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A framework for evaluating and enhancing alignment in self-regulated learning research

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Abstract We discuss the articles of this special issue with reference to an important yet previously only implicit dimension of study quality: alignment across the theoretical and methodological decisions that collectively define an approach to self-regulated learning. Integrating and extending work by leaders in the field, we propose a framework for evaluating alignment in the way self-regulated learning research is both conducted and reported. Within this framework, the special issue articles provide a springboard for discussing methodological considerations of increasingly sophisticated research on the dynamic, contingent, and contextualized features of self-regulated learning.

Keywords Self-regulated learning · Reporting standards

Contributors to this special issue pose important new questions about self-regulated learning as a dynamic, contingent, and deeply contextualized constellation of constructs that has proven challenging to conceptually and operationally define (Pintrich 2000; Winne and Perry 2000; Zeidner et al. 2000). This special issue represents the latest addition to a growing literature tackling these challenges (e.g., Azevedo et al. 2010; Greene and Azevedo 2010; Molenaar and Jarvela 2014; Schraw 2009; Veenman et al. 2006), framed by three topical themes that are increasingly acknowledged if not empirically tested in self-regulated learning research (Ben-Eliyahu and Bernacki 2015). Our commentary is thus organized around these themes, using the studies that address each as a springboard for exploring methodological promises and pitfalls of increasingly sophisticated self-regulated learning research.

In particular, we reflect on the articles and themes of this special issue through a framework for evaluating *alignment* in the way self-regulated learning research is both conducted and reported. That is, we propose interrelated recommendations that promote coherence or compatibility across the theoretical and methodological decisions that collectively define a scholar's approach to self-regulated learning from the first through final stages of a study.

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The remainder of this introductory section is devoted to describing the evaluative framework, after which we apply its recommendations in the subsequent sections organized around each special issue theme: dynamic relations, contingencies, and context. We conclude with suggestions for integrating these themes through series of primary studies and meta-analysis.

The diverse literature on self-regulated learning is characterized by multiple theoretical perspectives (see Zimmerman 2001), elaborate theoretical models (e.g., Efklides 2011; Winne and Hadwin 2008), different ways of defining or labeling their many constructs (Dinsmore et al. 2008; Zeidner et al. 2000), and evolving views on measurement (Azevedo 2014; Hadwin et al. 2007; Winne and Perry 2000; Zimmerman 2008). Once implying a relatively stable aptitude, both conceptual and operational definitions of self-regulated learning now reflect an unfolding series of events (e.g., Azevedo 2014; Winne 2014) sensitive to contextual factors ranging from task structure (e.g., Lodewyk et al. 2009; Malmberg et al. 2014) to societal stressors (e.g., Ben-Eliyahu and Bernacki 2015). Conceived this way, self-regulated learning can be facilitated or constrained by several ecological levels that manifest in task, sample, and setting characteristics. As a result, these characteristics influence how self-regulated learning operates in a given study.

Taken together, features of both self-regulated learning and its diverse literature produce several critical decisions that collectively define a scholar's approach to studying this complex phenomenon. From adopting a theoretical perspective to drawing inferences from findings, these decisions have assumptions and implications that reverberate throughout the research process. In this commentary, we integrate and extend work by leaders in the field (e.g., Azevedo 2009, 2014; Greene and Azevedo 2010; Schunk 2008; Wampold et al. 1990; Winne and Perry 2000; Zimmerman 2001) to identify nine decisions that shape the approach to and results of a given study on self-regulated learning. These decisions include the theoretical perspective, theoretical model, construct label, construct definition, research question, certain characteristics of the research design (i.e., task, sample, setting), measurement strategy, approach to data analysis, and inferences from findings that together guide how the study is conducted from its first through final stages. We argue for careful planning and transparent reporting of these decisions to improve their alignment, which ultimately influences both the interpretation of study findings and evaluation of study quality.

When combined, these decisions give rise to an interrelated set of recommendations for conducting and reporting self-regulated learning research that focuses on alignment across them. We argue that the degree of alignment across decisions is one dimension along which research on self-regulated learning should be evaluated, especially as increasingly sophisticated ways of modeling and measuring it render alignment more difficult to achieve. Therefore, we evaluate each study in the special issue through this framework for two main reasons. First, applying its recommendations to each article allows us to explain and exemplify them in action. Second, doing so provides a springboard for discussing methodological considerations when studying the dynamic, contingent, or contextualized features of self-regulated learning.

We propose two complementary levels of alignment that together produce a single evaluative framework for conducting and reporting research on self-regulated learning, among other constructs within or even beyond psychology. The first, broader level is comprised of three decisions for which alignment could be achieved in any behavioral science: the research question(s), approach to generating data, and approach to analyzing data (Fig. 1). Reflecting its more universal application in behavioral science, this level of alignment is not unlike hypothesis validity in clinical research (Wampold et al. 1990). The second, narrower level of alignment is comprised of several decisions specific to the complexities of self-regulated learning and its diverse literature. These decisions include the theoretical perspective, theoretical model, construct definition(s), construct label(s), construct measure(s), and certain features

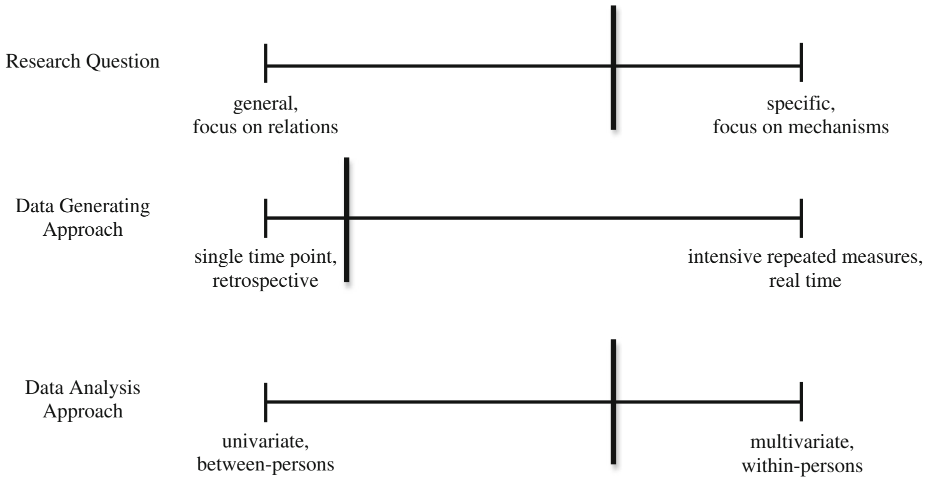

Fig. 1 Level of alignment applicable to research across the behavioral sciences. *Vertical bars* indicate location along the spectrum of research questions, measurement strategies, and approaches to data analysis for a hypothetical study displaying partial alignment across them. Misalignment producing the above location of vertical bars could arise from interrelated research questions proposing multiple mediators tested through structural equation modeling based on summative measures administered at two time points. For example, self-regulated learning processes (e.g., planning, metacognitive monitoring) are proposed as mediators of the relation between academic motivation constructs (e.g., goal orientations) and achievement in math or science. Self-regulated learning and academic motivation are then measured at the beginning of a semester through self-report questionnaires, while achievement is measured at the end of a semester through average course grades. In this hypothetical study, the location of research questions along their spectrum from a general focus on relations to a specific focus on mechanisms reflects an attempt to identify SRL processes that explain the relation between two other academic variables (i.e., motivation and achievement). The location of the data generating approach along its spectrum reflects the summative, retrospective nature of each measure and their administration at two time points (i.e., self-regulated learning and academic motivation at the beginning of a semester and achievement at the end). The location of the data analysis approach closely tracks the research questions by modeling multiple correlated mediators of two multidimensional constructs through statistical tests that can accommodate both. In this hypothetical study, alignment could be improved by measuring students' academic motivation for a task then their SRL processes during and performance on it. Capturing self-regulated learning in real time would preserve its contingent and contextualized features while more closely tracking the complex research questions tested through structural equation modeling. Alignment in this and many cases is improved by critiquing the assumptions underlying theoretical or methodological decisions that shape how a study is conducted from its first through final stages

of the research design (i.e., task, sample, setting). The two levels of alignment share a common component, namely the approach to gathering data about focal constructs that we refer to as the *measurement strategy* in a study (e.g., retrospective self-report, think-aloud protocol). The shared and unique components of alignment at each level also influence a final decision in self-regulated learning research, namely inferences from findings.

As a result, our evaluative framework reflects nine components of alignment that together underlie an important yet previously only implicit dimension of study quality. Alignment at the broader level can be deceptively difficult given the proliferation of sophisticated statistical options, each with its own nuanced implications for precisely how a hypothesis is tested. Alignment at the narrower level is essential to ensure results are interpreted correctly and theory is revised appropriately, especially as models and measures of self-regulated learning evolve to more accurately reflect its dynamic, contingent, and contextualized processes. For these reasons, there is perhaps no better time or forum to focus a methodological lens on both levels of alignment within self-regulated learning research.

Our evaluative framework thus emphasizes alignment in how self-regulated learning research is conducted *and* reported, recognizing that determining how well the former has been achieved hinges on precision and transparency in the latter. Therefore, we argue that demonstrating the degree of alignment across theoretical and methodological decisions should be a new reporting standard in self-regulated learning research. To facilitate adoption of this standard, recommendations for enhancing and evaluating alignment are provided in Table 1. Although this table focuses on reporting, it could be consulted when planning and conducting studies on self-regulated learning to promote alignment at these pivotal stages of the research process. Reviewers could also consult Table 1 when evaluating alignment as a new dimension of study quality in order to critique empirical manuscripts or proposals through consistent and comparable standards. We explain and exemplify recommendations in Table 1 within the next sections, which are organized around the themes of this special issue.

Dynamic relations

Although long considered a defining feature of self-regulated learning (e.g., Zimmerman 1989), dynamic relations among its phases or processes have only recently gained empirical traction with the emergence of sophisticated measures that can capture them in real time. Bernacki et al. (2014) build a compelling case for the dynamic interplay among motivational precursors, metacognitive processes, and academic products of self-regulated learning during a task, doing so with a creative methodological approach capable of validly testing their theoretical argument. This argument gives rise to novel research questions that underscore both the empirical importance and scholarly value of considering the assumptions underlying how self-regulated learning has been conceptually and operationally defined.

Considering these assumptions is critical because alignment among theoretical and methodological decisions often depends on them. For example, Bernacki et al. argue that measures of self-efficacy have historically portrayed this motivational process as relatively stable during self-regulated learning despite both classic and modern conceptualizations implying sensitivity to contextual or cognitive cues of task competence. The theoretical assumption underlying this centerpiece of prominent self-regulated learning models (e.g., Zimmerman 1989, 2008) is thus misaligned with the assumptions underlying how it is often measured. This misalignment produces inferences about self-regulated learning that may misrepresent the dynamic relations among its motivational or metacognitive processes, reinforcing the empirical importance of alignment among decisions *and* their assumptions. Ensuring this alignment enhanced both the hypothesis validity and scholarly value of Bernacki et al.'s study.

Their study also highlights how misalignment among decisions may only be uncovered when theoretical or methodological assumptions are specified and critiqued. As a result, we recommend transparent reporting of assumptions that underlie how self-regulated learning is conceptually and operationally defined in a study. Researchers should supplement the reporting of relevant assumptions with an argument for their degree of alignment to further the goals of both enhancing and evaluating it.

Bernacki et al.'s study illustrates the importance of another reporting standard for evaluating alignment between methodological decisions and inferences in self-regulated learning research. The increased popularity and prevalence of real time measures has been met with concerns that they disrupt how self-regulated learning unfolds during an academic task (see Binbasaran-Tuysuzoglu and Greene 2014). Although these concerns have been successfully

Table 1 Summary of recommendations to improve alignment when conducting and reporting self-regulated learning research

	Alignment Component	Recommendations
Conceptualizing the Study	Theoretical Perspective	- If a theoretical perspective or its assumptions about self-regulated learning (see Zimmerman 2001) inform how the study is conceptualized or conducted, they should be reported in the Introduction. - Implications of adopting a theoretical perspective and its assumptions about self-regulated learning should be explained in the Introduction.
	Construct Label(s)	- Labels of self-regulated learning and its constructs examined in the study should be reported in the Introduction. - Labels of self-regulated learning constructs should be situated in the literature, with connections to the nomenclature of certain theoretical perspectives, theoretical models, or prevailing trends noted. - Alternative labels denoting the same self-regulated learning construct should be acknowledged to promote integration of the study within the literature. - To promote more precise construct specification, labels denoting similar constructs could be noted and differentiated (e.g., self-regulation vs. self-regulated learning; co- vs. self-regulated learning). - To promote clarity of construct specification, labels should be used consistently with any departures from them explained.
	Construct Definition(s)	- Conceptual definitions of self-regulated learning and its constructs examined in the study should be reported in the Introduction. - Alignment between the construct definition(s) and label(s) should be demonstrated in the Introduction. - Definitions of self-regulated learning and its constructs examined in the study should be situated in the literature, with connections to theoretical lineages or prevailing trends noted. - If definitions of self-regulated learning or its constructs examined in the study are tied to a certain theoretical perspective, this connection and its implications for alignment should be reported in the Introduction. - Theoretical assumptions about self-regulated learning underlying construct definitions should be acknowledged in the Introduction. - Methodological implications of construct definitions and their assumptions about self-regulated learning should be explained in the Introduction.

Table 1 (continued)

	Alignment Component	Recommendations
	Theoretical Model	- A theoretical model of relations among the phases and processes of self-regulated learning should be clearly articulated (Azevedo 2009, 2014) in the Introduction. - If the chosen or created model is tied to a certain theoretical perspective, this connection and its implications for alignment should be reported in the Introduction. - Theoretical assumptions underlying the model of self-regulated learning should be acknowledged in the Introduction. - Methodological implications of the model and its assumptions about self-regulated learning should be explained in the Introduction. - Alignment among the theoretical model, construct definition(s), and their assumptions about self-regulated learning should be demonstrated in the Introduction.
	Research Question(s)	- Research question(s) and the hypothesized direction of findings, if any, should be reported in the Introduction. - Theoretical assumptions underlying the research question(s) should be acknowledged in the Introduction. - Methodological implications of the research question(s) should be explained in the Introduction. - Location along the spectrum of research questions ranging from a general focus on relations to a specific focus on mechanisms should be identified (see Fig. 1). - Alignment among the research question(s), measurement strategy, and data analysis approach should be described in the Introduction or Method.
Conducting the Study	Research Design	- Design characteristics (e.g., sample age, task structure) that may influence the way self-regulated learning operates or appears in a study should be reported in the Method. - Theoretical and methodological implications of design characteristics should be explained in the Introduction. - Compatibility of sample characteristics (e.g., age) and measurement choices (e.g., self-report) should be described in the Introduction, with limitations acknowledged.
	Measurement Strategy	- Features of the measurement strategy that may influence how self-regulated learning operates or appears in the study should be reported in the Method.

Table 1 (continued)

Alignment Component	Recommendations
	- Theoretical assumptions about self-regulated learning underlying the measurement strategy should be acknowledged in the Introduction. - Compatibility of the measurement strategy with the theoretical model, construct definition(s), and their assumptions about self-regulated learning (see Winne and Perry 2000) should be described in the Introduction, with limitations acknowledged. - The theoretical perspective(s), model(s), or assumptions guiding how qualitative or real time data is coded and interpreted (see Perry and Winne 2006; Winne 2010) should be described in the Method. - Location along the spectrum of measurement strategies ranging from retrospective single time point to repeated measures in real time should be identified (see Fig. 1).
Data Analysis Approach	- How the data analysis approach and specific statistical tests directly address the research question(s) should be described in the Method. - Statistical tests beyond those that directly address the research question(s) should be minimized to enhance hypothesis validity (Wampold et al. 1990). - Assumptions underlying the data analysis approach should be acknowledged in the Method when relevant to other theoretical or methodological decisions that collectively define the approach to self-regulated learning. - Implications of assumptions underlying the data analysis approach should be explained in the Method when relevant to other theoretical or methodological decisions that collectively define the approach to self-regulated learning. - Location along the spectrum of data analysis approaches ranging from univariate, between-persons to multivariate, within-persons should be identified (see Fig. 1).
Inferences	- Inferences should be qualified based on the generalizability of sample, task, and other design characteristics that may have shaped how self-regulated learning operated or appeared in the study. - Inferences should be qualified based on the degree of alignment among decisions that collectively defined the approach to self-regulated learning, which should be evaluated in the Discussion.

addressed (e.g., Ericsson and Simon 1993, 1998; Greene et al. 2011), implications of the task through which self-regulated learning is measured have received relatively less attention. Researchers agree that self-regulated learning can be facilitated or constrained by characteristics of an academic task (Lodewyk et al. 2009) and even domain (Wolters and Pintrich 1998), with more structure (e.g., detailed instructions, sequential steps) providing fewer affordances or demands for students to engage in this dynamic process. As a result, task characteristics such as the degree of structure influence how students self-regulate their learning (Lodewyk et al. 2009; Malmberg et al. 2014).

This sensitivity of self-regulated learning to contextual factors may limit the generalizability of findings to tasks with similar characteristics as the one used to measure it in real time (Winne and Perry 2000). Therefore, misalignment could occur between the academic task used in a study and the breadth of inferences about self-regulated learning drawn from it. For example, the Cognitive Tutor Algebra (Carnegie Learning 2011; Bernacki et al. 2014) provides an enriched learning experience during which the computer program scaffolds some self-regulated learning processes (e.g., knowledge judgments via the *skillometer*, metacognitive monitoring via embedded feedback) while students solve math problems. Taken together, the relatively well-structured academic task and domain in Bernacki et al. may constrain students' need or opportunity to engage the full array of self-regulated learning processes. As a result, inferences about specific processes should be qualified if the academic task may alter how they operate or appear in a study. As this example illustrates, researchers should report the generalizability of task characteristics when interpreting findings and revising theory based on data from real time measures of self-regulated learning.

Despite distinctive task characteristics that may limit the generalizability of findings beyond intelligent tutoring systems or math, their combination in this study provides an ideal proving ground for Bernacki et al.'s hypotheses about dynamic relations during self-regulated learning. For example, observable traces of metacognitive processes were recorded in a way that preserves their temporal order and spacing. Moreover, automated prompts were frequent enough to capture meaningful fluctuations in self-efficacy without disrupting students' progress or self-regulation through the math problems. Although commendable, this methodological approach also reveals considerations for future research on dynamic relations.

Given their focus on fluctuations in students' self-efficacy during an academic task, the reliability of a single item to capture this construct deserves further attention. From an analytic perspective, the concern is how to distinguish valid sensitivity to change from unreliability of measurement. Bernacki et al. note that a high correlation (e.g., $r=.90$) between pairs of self-efficacy judgments would suggest test-retest reliability (i.e., temporal stability), yet their range of observed correlations did not reach this threshold. The authors conclude that a single item measure is suitable for detecting within-person variability because it failed to demonstrate test-retest reliability, a reflection of construct stability. However, this argument is compelling only if self-efficacy can be established as actually fluctuating between real time measures of it. Bernacki et al. address this concern by separately estimating reliable change (beyond that induced by measurement error) and stability of self-efficacy judgments while focusing predictive models on the former. In doing so, the authors illustrate a successful approach to capturing meaningful change in process data.

Another consideration arising in longitudinal research on processes assumed to be autoregressive, including those in this study, is the appropriate frequency of measuring focal constructs (see Azevedo 2014 for complementary discussion). Bernacki et al. assessed self-efficacy after every fourth math problem, raising the question of whether efficacy judgments influenced by performance four problems prior provide an optimal view of variability and causal influence of those judgments. If more recent efficacy judgments supersede ones four problems prior, then their findings underestimate the influence of prior performance and motivation on subsequent performance. A related concern is what constitutes a complete cycle, or instance, of self-regulated learning. Do students progress through its loosely-sequenced phases from forethought through reflection (Pintrich 2000) within each new math problem or across an entire set of them? Does the duration of self-regulated learning cycles vary from student to student, or problem to problem? These questions, and evidence of their answers, are important to consider when interpreting findings from academic tasks with multiple problems or stages.

Implications of design characteristics, such as the academic task through which self-regulated learning is measured, are thoroughly reported by Lichtinger and Kaplan (2015).

Doing so was facilitated by their rich qualitative account of self-regulated learning across relatively diverse tasks, a methodological approach revealing complex ways motivation and metacognition can be dynamically related during self-regulated learning. Intensively focusing on a small sample underrepresented in this growing area of research, Lichtinger and Kaplan painstakingly describe potential challenges participants face in both reporting and undertaking self-regulated learning. Coupled with the authors' research questions, these challenges limit how self-regulated learning should be measured. Lichtinger and Kaplan make this connection transparent, transforming it into a noteworthy strength of their approach. Doing so highlights another important yet often overlooked aspect of alignment, namely between sample characteristics and measurement choices. Ensuring this methodological alignment enhances the scholarly value and hypothesis validity of self-regulated learning research, as both contributions to the dynamic relations theme of the special issue demonstrate.

However, alignment can be obscured when constructs are labeled or defined in a way that belies their continuity with prevailing or historical trends in the literature. The literature on self-regulated learning is characterized by variation in labels and definitions (Dinsmore et al. 2008; Zeidner et al. 2000) that can often be traced to different theoretical models, theoretical perspectives, or empirical traditions. Common themes across them have been catalogued by several researchers (e.g., Pintrich 2000; Puustinen and Pulkkinen 2001; Zimmerman 2001), providing integrative definitions and frameworks that can orient future research on self-regulated learning. Prominent among these contributions is Pintrich's (2000) working definition, which unites the assumptions underlying many models of self-regulated learning and reflects their shared metacognitive processes (e.g., monitoring, control). This definition is featured by authors in the special issue, including Lichtinger and Kaplan. While situating their study in the self-regulated learning literature, the broader construct label self-regulation was often applied. This apparent misalignment highlights the importance of precise construct specification to ensure its consistency with current conceptualizations and nomenclatures. For example, we encourage careful delineation between self-regulation and self-regulated learning when labeling and defining these elusive constructs. Doing so will become particularly important as the relatively distinct areas of research increasingly cross-pollinate as authors have advocated in this special issue (e.g., Ben-Eliyahu and Bernacki 2015; Ben-Eliyahu and Linnenbrink-Garcia 2015). Although theoretical misalignment (e.g., between construct labels and definitions) may not undermine methodological decisions, it can obscure the overall approach to self-regulated learning within a study and the implications of findings beyond it.

Contingencies

Like dynamic relations, contingencies among metacognitive processes have been an essential if elusive feature of self-regulated learning since its first theoretical models (e.g., Winne 1996).

Validly capturing contingencies lagged behind conceptualizations of them, with think-aloud protocols and other real time measures reinventing how researchers do so. Binbasaran-Tuysuzoglu and Greene (2014) capitalize on this development within a study exemplifying consistency across the theoretical and methodological decisions that collectively define an approach to self-regulated learning. Therefore, it serves as a flexible template for how to report these decisions and indirectly demonstrate alignment among them.

Like many recent studies (e.g., Lichtinger and Kaplan 2015), Binbasaran-Tuysuzoglu and Greene is framed by Pintrich's (2000) integrative definition. This definition is compatible with most theoretical perspectives of self-regulated learning (see Zimmerman 2001), sharing common assumptions about its dynamic, contingent, and contextualized features (Pintrich 2000). This connection is noted by Binbasaran-Tuysuzoglu and Greene, who adopt a theoretical model (Winne and Hadwin 2008) consistent with Pintrich's definition that is particularly suited to their research questions. These questions were answered through a think-aloud method capable of capturing metacognitive contingencies in real time as the theoretical model both predicts and requires. Rich qualitative data were collected during an academic task for which the authors describe its self-regulatory implications, aligning them with the breadth of inferences from findings. Findings were derived from an analytic approach that mirrors the complexity of their research questions based on quantitative data generated by a theoretically grounded coding scheme (Azevedo 2005; Azevedo et al. 2004). Taken together, these decisions create a coherent approach to self-regulated learning that demonstrates alignment in how the study was both conducted and reported. Although often demonstrated indirectly, we recommend making connections among theoretical and methodological decisions explicit to both encourage and evaluate their alignment.

The measurement strategy in Binbasaran-Tuysuzoglu and Greene reveals an additional methodological consideration in Lichtinger and Kaplan. Although both studies richly capture self-regulated learning in real time, Binbasaran-Tuysuzoglu and Greene do so with an a priori protocol validated and refined in several recent studies (e.g., Azevedo and Cromley 2004; Greene et al. 2013). Rather than evoking verbalizations during an academic task, which would pose a challenge for their sample, Lichtinger and Kaplan recorded both behavioral manifestations and observations of self-regulated learning (e.g., students' outlining and re-reading instructions, respectively). Piecing this real time data together with students' retrospective explanations of their behavior during the academic task, Lichtinger and Kaplan create a complex picture of situated self-regulated learning that answers a common call for triangulation among measures (e.g., Schraw 2009; Winters et al. 2008). Although coding of their qualitative data did not appear to follow from a priori categories grounded in self-regulated learning theory, doing so improves alignment within a study and confidence in its findings. Therefore, we recommend that researchers report how their coding protocol reflects a theoretical perspective or model of self-regulated learning along with implications for interpreting results.

Context

Studies demonstrating the special issue themes of dynamic and contingent relations among self-regulated learning processes did so through real time measures embedded within distinctive academic contexts. These contexts are defined by both immediate and indirect factors ranging from task structure (e.g., Lodewyk et al. 2009; Malmberg et al. 2014) to societal stressors (e.g., Ben-Eliyahu and Bernacki 2015). As a result, real time measures are inherently and perhaps inextricably contextualized. Yet studies representing this third theme of the special issue approach self-regulated learning differently, relying on students' retrospective reports to capture the influence of novel contextual factors. Although doing so raises questions about alignment, both studies make important theoretical or methodological contributions to the self-regulated learning literature.

Ben-Eliyahu and Linnenbrink-Garcia (2015) propose an innovative integration of self-regulated learning and self-regulation, supplementing existing models of the former with somewhat overlapping strategies for the latter (e.g., planning and environment structuring appear in both literatures). In their conceptualization, self-regulation of domains beyond learning (e.g., emotion) sets the psychosocial stage for learning strategies to operate and function optimally. Ben-Eliyahu and Linnenbrink-Garcia then test whether students' enactment of learning strategies mediates the relation between self-regulation and achievement across two important yet previously unexplored contexts: favorite or least favorite courses. The influence of these novel contexts was tested among both high school and college students, representing different developmental periods and academic environments that together shape self-regulated learning.

In the study, retrospective self-reports aggregated across tasks within courses that could differ from student to student (i.e., one student's favorite subject may be another student's least). These tasks and domains likely vary in structure, among other characteristics that could have facilitated or constrained students' situated use of learning strategies. Therefore, even small effects from summative measures may provide (attenuated) evidence of the general predictions tested through structural equation modeling. However, fluctuating demands on self-regulation and affordances for learning strategies are inevitably lost in summative measures. As a result, they cannot fully capture complex relations implicit in the theoretical model (iSRL; Ben-Eliyahu and Bernacki 2015) adopted by Ben-Eliyahu and Linnenbrink-Garcia. However, future research could test more precise predictions from the model as its defining processes dynamically unfold in different academic contexts, including favorite or least favorite classes. For example, ecological momentary assessment (Shiffman et al. 2008) could capture students' self-regulatory state *during* class or *while* studying and their contingent use of learning strategies as a result. Suggestions such as this for improving alignment between measures and models should be provided when they do not capture self-regulated learning within the same time scale or grain size.

Time scale and grain size are only two considerations in the ongoing debate over the relative merits of different self-regulated learning measures. McCardle and Hadwin (2015) contribute to this debate by arguing for an often overlooked benefit of self-report, namely its unique opportunity to capture students' perceptions that presumably influence their self-regulated learning. McCardle and Hadwin propose purely methodological hypotheses about two relatively new options for measuring self-regulated learning retrospectively that overcome some of its strongest criticisms. In particular, prompting students to reflect on a single type of academic task (e.g., exam preparation) at a single time point within a certain course defines the contextualized nature of responses more clearly and narrowly compared to traditional self-report measures (see Winne and Perry 2000).

This measurement strategy also enhances the specification of context we recommend reporting in self-regulated learning research. As conceptualizations of this elusive construct increasingly acknowledge its sensitivity to contextual factors, inferences from findings should follow suit. That is, researchers should take into account design features of their study (e.g., task, setting, sample characteristics) when drawing inferences from its results and generalizing to other instances of self-regulated learning (Winne and Perry 2000). Although doing so likely limits the scope of inferences, it produces a systematic opportunity to empirically test whether results are robust across contextual factors as described in our next section. Like construct specification, context specification improves alignment between methodological decisions and the interpretation of findings from increasingly sophisticated self-regulated learning research.

Through modern statistical methods, this research is capable of testing precise theoretical predictions about dynamic and contingent relations during self-regulated learning or its complex change over time. McCardle and Hadwin conduct exploratory analyses to capture change across a semester-long course, doing so through latent class analysis that revealed four groups of students with different patterns of improvement in self-regulated learning skills the course promoted.[1] Although promising, these results are not tied to a priori predictions about how self-regulated learning may improve or dynamically unfold over time in this unique context. Absent theoretical predictions or a demonstrated need for data of the kind produced by their new measure, it is an innovative methodological approach in search of research questions.

Yet purely methodological questions about self-regulated learning are not without merit, especially during an empirical era where measurement and statistical advances threaten to outpace the theoretical refinements they can inform. McCardle and Hadwin reinforce the value of stepping back to appraise and compare new measures, whether capturing self-regulated learning in real time or retrospectively. Their approach to doing so could serve as a template for future research testing the congruence of different established measures, including real time options competing for status as the gold standard.

Conclusion

Like measures and models of self-regulated learning, the behavioral sciences more generally have reached a golden era of empirical advances in many respects. Theories of social, emotional, and cognitive processes implicated in behavior have evolved into sophisticated accounts of what shapes and underlies it. Rapid technological progress has transformed data collection, allowing for the acquisition of detailed information about those processes either in summary or as they unfold in real time. New statistical methods (e.g., latent growth curve modeling) and accessible software for applying them (e.g., M*plus*) enable nuanced analyses that richly capture the complexities of processes implicated in self-regulated learning, among other constructs of considerable interest in the behavioral sciences. As a result, sophisticated theoretical accounts of behavioral phenomena can be evaluated more thoroughly and rigorously than ever before. The special issue catalogues and embodies this exciting progress in self-regulated learning research.

Moreover, innovative methods of data collection and analysis that facilitate this progress also suggest creative new ways to think about patterns of change and relations between variables that can lead to greater specificity in theoretical accounts. For example, ecological momentary assessment and other intensive repeated measurement strategies yield detailed information about personal experience close in time and context. Measuring self-regulated learning in real time can also produce analytic possibilities for which suitable data are rarely available, as two studies of the special issue demonstrate.

[1] An alternative and perhaps more appropriate statistical approach to capture variation in patterns of improvement within this context is factor mixture modeling (Lubke and Muthen 2005). In particular, factor mixture modeling permits the possibility that the marginal fit of the measurement model could be attributed to nonequivalence of the latent structure over time or across subgroups within the sample.

In Bernacki et al., the data allow for estimating individual trajectories of self-regulatory processes across the entire academic task through which they were measured. In Binbasaran-Tuysuzoglu and Greene, several additional questions about contingencies could be addressed from their think-aloud data. Do students differ in how frequently or when they follow negative judgments of learning with strategy change? Do adaptive changes early in the academic task influence the timing or frequency of negative judgments as it unfolds? Under what conditions is strategy change more or less adaptive? Although these additional questions were not raised by the researchers, data were collected in a way that they could be addressed.

As these exciting possibilities illustrate, empirically testing theoretical predictions about dynamic and contingent relations that have come to define most models of self-regulated learning is accomplished through real time measures that richly capture metacognitive or motivational processes while they occur. These processes occur within a specific context defined by task characteristics, among many other nested factors that influence how self-regulated learning operates in a given study and for a given student (Ben-Eliyahu and Bernacki 2015). As a result, findings from real time measures are inherently and perhaps inextricably tied to tasks, domains, settings, and even students exhibiting a similar profile of characteristics. Therefore, we encourage qualified inferences based on the generalizability of salient contextual factors (e.g., structure of the academic task or domain, computerized vs. classroom setting) that may facilitate or constrain students' self-regulated learning. Yet the effect of contextual factors has received increasing empirical attention (e.g., Ben-Eliyahu and Bernacki 2015; Hadwin et al. 2001; Lodewyk et al. 2009; Malmberg et al. 2014; Wolters and Pintrich 1998) as prevailing views of self-regulated learning converge on its sensitivity to them, producing a new frontier for research represented in the special issue as its third theme.

This confluence of theoretical and methodological advances finds research on self-regulated learning at a crossroads. How can studies accurately reflect the dynamic and contingent nature of self-regulated learning while testing contextual influences on it? This is a deceptively difficult question to answer in a single, feasible study. Although real time measures are often necessary to capture self-regulated learning as most theoretical models and definitions now conceive it, they are embedded within tasks, domains, and settings that exclude these contextual factors as testable moderators. Despite the strengths of real time measures diversely represented in this special issue, practical limitations (e.g., prohibitive cost) of intensive data collection and coding can limit the number of students sampled. As a result, sociocultural or demographic differences among them likely cannot be tested as moderators given underpowered or impossible statistical approaches within relatively small samples. This paradoxical challenge leaves series of relatively small studies that vary in their task, domain, setting, and sample characteristics to uncover contextual moderators of how self-regulated learning operates. Findings or even data from these studies can then be combined through meta-analysis to systematically identify moderators of how self-regulated learning operates or its relation with other academic variables (e.g., achievement).

However, combining studies through meta-analysis or evaluating their quality requires transparent reporting of theoretical and methodological decisions that collectively define an approach to self-regulated learning. These are two of the many reasons we propose a framework for conducting and reporting self-regulated learning research that focuses on alignment from its first through final stages. Although even perfect alignment does not ensure the impact of research, it is a goal worth pursuing perhaps now more than ever.

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