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INTRODUCTION

# Leveraging Learning Theory and Analytics to Produce Grounded, Innovative, Data-Driven, Equitable Improvements to Teaching and Learning

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Research in educational psychology involves empirical investigation into the learning process with an aim to refine psychological theories of learning and their application to real-world settings where they can be used to benefit learners. Emergent methodological processes involved in learning analytics include the study of event-based data produced by individuals in learning environments where they use technology. Paradigms for substantive-methodological synergy can be used to align the strengths of educational psychology and learning analytics research. The *Journal of Educational Psychology* invites such collaborations. This issue illustrates the advancements to educational theory and practice that can be attained when learning analytics practices are aligned to reflect the assumptions within psychological theories of learning and learning analytics methods including feature engineering and multimodal modeling are leveraged. Exemplars demonstrate learning analytics' potential contribution to the refinement and application of theories of learning and motivation.

***Educational Impact and Implications Statement***
Theories about learning describe complex processes and how the ways individuals undertake them affect the understanding they obtain and performances they achieve. Many of these learning processes are difficult to observe in the naturalistic settings where people learn. When data individuals produce during learning with technologies are collected and modeled in alignment with learning theories and using learning analytics methods, they can make learning processes observable. Incorporating learning analytics into the study of learning and the development of instruction can help refine learning theories and the design of technologies that individuals use to learn.

*Keywords:* learning analytics, theory development, motivation, learning processes, feature engineering



The *Journal of Educational Psychology* is a scholarly outlet that holds within its aims and scope, an intention to empirically investigate learning and to contribute to "the refinement of theories that describe learning, and practices that achieve a demonstrable impact in authentic educational settings" (i.e., American Psychological Association, 2024). The leadership of the journal places particular focus on transparency in the collection of data meant to reflect diverse populations of learners and the analyses of these data as they test and refine inferences about the generalizability and application of theories of learning (Kendeou, 2021). This issue of the *Journal of Educational Psychology* echoes these aims and highlights the potential advantages of integrating learning theories common to educational psychology scholarship with learning analytics as a methodological approach that can improve the representation of individuals and their actions in the environments where they learn. The studies published in this issue serve as exemplars that demonstrate (a) how the tremendous potential of learning analytics can be more fully realized when practices are informed by insights and guidance from psychological theories of learning and (b) that when analytics are aligned to reflect theorized phenomena, learning analytics can be plied to test novel research questions that include variables that heretofore were challenging to observe and that have stymied the study of learning.

*Editor's Note.* This is an introduction to the special issue "Leveraging Learning Theory and Analytics to Produce Grounded, Innovative, Data-Driven, Equitable Improvements to Teaching and Learning." Please see the Table of Contents here: https://psycnet.apa.org/journals/edu/117/1.—PK

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## A Convergence of Learning Theory and Learning Analytics Scholars and Scholarship

The learning analytics community has coalesced over a decade into a formalized scholarly network that includes information and computer scientists, as well as learning scientists, learning technologists, and members of the educational psychology community (Society of Learning Analytics Research, 2024). In the most recent edition of the society's *Handbook of Learning Analytics* (Lang et al., 2022), the editors placed learning analytics at the nexus of concerns related to outsized growth in data about the individuals who use technologies. They identified an opportunity to use such data for societal good, which together produce an emergent need for a community of inquiry to inform how data can be made to benefit the individuals who produce them, and those who come after. This recent redoubling of focus in the learning analytics community's aims converges with the aims of the educational psychology community and approaches the aims of the *Journal of Educational Psychology.*

Established scholars in educational psychology have joined the learning analytics community and brought with them expertise in learning theory and experimental and measurement practices (e.g., Winne, 2017, 2022). This special issue was designed to deepen the intersection between educational psychology and learning analytics by making that relationship a bidirectional one. By welcoming the learning analytics community to contribute to the discourse in the *Journal of Educational Psychology* and broader conversations hosted by the American Psychological Association, we aim to recruit the analytical expertise and innovative spirit of learning analytics scholars and the opportunities presented by the research they conduct. Those who responded to this call included collaborative teams with backgrounds in educational psychology and in learning analytics, and their work illustrates this synergistic relationship through the scholarship that such collaborations have produced.

The specific goal of the special issue was to leverage the empirical and analytical promise of learning analytics by aligning closely to learning theory to refine models of learning and enhance and ensure the equity of the impact of learning technology for learners. In doing so, we sought exemplars of learning analytics research that (a) were grounded to specific theories of learning in ways that deeply instantiate a theoretical model into a learning context and the data that derive from it, (b) leveraged the volume of data and analytical methods to test complex assumptions of learning theories, and (c) drew data from learning environments that represented learners and contexts richly, in order to demonstrate the impact that learning analytics can have on practice.

The result is a collection of articles that involved a systematic undertaking and reporting of the convergence of theory and analytics. We welcomed all scholars who proposed a paper for this special section to (a) declare a theory of learning and instantiate a conceptualization of that theory within an educational context (e.g., Schunk, 2019), (b) describe an empirical study in which data produced by individuals who engage with a technology can be understood through the lens of that theory and analyzed using novel methods to derive insights that (c) produce a demonstrable impact on an educational outcome of value to teachers or learners in kindergarten through 12th grade (K–12) or higher education settings.

## Opportunities to Refine Theories of Learning

The use of learning analytics affords opportunities to observe samples that are highly representative of the populations they reflect and in the naturalistic contexts where they learn, without disrupting learning processes (Aleven et al., 2010; Greene & Azevedo, 2010). Furthermore, the volume of data collected from these many learners, at a granularity that reflects moment-to-moment learning processes over long periods of time, produces a record of learning that is ripe for educational data mining (Romero et al., 2010) and the study of "Learning at Scale" (Reich, 2022). Applications of learning analytics to fields of inquiry include the study of self-regulated learning (SRL; Winne, 2022), collaboration (Chen & Teasley, 2022), discourse (Dowell & Kovanović, 2022), writing (Gibson & Shibani, 2022), as well as cognitive and metacognitive (Roll & Winne, 2015), motivational (Bernacki et al., 2015), and emotional processes (D'Mello & Jensen, 2022).

However, leaders within the learning analytics community who have lauded the growth of their field, innovation in methods, and the scale of their application have also cautioned the community to "not forget: learning analytics are about learning" (Gašević et al., 2015, p. 64). Such clarion calls were offered during the formation of the community (Clow, 2012) and periodically thereafter (Gašević et al., 2015; Merceron, et al., 2015; Wise & Shaffer, 2015). Some also conduct empirical self-studies to monitor ways research activity shifts in or drifts from theory (Guzman-Valenzuela et al., 2021; Khalil et al., 2022a, 2022b). To address this challenge, some have provided guided examples to help researchers ground their inquiries to theories of learning (e.g., SRL; Winne, 2017, 2022). Others recommend careful consideration to ensure measurement approaches reflect specific learning constructs (Gray & Bergner, 2022), and underscore that data collected unobtrusively must be validated to ensure the inferences made from data validly reflect the experiences of learners (Winne, 2020). These theoretical conceptualizations and the validation of their application to data are necessary for learning analytics to achieve a robustness that enables them to be applied productively in practical settings (Wise, et al., 2018) and positively impact learners (Knight et al., 2019; Ochoa et al., 2020).

### A Renewed Focus on Theoretical Refinement

In educational psychology, renewed focus has been placed on theoretical refinement and the ways that scholars can undertake focused programs of empirical research to interrogate and support or refine assumptions made in the major theories that form the basis of our collective beliefs about learning and instruction. For instance, Greene (2022) questioned how the field of educational psychology could benefit from engaging with theory development. This involves the consideration of "virtues" of theories that might focus on a theory's capacity to describe phenomena related to learning, as well as how the empirical scholarship investigating the theory can generate evidence of these phenomena and provide opportunities to scrutinize assumptions. At the center of such a model that converges descriptive and explanatory aspects of a theory is a space for praxis, where the coherence of what is theorized and what is observable is put to the test, and support for a theory—or the potential for its revision—is produced. This renewed focus has co-occurred with special issues that focus on the reconsideration of prominent theories in areas like motivation (Wigfield & Koenka, 2020) and structured appraisals of the historical origins, evolution, and enduring virtues of theories (Greene & Robinson, 2024).

Theory development lies at the heart of the educational psychology research tradition, where a priori hypothesizing guides experimental design, hypothesis testing, and discussion of theoretical implications. This is indeed a virtue of the scholarship of educational psychologists, and publications resulting from the process comprise much of this journal's content. A contrasting set of virtues can be found in the learning analytics community's approach to the study of learning.

## Virtues of Learning Analytics for Theory Refinement

Unlike educational psychologists who often begin with theory and design measures of the phenomena they wish to observe, research in learning analytics often proceeds through the combination of an opportunity to access data from a learning task, and the ingenuity to make meaning and draw insights from it.

### *Approaches to Data*

Learning analytics researchers excel at drawing insights from machine data (Jordan & Mitchell, 2015) that are produced in order to afford communication between devices, and to serve content to the users who request them. Put simply, when a learner clicks a learning object, they initiate a "get" request to the server. The server responds to this "get" event by providing the requested object to the learner on screen, and a corresponding "post" event is logged. The timing of the event, the user's identifier, the object's identifier, and the action the user took (and input they made) comprise the key data in an event record that can be stored in one of a few standardized formats for interoperable use across learning technologies (e.g., Caliper events; Instructional Management Systems Global Learning Consortium, Inc., 2020). These event data can be enriched with the additional metadata available that can further describe the user, the object, or context (i.e., the course and unit) when these descriptors can be looked up in data tables of users, objects, and courses in the relational database of learning technology (e.g., learning management system fact tables; Bernacki, 2023).

Learning analytics researchers excel at the collection and organization of data (Khalil et al., 2022a, 2022b), visualization (Alhadad, 2018), and their combination into multimodal, multichannel learning analytics (Giannakos et al., 2022) that can represent learning processes in great detail across multiple tools instructors incorporate into course designs. They further excel at the application of established and emerging analytical tools including classical artificial intelligence approaches like machine learning (Arizmendi et al., 2022), and emergent, generative artificial intelligence (Khosravi et al., 2023). These methods often produce insights that can be fed back to the teachers and learners who use the technology, and this "closing the loop" is perhaps the most prized outcome of research in learning analytics and related communities (Campbell et al., 2007; Clow, 2012).

### *Approaches to Analysis and Applications Back to Learning Environments*

In higher education, event data can also be linked to databases at institutions that can describe the learner and their educational records (e.g., My Learning Analytics ( Teasley et al., 2021), and which can provide substantial details about courses as learning contexts. In K–12 settings metadata can also reflect learning task details when learning software includes a finely annotated alignment to an internal curriculum like a knowledge component model in an intelligent tutoring system (e.g., MATHia; Carnegie Learning, 2024) or mapping to external standards via metadata can inform instructors' assessments (e.g., of performance on math problems' aligned to a curriculum like Engage New York and its alignment to standards in learning platforms like ASSISTments; Heffernan & Heffernan, 2014).

When event data are collected and enriched in these ways, these data can be used by educational practitioners to make decisions about instruction in classrooms (Holstein et al., 2017), and instructional designers who refine learning tasks (i.e., on the design loop; Aleven et al., 2017). They can also serve as a powerful form of observation, as individual events, sequences, and their occurrence under specific conditions that enable researchers to make inferences about the learning process (Bernacki, 2018). These data thus afford an opportunity for researchers who study learning theories to organize these data about individuals, contexts, and events to reflect and test the assumptions made within their respective theoretical frameworks.

For example, both researchers from educational psychology (e.g., a special issue of *Educational Psychologist*; Greene & Azevedo, 2010) and learning analytics communities (e.g., a special section of *Journal of Learning Analytics*; Roll & Winne, 2015) have pursued these kinds of opportunities for studying the complexity described in theories of SRL (Winne & Hadwin, 1998). Those special issues and the host of empirical studies of SRL involving learning analytics have interrogated and refined assumptions about theorized temporal, sequential, and contingent processes (Ben-Eliyahu & Bernacki, 2015; Winne & Hadwin, 1998). SRL researchers' use of methods like process mining (Bannert et al., 2014; Saint et al., 2021), sequence mining (Mahzoon et al., 2018), coherence analysis (Segedy et al., 2015), and others (c.f., Bergner et al., 2018) illustrate the "substantive-methodological synergy" (Marsh et al., 2023, p. 1) that can be achieved when theories are used to prompt questions to be answered and learning analytics are used to collect, model, and analyze data.

This special issue is designed to promote this opportunity for theory development. We highlight the substantive-methodological synergy achieved by collaborative research teams who have pursued the evaluation of psychological theories of learning through focused empirical studies that leverage new forms of observation of phenomena that are challenging to study using learning analytics. We then consider how this synergy can be applied to the major theories in educational psychology and potentiate their revision.

## The Emergence of Substantive-Methodological Synergy as a Driving Praxis

At the contact point between the descriptive and evaluative aspects of the theory development cycle by Greene (2022) exists an opportunity to apply the affordance of learning analytics. Through the lens of a guiding theory, the use of richly annotated, contextualized event data can represent the phenomena a theory describes and complex analyses can be applied to test theoretical models. Marsh et al. (2023) have recently encouraged this practice and described the use of emergent methods like learning analytics as supporting substantive-methodological synergy in educational research. Researcher teams who contributed scholarship to this special issue each selected a guiding learning theory that provided a substantive basis for their scholarly aims, which focus on one or more components of a well-articulated theory. Teams also selected one or more forms of data produced by individuals' engagement with technology-based learning environments that were thoughtfully designed and instrumented in order to reflect learners and their actions on the platforms at a fine grain size of observation. This fine-grained, unobtrusive data source provides the opportunity for the synergy Marsh et al. (2023) describe, and the potentiation of theory revision through planful empirical testing of research questions and hypotheses. This convergence of the substantive strengths of the community of educational psychology and the methodological innovations being developed by the learning analytics community has tremendous potential to improve theories of learning and their practical application in educational settings.

## Contemporary Examples of Substantive-Methodological Synergy

Articles in this issue provide a collection of exemplars of substantive-methodological synergy. The authors illustrate a variety of technologies designed to support learning, distinct populations of learners engaged in different academic domains, using diverse ways of engaging in learning with technology. They also intentionally provide extensive descriptions of their instructional design, data collection, and learning analytics processes to document the methodological details. The authors do so as a service to the field so that others might adopt similar approaches as suit their research aims, extend to additional learning technologies, and leverage the methodological affordances they describe. Each research team also provides an overview of a learning theory that guides their work, and a focused description of the key assumptions within that learning theory that they aim to interrogate with data well suited to reflect the phenomena involved. Examples of substantive-methodological synergy are summarized in the following sections, and readers can observe how leveraging learning theory and analytics can indeed achieve the aim of the special issue: the production of grounded, innovative, data-driven, equitable improvements to teaching and learning.

Learning analytics provides an opportunity to acquire data to represent these learning processes, and language from theory can inform the engineering of features to reflect focal processes. New developments in multimodal learning analytics (Giannakos et al., 2022) now provide an opportunity to collect multiple channels of data from learners to further validate the assumptions that engineered features reflect learners' processes (Bernacki et al., 2024; Fan et al., 2022a, 2022b), and that future applications of those features continue to explain variance in the outcomes that learning processes are theorized to produce (Bernacki et al., 2024).

### Theory-Guided Feature Engineering to Observe Learning Processes During Homework

Deininger et al. (2025) explicitly conceptualized their investigation through the lens of Marsh et al.'s (2023) substantive-methodological synergy approach and drew substantive guidance for their empirical inquiry from Trautwein et al.'s (2006) homework model. In this model, student characteristics and motivation are theorized to predict homework behaviors, which include homework engagement in the forms of effort and time expenditure, and the learning strategies undertaken during task completion. This engagement is theorized to predict learning and achievement in turn. Historically, interrogation of the model has relied on self-reports by students and adults responsible for them, and these data have been deemed insufficiently reliable to predict outcomes or adequately capture evidence of effort and time dimensions of engagement. Deininger and colleagues collected self-reports of homework effort to establish a baseline measure and sustain the methodological connection to the prior literature. They augmented it with data obtained from the Feedbook platform where learners completed language lessons, and which provided log files of their learning events. This record of students' activities provided the methodological opportunities that achieve their desired substantive-methodological synergy, through the process of feature engineering (Botelho et al., 2019). Of the many methods used in learning analytics to observe, model, understand, and predict learning, feature engineering most closely aligns with traditions in educational research like microgenetic analyses (Siegler & Crowley, 1991) and cognitive task analysis (Clark et al., 2008). In these approaches researchers, designers, and practitioners with extensive knowledge of guiding learning theories, tasks, and learners who engage in them work together to develop variables from raw data and corresponding metadata to reflect important aspects of learning described by a theory (e.g., Bernacki, 2018, 2023; Botelho et al., 2019). Deininger and colleagues did so with input from developers of Feedbook and teachers who assigned Feedbook lessons in their classes in Germany and produced a set of features that reflected dimensions of homework engagement that aligned to theory based on a principal components analysis. These features better explained variance in learners' outcomes than did the self-reports that had been obtained from students. They also afforded more precise modeling opportunities that reflected the key assumptions of the homework model in a testable path model. Results of the path model provided additional evidence that features of engagement including effort and time contributed to explaining variance in language learning performance, and that effort variables contributed substantially more than time variables in the model. Their findings illustrate substantive-methodological synergy, potentiate possible refinement to the homework model, and provide a cautionary note for future researchers who may reconsider reliance on self-report and instead adopt learning analytics to study this ubiquitous out-of-school practice.

### Building Tools to Detect Processes Essential to One's Ability to Learn

Bühler and colleagues (2025) focused on the core process of regulating attention during learning (Pashler, 1998), and investigated different varieties of mind wandering (Smallwood & Schooler, 2006) that students report when engaged in learning tasks. They found that the eye-tracking data they collected while students engaged in reading could be used to detect mind wandering and that self-reports from learners could be applied as metadata that described whether the mind wandering was related or unrelated to the task. This allowed them to consider the varieties of mind wandering that are theorized to distract from learning and diminish its efficiency, versus those that reflect intentional breaks that afford offloading of distraction and have restorative effects, where attention can be productively redirected to the focal task after the break.

Using multimodal learning analytics methods (Giannakos et al., 2022), Bühler and colleagues (2025) aligned self-reports to eye-tracking data which they had segmented into events (comprising fixations, saccades, and other eye movements). These could be used to reflect engaged attentive moments and instances of mind-wandering types. They undertook an algorithm development process to build detectors of mind wandering (e.g., Baker et al., 2020) which, when reapplied to a held-out subset of data, could detect mind wandering from gaze patterns and also discriminate when the learner may versus may not be aware of their own mind wandering. This methodology pairs with substantive information about attentional processes and can be used as a tool for ongoing research into attention on related tasks. The investigation also produced important evidence about learning outcomes. Findings suggest that these different kinds of aware and unaware mind wandering affected learning in different ways, where learners who are unaware they are mind wandering were found to struggle with fact- and inference-based learning tasks, and those who were aware of and engaged in persistent, intentional mind-wandering patterns showed poorer deep-level understanding of the focal task's features.

Because detectors can be programmed into technologies used by teachers in classrooms (e.g., Holstein et al., 2017), the findings can also have a direct impact on educational practice. If a mind-wandering detection algorithm is applied and its indicators can be detected in real time, adaptive support can be provided to (a) regain students' attention when they are unaware they have drifted from their task and (b) to encourage the focus of those who choose to mind wander. These detection-and-response approaches could offset the newly discovered risks that mind wandering poses to factual and conceptual understanding. Such detectors can also be used to observe patterns in mind wandering over longer periods of learning and to additional learning tasks hosted on the same technology. In this way, detectors can provide broader benefits where mind wandering across tasks can be detected and instructors can consider providing additional support to help students who encounter persistent challenges regulating their attention. For example ,these might include teaching strategies for motivation regulation (e.g., Wolters, 2011).

## Observation of Complex Learning Processes and Real-Time Support for Them

Gerard et al. (2025) focused on the domain of science through the lens of knowledge integration theory (Bell et al., 1995) and studied the challenges learners have activating and leveraging prior knowledge, generating new knowledge, and refining ideas from vague to more crystallized states. They observed such challenges in an established science learning platform and leveraged natural language processing (NLP) to understand the nature of the idea units learners would generate during tasks, as well as learners' ongoing revision of these ideas over time. They further leveraged the capacity of real-time application of NLP to detect idea units that could be improved, then experimented with scaffolded approaches to improve students' knowledge integration. In this design, the authors demonstrated the value of learning designs that provide learners with opportunities to record their thinking in written form—a generative process that is good for learning—and further demonstrated that through learning analytics involving NLP, the products of students' engagement can become a resource for assessing and improving on learners' developing understanding. They further demonstrated how learning analytics methods involving tools like NLP can not only provide learners and instructors with a sense of learners' progress integrating knowledge into a current state of understanding but also that tools that can detect the presence of ideas can also present those ideas back to students in ways that prompt further refinement and integration of ideas into deeper and more elaborated mental models of phenomena. The study sequence thus illustrates a tight instantiation of substantive-methodological synergy where knowledge integration is observed and improved through real-time application of learning analytics.

## Ongoing Observation of Time-Varying Processes Over Long Periods of Time and Varying Conditions

Goslen et al. (2025) extended research on metacognitive processes related to the planning phase within the theoretical frameworks of SRL (Winne & Hadwin, 1998). They examined the ways that initial planning and revisitation of initial plans over the course of the task reflect sustained metacognitive supervision of cognitive engagement during challenging science learning tasks. While planning tools were initially made available to help learners establish an organized approach to the task, their continued availability during task engagement enabled learners to continue to use the tool in a variety of ways. The authors used event data from science gameplay to trace learners' behaviors and developed learning analytics to evaluate patterns of events as potentially reflecting emergent SRL processes that are theorized to benefit learning. This innovation in methods is important because earlier work in SRL often treated planning as a phenomenon constrained to the beginning of a learning cycle. Furthermore, obtaining information about one's plans is challenging. When active methods of soliciting information about planning are used, they may fail to capture the ongoing behaviors related to one's initial plan, evolutions of it, or responses to it after engagement with the task, where progress made and lessons learned fundamentally change the nature of the task that remains and ways it should be engaged. Briefly, they found that most but not all students planned. Among those who did, plans were often revisited as a tool to continue to monitor learning. This phenomenon confirms an ongoing metacognitive process during learning (Azevedo & Gašević, 2019) and the additional actions that learners undertook after revisitations confirm the tight connection between cognition and metacognition described in theories of SRL where learners' engagement in metacognitive monitoring could be observed to precede and inform the metacognitive control processes they enact (Nelson & Narens, 1990; Winne & Hadwin, 1998). Learners could be seen to access their plans, update them by documenting progress, alter them as they evaluate that their methods need to change, or adjust their goals as they come to better understand their task and their ability to engage in it. While it is only a single study, this inquiry serves as an exemplar of the ways that learning events tied to tools meant to facilitate metacognition can capture many metacognitive processes including planning, monitoring, and evaluation. One critical challenge to such lines of inquiry is that these metacognitive processes themselves are seldom explicitly captured in learning technologies that only record action events (Bernacki et al., 2024). Unlike think-aloud and self-reports where learners make their thoughts known through verbalization, metacognitive processes must be inferred from log data based on the kinds of actions that followed them. It is reasonable to infer that a plan is established by the setting of a goal and establishment of strategies that can be used to achieve it. Thereafter, the crossing off or adding of new steps can be seen as a response to monitoring of progress toward a goal. The altering of strategies can be inferred as reflecting a previously occurring judgment that the prior strategies were not (or were no longer) successful in promoting learning or advancement toward the goal, and adjustments to the nature of the goal itself can be used to infer that learners' perceptions of the task and their interactions with it need to be altered to achieve a desirable resolution. All these fall within the theorized SRL moves that constitute learning cycles in information processing models of SRL, but such models are sufficiently complex that it is difficult to test their assumptions because prior events influence future ones, and any given instance of a learning event needs to be understood in the context of the conditions under which it occurs (Winne & Hadwin, 1998). Thus, these learning analytics methods involving only unobtrusive data collected passively from many learners provide unique promise for the future refinement of SRL as a psychological theory of learning. Metadata about learners, task conditions, and the previously logged activities can all be used in ways that approach a computational model of SRL. This can afford opportunities to test assumptions about the likelihood of learners' future actions, and about the value of one action over another for learning under specific task conditions, for specific learners.

### Multimodal Modeling Can Decompose the Complexity of Collaborative Learning

Both Yan et al. (2025) and Reitman et al. (2025) leverage the capacity of multimodal learning analytics platforms to examine different dimensions of collaborative learning and together provide a model of the ways that such modeling of multiple learners' collaborative engagement across different tasks. Individuals' learning can be observed across units of analyses that clarify how collaborative learning unfolds naturalistically, and under what conditions it may be more or less productive for learning and performance. Yan et al. (2025) illustrate the potential of multichannel, multimodal learning analytics (Giannakos et al., 2022) to investigate complex theories of both embodiment of individuals as they learn (Abrahamson & Lindgren, 2014), and in even more complex learning environments, the interactions of multiple individuals who move in space with and around one another while collaboratively engaging in open-ended learning and problem-solving tasks during simulations (Danish et al., 2020). These require thoughtful instrumentation of individuals to capture channels of physiological, behavioral, cognitive, and metacognitive metrics described by these multiple learning theories. This wealth of instrumentation and orchestration of multiple, multimodal data models of collaborative learners documents a path toward modeling the complex learning theories that span channels and modes of investigation (Molenaar et al., 2022) and grander theories of learning such as constructivism (Vygotsky, 1978). Each of these enterprises is not without immense challenge in maintaining data quality on all channels, dealing with its missingness, and modeling it in all the complexity proposed in theory when learners collaborate within tasks in space and over time as the demands of a task change.

Reitman and colleagues (2025) also focus on the engagement of multiple learners within a collaborative task and draw their substantive elements of their research from theories of cognition and collaboration (Hesse et al., 2015) to understand collaboration through the lens of team cognition (Gorman et al., 2020), interactive team cognition (Cooke, 2015), and the ways teachers and learners exert communicative influence during collaborative learning (Fleur et al., 2023). They draw upon methodologies of tracking a series of events enacted by individuals within a collaborative team to understand how individuals' inputs into the team's process influence outputs and are influenced by mediational processes exerted by other members of the team and the processes they enact. Capturing activities of multiple individuals working in collaborative teams, and at the granularity and detail needed to understand theoretically aligned processes within timed series of events as enacted by individuals, can be challenging. However, data produced by individuals during learning activities has long been captured and studied via transcripts in qualitative and mixed methods research in educational psychology (McCrudden et al., 2019), and chat logs from learning technologies have long been studied in communities of research on computer-supported collaborative learning (Schnase & Cunnius, 1995). Reitman and colleagues (2025) drew upon experimental methods to isolate roles and establish information about the communicative influence of members with assigned roles, then examine communicative influence in the context of collaborative problem-solving in middle school classrooms. Thereafter, they interviewed teachers to consider how the communicative influence observed to influence the collaborative learning process could be visualized for instructors, who can monitor and support collaboration. In doing so, they demonstrate the value of multiple study designs for the advancement of a learning theory (Alexander & Murphy, 2024), and how multimodal learning analytics drawn from in situ studies enacted with technologies in classrooms can provide opportunities to observe theorized phenomena validated in laboratory settings, and how those theorized and observed phenomena might be further orchestrated during instruction.

## Advancing an Educational Psychology Research Agenda Through Substantive-Methodological Synergy and Codesign Partnerships With Practitioners

As methods for observing, modeling, and analyzing learning and instruction continue to evolve, they afford new opportunities for representing theorized phenomena, and for developing psychological theories of learning through evaluation cycles. This special issue is meant to encourage expansion in substantive-methodological synergy in the scholarship of the educational psychology community and to broaden the aims of the *Journal of Educational Psychology* by encouraging scholars to adopt innovative methods that can test and refine theories and lead to advancements in educational practice. In alignment with conceptual special issues on motivation (Wigfield & Koenka, 2020) and learning (Greene & Robinson, 2024) published in other educational psychology journals, Table 1 summarizes the psychological theories of learning that have recently been considered through the lens of theory development (Greene, 2022). Within each theory, one or more observable phenomena exist and are often measured using methods that can intrude on students' learning process and yield self-reports that often lack the precision and reliability to afford close evaluation (Winne & Jamieson-Noel, 2003; Wolters & Won, 2018). The table summarizes the many opportunities that representing constructs via learning analytics may present to researchers whose work aligns with these specific theories. This approach will require researcher–educator co-design partnerships (Bernacki, 2023). Co-designing with instructors who know their students and their course design intention can improve the modeling of individuals and their theoretically grounded learning processes enacted within technologies, which learning analytics can describe. Through aligned design and analytics, data that align with learning theory and validly reflect learning processes can be shared back with those who can act to support learners (Lockyer et al., 2013).

## Opportunities to Impact Practice

As the use of learning technologies expands under typical and disrupted conditions in both K–12 and higher education settings, the potential value of the insights produced by learning analytics inquiries continues to grow in magnitude (Reich, 2022). Technology forecasts like the EDUCAUSE Horizon Report that track industry trends and priorities of K–12 and higher education administrators continually signal the desire for data-informed decision making, and the promise of learning analytics for meeting these needs (Pelletier et al., 2021).

**Table 1**
*Theories and Components Observable via Learning Analytics*

| Theory of learning | Components amenable to observation via learning analytics |
|---|---|
| Motivation[a] | |
| Situated expectancy value theory (Eccles & Wigfield, 2020, 2024) | Behavioral events reflecting achievement-related choices in contexts, contextual metadata reflecting situational conditions |
| Achievement goals (Elliot & Hulleman, 2017) | Behavioral events reflecting strategy engagement predicted by goal orientations |
| Attribution theory (Weiner, 1985) | Contextual data that provide information about conditions under which attributions are made |
| Self-efficacy (Bandura, 1986) | Performance data reflecting success, behavioral data reflecting related actions |
| Self-determination (Ryan & Deci, 2000) | Choice behaviors, metadata on environments (and their support for autonomy) |
| Learning[b] | |
| Apt AIR model of epistemic cognition (Barzilai & Chinn, 2024) | Epistemic processes (individual, collective strategies to achieve aims; evaluate claims or sources, engage in group argumentation) |
| Cognitive load theory (Sweller, 2023) | Contextual metadata reflecting details of media engaged; timestamped events capturing time spent engaged, navigating, interacting |
| Control value theory (Pekrun, 2024) | Institutional data that describe antecedent learner characteristics, behavioral event data reflecting actions |
| Multimedia learning theory (Mayer, 2024) | Contextual metadata reflecting details of the media engaged, timestamped events capturing time spent engaging and navigation and interaction choices |
| Metacognitive affective model of SRL (Efklides & Schwartz, 2024) | Behaviors reflecting metacognitive control; multimodal, multichannel models that collect emotion data; behavior logs reflecting cognitive strategies enacted |
| Knowledge revision (Kendeou, 2024) | Navigation behaviors across media and resources, inputs reflecting knowledge state, with scoring via natural language process methods; timestamps capturing revision processes |
| Race-reimaged learning theory (DeCuir Gunby & Schutz, 2024) | Institutional data applied as metadata to describe background demographics and achievement of learners; metadata about the learning context and instances where individuals access and opportunity are limited; inputs by learners and teachers during learning |
| Scientific thinking (Lombardi et al., 2024) | Navigation behaviors across media and resources reflecting cognitive engagement and reasoning with media, scoring of inputs via NLP. Contextual metadata inform coding of engagement |
| Self-regulated strategy development (Harris, 2024) | writing quality and length, and features within writing (via NLP, e.g., observation of activation of background knowledge) |

*Note.* AIR = aims, ideals, reliable processes; SRL = self-regulated learning; NLP = natural language processing.
[a] Article reconsidering theory appearing in Wigfield and Koenka (2020). [b] Article reconsidering theory appearing in Greene and Robinson (2024); situated expectancy value theory appeared in both issues.



In the United States, educational policies include initiatives and sources of funding to advance personalized learning (e.g., ESSA, 2015) and these are reliant on the data that inform learning analytics (Bernacki et al., 2021). K–12 students' learning experiences and performances stand to benefit from (a) teacher and student-facing dashboards and tools (Matcha et al., 2019; van Leeuwen et al., 2022; Verbert et al., 2013); (b) rich records of preference, progress, and performance that can inform adaptive technologies (Aleven et al., 2017; Bernacki et al., 2021; Plass & Pawar, 2020); and (c) nationwide policies on the hosting of data on learning, so that can be adaptive instruction can be provided at scale (e.g., Aguerrebere et al., 2022). In higher education settings, administrators focused on retention, progression, and completion further seek to leverage learning analytics approaches to produce algorithms and other tools that can benefit learners. Students in these settings might benefit from tools that (a) observe and predict student success (e.g., Arizmendi et al., 2002; Arnold & Pistilli, 2012, Plumley et al., 2024) (b) provide timely learning support to improve student achievement (Cogliano et al., 2022); or (c) deliver "institutional intelligence" (Wells, 2007) to improve the efficiency of operations and responsiveness to students (MacFadyen, 2022), among other beneficial aims.

## Developing an Educational Psychology Community That Can Pursue This Agenda

Educational psychologists have deep knowledge of learning theories, the ability to conceptualize problems of practice through the lens of theory, and the skill to build research designs that answer their questions and address their aims. They also often possess well-practiced analytical skills needed to do so, as well as the skills needed to obtain access to populations of learners, engage key stakeholders who can provide insights about learning contexts and learner populations, and recruit colleagues whose complementary expertise contributes to the team science needed to achieve research goals (Ledford, 2015). As learning theories become increasingly well-researched, however, educational psychologists now enact theory development cycles that have progressed to testing of specific assumptions that involve investigation of highly complex relationships. These studies often require collection of large amounts of data and often under criteria that reflect contingent, sequential, and context-specific processes that capture the most nuanced assumptions of a learning theory (e.g., theoretical frameworks of SRL; Ben-Eliyahu & Bernacki, 2015; Winne & Hadwin, 1998). This level of precision in the theoretical assumptions to be modeled necessitates complex research designs and underscores the importance of establishing research partnerships that can provide data obtained in naturalistic settings, where well-contextualized environments can be understood, and data can be obtained at an appropriate grain size for a valid representation at this unit of analysis (Winne, 2020). Team science is a necessity at this phase of theory development, and a complementary team likely includes technology developers, teacher and student users, and other key stakeholders alongside the educational psychologist.

Educational psychologists in training would benefit from completing coursework that prepares them to lead research teams with complementary expertise, and opportunities to study of theories and their assumptions closely, alongside opportunities to conceptualize, design, and instrument studies that can advancetheory development and application of theory to problems of practice. This might include coursework, internships, and other experiences that (a) prepare them to work with learning technology developers and the teachers and learners who use software so that they might use learning analytics to engineer features that better reflect the phenomena theories describe, (b) develop their ability to conceptualize research design informed by theory and instrumented with data-intensive methods that reflect that theory, and (c) provide training in the data modeling and analyses necessary to test the complex assumptions posed in psychological theories of learning. With such collaboration and training, the collaborative teams that such newly minted education researchers will lead can leverage their understanding of learning theory and pursue skillful application of learning analytics to produce grounded, innovative, data-driven, equitable improvements to theories, designs, and teaching and learning practices.

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