knowledge, visuospatial abilities, reading ability, and working memory capacity are a well-recognized phenomenon (DeBra, Kobsa, & Chin, 2010). The conventional approach to addressing state differences is to conduct a pre-task assessment and then adjust the content difficulty, presentation of information, or navigation within the task based on the results of that assessment. This approach has been successfully used to design multimedia and hypermedia applications, games and simulations, and intelligent tutoring systems (ITSs). For example, Kalyuga (2008) demonstrated that while learners with higher levels of prior knowledge showed better learning results after studying animated procedural examples in transforming graphical representations of linear and quadratic functions in mathematics, less knowledgeable learners performed significantly better after studying sets of static representations demonstrating main steps of the transformations on a single screen (Kalyuga, 2008). This expertise reversal effect has also been observed during learning with chemistry simulations (Homer & Plass, 2014), hypermedia-based concept maps in biology (Amadieu, Tricot, & Marine, 2009), and many other educational contexts. Thus, a number of learning technologies have been designed to assess student domain knowledge before instruction and then customized the content or the system to student's knowledge level (Corbett, McLaughlin, & Scarpinatto, 2000). A number of systems have also been built to adapt to changes in student understanding of the content based on student successes and errors during learning using approaches like adaptive worked examples (Booth, Lange, Koedinger, & Newton, 2013), adaptive feedback (Ohlsson, 2016), and adaptive fading of scaffolding (Salden, Aleven, Schwonke, & Renkl, 2010). For example, Salden et al. (2010) found that the adaptive fading condition in their study outperformed two nonadaptive conditions (problem solving and fixed fading) on both the immediate and the delayed posttest. Additionally, learners in the adaptive fading condition needed significantly fewer worked steps than those in the fixed fading condition, which indicates that overall the students' knowledge levels increased faster in the adaptive condition.

Working memory capacity (WMC) is another important state variable that is known to have important effects on learning. In fact, individual differences in WMC are a new principle in the cognitive theory of multimedia learning, a well-known framework for understanding and designing multimedia learning environments (Wiley et al., 2014). Many studies on multimedia and hypermedia learning have found that when learners are given more information, including additional information that should be helpful for their understanding, they may actually learn less, not more. For example, Fenesi, Kramer, and Kim (2016) examined the relationships between working memory capacity (WMC) and the principles of split attention in multimedia learning. Undergraduate students with lower WMC performed worse compared with those with higher WMC when learning from the split attention condition (audio, on-screen text, and images), but not when learning from the complementary condition (audio and images). This finding demonstrates that removing split-attention components selectively improves multimedia learning for lower WMC learners. A similar finding was reported in the context of learning from paginated versus long scrolling hypermedia pages (Sanchez & Wiley, 2009). While scrolling presentations reduced learning overall, this effect was localized to individuals lower in WMC. Adaptive learning technologies sensitive to differences in learners' WMC are still rare; however, some promising research is under way. For example, Chang et al. (2015) have proposed a system that employs six types of adaptive recommendations (e.g., suggesting note taking, summarizing, rehearsal, and other strategies) to remind and suggest additional learning activities to students based on their WMC.

Similar to WMC and prior knowledge, visuospatial abilities (VSA) represent a set of important state-level individual difference variables that allow us to search for relevant stimuli in the visual field; apprehend the forms, shapes, and positions of objects; form mental representations of those forms, shapes, and positions; and mentally manipulate them (Carroll, 1993). A recent meta-analysis demonstrated that when visualizations are present in learning materials, high VSA learners achieve significantly better learning outcomes compared to low VSA learners (effect size of $r = 0.34$). Additionally, this meta-analysis revealed that learners with low VSA can be supported using dynamic (i.e., animated) instead of static visualizations and using three-dimensional rather than two-dimensional illustrations (Höffler, 2010). Combined with the results of Kalyuga's (2008) expertise reversal study described earlier, we can see that students who tend to benefit most from instructional animations are those who have a high level of prior knowledge even when their spatial ability is relatively low. These findings produce important implications for designing instructional adaptations based on pre-task assessment of learners' prior knowledge and spatial ability states.

Pretraining Approaches

In addition to preassessing learners on state individual differences and designing variants of instructional systems or tools to accommodate the abilities, traits, and prior knowledge of individual students, a promising approach is to conduct pretraining on these respective variables prior to learning (Mayer, Mathias, & Wetzell, 2002). Despite being fairly stable over long periods of time, many of the state variables are in fact malleable and can be improved using carefully designed training interventions. For instance, promising findings have been reported regarding working memory training interventions (Schwaighofer, Fischer, & Bühner, 2015). This particular meta-analysis examined 47 studies with 65 group comparisons and revealed positive near-transfer effects to short-term and working memory skills that were sustained at follow-up for immediate transfer and long-term transfer. Similarly, a meta-analysis of 25 years of research on spatial ability training (Uttal et al., 2013) revealed that overall spatial training is quite effective ($r = 0.47$). Spatial training interventions ranged from semester-long spatial visualization courses (e.g., Sorby, 2009) to spatial training with video games with much shorter game play. For example, Feng, Spence, and Pratt (2007) investigated the effects of video game playing on spatial skills, including transfer to mental rotation tasks, and found that playing commercial off-the-shelf action videogames like *Medal of Honor* can enhance spatial thinking substantially, even when compared to a control group that played a 3D puzzle game.

Games have also been found to be useful for the training of selective attention. Chukoskie et al. (2017) developed gaze-contingent video games that provide users visual and auditory feedback in real time from a remote eye tracker designed for in-home use. The games – *Whack The Moles*, *Shroom Digger*, and *Space Race* – require players to control the distribution of their visual attention and fixate their gaze on select objects based on the rules of the game. In *Whack The Moles*, for instance, players are to look at the moles as they appear out of the ground and use their gaze to "hit" ninja moles but avoid hitting the professor mole. Playing these games has helped individuals improve both the speed of attentional orienting and duration of fixation on task-relevant stimuli (Chukoskie, Soomro, Townsend, & Westerfield, 2013).

Addressing Process-Level Differences

Unlike state differences, process-level variables fluctuate during the learning task and are notoriously difficult to measure and adapt to. Intelligent tutoring systems (ITSs) are advanced learning technologies that are well suited for adapting to process variables. They have been developed for many different content areas (e.g., reading, algebra, statistics, physics, computer science, medicine). Examples of such systems include *AnimalWatch* (Beal, 2013), *ALEKS* (Assessment and Learning in

Knowledge Spaces; San Pedro, Baker, & Rodrigo, 2014), *AutoTutor* (Graesser, 2016), *Cognitive Tutor* (Koedinger & Aleven, 2016), and *MetaTutor* (Duffy & Azevedo, 2015), among others. A recent meta-analysis compared the outcomes from students learning with ITSs to those learning with non-ITS learning environments (Ma, Adesope, Nesbit, & Liu, 2014). The use of ITS was associated with greater achievement in comparison with the traditional teacher-led, large-group instruction (g = .42), non-ITS computer-based instruction (g = .57), and learning with textbooks or workbooks (g = .35). Significant, positive effect sizes were found at all levels of education, in almost all subject domains evaluated, and whether or not the ITS provided feedback or modeled student misconceptions (Ma et al., 2014).

ITSs are adaptive in the sense that they change the presentation and navigation of learning content and the degree of system-learner interactivity (e.g., hints, questions, worked examples) based on the user model or data on the current level of learner knowledge, cognitive and metacognitive strategies used in the system, types of errors produced, and emotional responses and, more generally, based on learner actions in the system. Data on students' cognitive, affective, and engagement processes are collected during the learning task using a variety of strategies and technologies. Traditionally, online assessment has relied on experience sampling (Csikszentmihalyi & Larson, 2014), a method of providing learners with a brief self-report measure delivered in the ITS or on their smartphone asking them to indicate the amount of mental effort, level of engagement, boredom, confusion, or the types of emotions they are currently experiencing. The experience sampling methodology (ESM) allows collection of dynamic, online data relative to the variations in learners' self-reports of engagement, cognitive load, and other relevant process variables. For example, Kane et al. (2007) conducted an ESM study of undergraduate students focusing on the relation between working memory capacity (WMC) and the experience of mind wandering in their daily life. Personal digital assistants notified students eight times daily for a week to report immediately whether their thoughts had wandered from their current activity and to describe their psychological and physical context. They found that during challenging activities requiring concentration and effort, higher-WMC subjects maintained on-task thoughts better and mind-wandered less than did lower-WMC subjects. An apparent but untested implication of this study is that low-WMC learners need to be provided with adaptive scaffolding to reduce the detrimental effects of mind wandering or unintentional lapses of attention.

The benefit of using ESM in education is that online data on affective or cognitive dynamics can be collected anytime and anywhere (e.g., students reviewing study materials for an upcoming exam in their dorm room). However, because ESM relies on self-reported data, this methodology is prone to the limitations of all self-reported data such as lack of accuracy, failure to capture important changes in cognition, problems with collecting data from young children, and so on (Anderson & Beal, 1995; Antonenko & Keil, 2018; Gobert, Sao Pedro, Baker, Toto, & Montalvo, 2012; Leahy, 2018). To circumvent these limitations, scholars of learning from various disciplines have proposed a number of new methods informed by advances in psychology, computer science, and neuroscience. For instance, in the context of measuring cognitive load, which is a process variable that constantly fluctuates during the learning task and is difficult to measure, recent advances include the use of physiological techniques with a high temporal resolution, such as brain-based measures of electroencephalography (EEG; Antonenko & Keil, 2018) and functional near-infrared spectroscopy (fNIRS; Ayaz et al., 2012), as well as a combination of EEG and fNIRS (Liu, Ayaz, & Shewokis, 2017), ocular-motor measures such as eye tracking (Cook, Wei, & Preziosi, 2018), and multimodal measures that incorporate data from speech, writing, system interactions, and physiological responses (Chen, Zhou, & Yu, 2018).

A promising multimodal method for assessing engagement was proposed by D'Mello, Dieterle, & Duckworth (2017). The Advanced, Analytic, and Automated (AAA) approach employs machine-learned computational models to automatically infer mental states associated with engagement (e.g., interest, flow) from machine-readable behavioral and physiological signals (e.g., facial expressions, eye tracking, clickstream data) and from aspects of the environmental context (D'Mello et al., 2017). Other researchers have advocated for the use of sensor-free assessment that relies primarily on learning environment navigation data from server logs and analytic techniques that examine log data in the context of student performance relative to learning, problem solving, or collaboration (Antonenko, Toy, & Niederhauser, 2012; Baker & Siemens, 2014; Rowe et al., 2017).

A lot of promising research and development has recently focused on affect-aware and affect-adaptive learning technologies (Aleven et al., 2017; D'Mello & Graesser, 2014; San Pedro, Baker, & Heffernan, 2017). This line of inquiry emphasizes the role of such variables as frustration, boredom, confusion, engaged concentration, or flow because they are frequently observed during learning and influence student motivation, cognitive, and metacognitive processing (e.g., D'Mello, 2013). For example, D'Mello, Lehman, Pekrun, and Graesser (2014) explored the effects of confusion on learning within the context of an ITS (*AutoTutor*) and research design as the learning content. The system used a natural language speech interface to afford trialogs, in which a human learner, a computer learner, and a computer tutor reasoned through a challenging question. The two computer agents frequently contradicted each other and even expressed false information during the trialog, which was intended to cause confusion on the part of the human learner and drive the human learner to bridge the cognitive disequilibrium and resolve the confusion. This trialog-based learning environment did indeed lead to deeper learning, but such enhancements occurred only when the human learner was confused (D'Mello et al., 2014). Another work has focused on exploring relationships between positive and negative emotions and learning, focusing specifically on the incidence, persistence, and impact of boredom, frustration, confusion, delight, surprise, and engaged concentration (Baker, D'Mello, Rodrigo, & Graesser, 2010). They found that confusion and engaged concentration were the most common states within all three learning environments, whereas delight and surprise were rare. Boredom was very persistent across learning environments and was associated with poorer learning and problem behaviors such as gaming the system. Frustration was less persistent and less associated with poorer learning. These findings suggest that ITSs and other learning technologies should incorporate detection and adaptive scaffolding based on boredom and confusion data, in addition to the more widely used data on cognitive states and processes.

Translating Research on Individual Differences to Educator Practice: Universal Design for Learning

This chapter demonstrates the complexity associated with researching how technology may be used to address state- and process-level individual differences in learning. However, an arguably more complex dilemma relates to how to help educators translate research on technology and individual differences to their classroom practices. Universal Design for Learning (UDL) is a framework designed to support educators in this endeavor. The Center for Applied Special Technology (CAST) developed UDL as a result of efforts to help students with individual differences overcome barriers to learning. It gradually evolved into a framework educators can use to support all students by planning for learner variability in their classrooms.

The UDL framework, derived from research in education, psychology, and neuroscience, includes three main principles with associated guidelines and checklists (Meyer, Rose, & Gordon, 2014). The three main principles relate to designing learning environment to account for multiple means of (1) engagement, (2) action and expression, and (3) representation. The associated guidelines and checklists provide action-oriented strategies for implementing each principle. For example, one guideline under the Representation principle includes "providing options for perception," and checklist strategies include offering ways to customize how information is displayed and offering alternatives for auditory and visual information.

UDL is referenced in important US-based federal education policies at the K-12 (i.e., Every Student Succeeds Act (ESSA, 2015) and the National Educational Technology Plan (NETP, 2016)) and postsecondary levels (i.e., the 2008 Higher Education Opportunity Act). It is also referenced in the 2015 Educational Technology Developer's Guide for software designers published by the US Department of Education. The premise within all these documents relates to using UDL principles to minimize learning barriers and maximize student strengths by designing for individual differences, which UDL proposes are predictably variable across learners of all ages. Although UDL encompasses technology and nontechnology solutions to designing for individual differences, technology plays a major role in designing inclusive learning environments. For example, Strategic Reader, designed using UDL principles and Curriculum-Based Measurement (CBM) , is a technology intervention that supports individual differences in developing reading skills. A recent experimental study demonstrates its effectiveness in supporting comprehension, particularly when the tool was used online (Hall, Cohen, Vue, & Ganley, 2015).

Despite strong evidence for the component parts of UDL (Meyer et al., 2014), evidence that UDL-designed interventions can work and support for UDL in federal education policy, research on how to apply the framework to implementation is still emerging. A recent meta-analysis of UDL studies in PreK-12 classrooms found that UDL implementation varies considerably across studies, and importantly, the way implementation is described across studies makes it difficult to compare them or confirm that UDL is, indeed, being implemented at all. The meta-analysis also found that the success of UDL efforts, as measured by effect sizes, varied considerably although results of the overall meta-analysis suggest UDL is a promising framework to address individual differences (Ok, Rao, Bryant, & McDougall, 2017).

The UDL Implementation and Research Network (UDL-IRN) is a relatively new organization developed "to support the purposeful integration of Universal Design for Learning (UDL) and iterative design-based thinking to support the learner variability that exists in all learning environments." UDL-IRN includes strong focus on technology and on advancing research through its Research Committee which maintains a database of empirical studies on UDL (http://udl-irn.org/udl-research/).

Implications and Conclusions

The research on the problem of addressing individual differences among learners and educational technology solutions reviewed in this chapter demonstrates important contributions that have been made to individualize learning based on learner differences as well as promising directions for research and development to improve our understanding and design for differences in state and process variables that impact learning.

Perhaps the most important issue that researchers in educational technology and instructional design must address is the need to focus not only on the properties of learning materials (e.g., how a particular blend of technology, pedagogy, and content impacts learning) but, perhaps more importantly, how a particular educational technology solution affects learning relative to the important differences that exist among learners. A citation analysis conducted using terms "individual differences" or "cognitive differences" and "educational technology" revealed that (a) such studies are scarce, and (b) relevant studies are often designed and carried out by scholars with limited expertise in educational research (e.g., neuroscientists). Only one chapter in the latest edition of the *Cambridge Handbook of Multimedia Learning* explicitly focused on the issue of individual differences in multimedia learning (Wiley et al., 2014), with a focus on one important state-level variable – working memory capacity.

The most obvious contribution that addresses the issue of individual differences in learning is the extensive conceptual and empirical research on what we refer to in this chapter as state differences, that is, variables like prior knowledge, reading ability, metacognitive awareness, and so forth. This work resulted in the development of instructional design models and research paradigms such as aptitude-treatment interaction as well as educational technology products that individualize instruction based on state-level differences among learners. Research on adaptive learning technologies such as intelligent tutoring systems (Aleven et al., 2017) and using novel online assessment methodologies reflects more recent efforts to study and design individualized instruction technologies.

When it comes to the more dynamic individual differences variables, or what we referred to as process-level differences in this chapter, educational research in general and educational technology research in particular are still rather limited. Educational scholars have begun to call for more rigorous research on process differences in cognition and affect (e.g., Antonenko & Keil, 2018; Chen et al., 2018; D'Mello et al., 2017) for the design and study of educational technologies, but both empirical research and technological solutions that address process variables are scarce. This issue presents an important opportunity for the designers and scholars of technologies for learning and teaching. More translational research between neuroscience, cognitive psychology, educational psychology, computer science, and educational technology should focus on integrating physiological measures, server log and interaction analysis, self-reported instruments, and machine learning techniques for automatized analysis to devise comprehensive multimodal assessment paradigms to help study and design for individual differences in learning. This interdisciplinary research is needed to improve the sharing and cross-fertilization of conceptual frameworks, methodological approaches, and empirical findings between these diverse but complementary fields.

To summarize, the following implications for research may be worth addressing to advance the study of individuality and variation in learning and to design educational technologies that are sensitive to individual differences among learners:

- Acknowledge the important role of individual differences in learning and conduct rigorous research to understand the interplay between "system" variables that reflect the properties of the learning materials and "learner" variables that represent interindividual differences in cognition, motivation, and affect.
- Place more emphasis on the study of dynamic process-level differences in cognition and affect such as cognitive load, distraction, confusion, mind wandering, etc.
- Advance our understanding of the measurement techniques that can be used to unobtrusively assess process-level variables during the learning task.
- Employ the recently developed measurement paradigms and tools (e.g., NIH Toolbox) to explore the important interactions between:
  - State-level variables such as prior knowledge, reading ability, visuospatial skills, working memory capacity (verbal and visuospatial), and metacognitive awareness and process-level variables such as boredom and cognitive load
  - Affective, motivational, cognitive, and metacognitive variables during learning and the independent as well as combined effects they produce on the effectiveness and efficiency of learning, situational and sustained interest on the subject matter, learning self-efficacy, etc.
- Develop and test design strategies and solutions to address process-level individual differences and create more nuanced learner models for adaptive learning technologies.

Acknowledgments This article is based on work supported by the National Science Foundation under Grant No. 1540888.

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