Methods of research design and analysis for identifying knowledge resources

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[This paper is part of the Focused Collection on Qualitative Methods in PER: A Critical Examination.] Within physics education research (PER), resource theory has proven to be a useful framework for investigating knowledge and learning and informing instructional design. To analyze learning over longer timescales and across cases, PER scholars must first identify and describe the resources activated within and across physics contexts and domains. Despite its importance, a reliable method for identifying resources has not been clearly outlined. This paper presents guidelines for the design of research aimed at identifying knowledge resources. We begin by describing the origin, assumptions, and utility of resource theory. We then introduce methods of data collection and analysis. We end with a discussion of validity and reliability, drawing connections with general principles of qualitative research. With this work, we hope to promote coordination among the many PER scholars who utilize resource theory and to invite new scholars to join in its application and development.

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I. INTRODUCTION: WHAT IS RESOURCE THEORY?

A core assumption of constructivist learning theories is that new knowledge is built on the foundation of prior knowledge. Research aligned with this perspective seeks to understand how students' informal ideas might play a productive role in their reasoning and how they might be refined into scientific knowledge. Addressing these questions requires identifying *what* ideas students have–sketching their landscape of prior knowledge. The aim of this paper is to present methods for this initial step in the research process. The paper is focused on methods for characterizing a student's state of thinking, leaving for other papers the description of methods for determining the *dynamics of knowledge in use* or *transitions from one state to another* (i.e., learning).

The methods correspond with an ontology of mind known as resource theory. Resource theory views the knowledge of an individual as a complex system of elements, which are activated in networks depending on the sensemaking demands of the context at hand. This view of knowledge stands in contrast with unitary ontologies of mind, which view knowledge as a rigid structure [1,2]. In resource theory, the individual elements of knowledge are referred to as *resources*, signaling their productive role in the construction of new knowledge. Resources can be thought of as the raw material out of which scientific thinking can be built. Resources have been proposed for a number of different kinds of knowledge, including conceptual [3], epistemological [4], and procedural knowledge [5].

Resource theory seeks to characterize the resources that feed into the construction of new knowledge, namely, their structure, organization, and how they change over time. Resources have been defined as "small reusable pieces of thought that make up concepts and arguments" [6]. Rooted in a computational metaphor for learning, resources can be thought of as chunks of computer code that are incorporated into more complex procedures [3]. They are often fine-grained and their activation is context sensitive. Researchers typically give particular resources a descriptive title. For example, one widely discussed resource is *closer is stronger* [7]. Young learners intuitively recognize that the closer one stands to a source of heat, light, or sound, the stronger the effect can be felt. A researcher could examine how this resource is related to other resources used in reasoning about related phenomena and how the organization of such resources changes with respect to the particular phenomenon being explained, the framing of the phenomenon, or where an individual is in their learning trajectory. Some of the existing scholarship on resource theory has been intentionally vague about the precise definition of "resource" (see Ref. [3]), which has allowed for subsequent flexibility [8]. We view this as an early step in theory development. As proponents of the theory have developed new analytical strategies and conducted empirical studies, the definition of resource and the theory as a whole become more refined.

Fundamentally, resource theory is a cognitive model that aims to describe knowledge in terms of mental representations. As such, it operates on a few important assumptions. First, resource theory is constructivist: it assumes new knowledge is constructed out of prior knowledge and that the transition from novice to expert consists of reorganization and refinement of the knowledge system [9]. The second assumption of resource theory is that all resources can be productive when applied to the appropriate context. In this way, the theory views learners through an asset-based, antideficit perspective. Third, resource theory assumes that the learning context significantly affects the learner's cognition, as it can influence which resources are activated and used in reasoning. Importantly, contextual factors can influence how students view the physics problems they are asked to solve. These problems may be conceptualized differently by instructor and student [10]. For instance, an instructor may view homework problems as exemplifying particular physics principles, such as conservation of energy or Newton's laws, while a student might view them as examples of particular kinds of problems, such as ramp, cart, or pulley problems [11,12]. Furthermore, the student might distinguish "idealized physics" problems (where factors like friction are ignored) from "real-world problems," which may contribute to a view of physics problems as less relevant to their everyday lives. Finally, resource theory is built on the assumption that knowledge systems are complex networks consisting of many resources, with individual resources being activated or not according to their perceived relevance to the context.

These assumptions can be seen in the way resource theory describes sensemaking about specific physical phenomena. For example, when young learners are asked to explain the origin of seasons, they may respond by saying that the earth is closer to the sun during summer and further away during winter [13]. This explanation can be satisfying to the learner because it activates the fundamental resource, *closer is stronger* (described earlier), which they have experienced in numerous situations. However, when the learner is reminded that summer in the northern hemisphere happens at the same time as winter in the southern hemisphere, their application of *closer is stronger* is challenged, and they may realize that the seasons must be caused by something else. Interestingly, the learner may have already known about the reversal of seasons across the equator, but when asked the original question, only the most salient features of the context-activated resources. If the conversation had instead begun with a discussion of the simultaneity of summer and winter in opposite hemispheres, it is possible that the learner may not have provided the *closer is stronger* reasoning to begin with. In this manner, the way a question is framed can influence the elements of the question context that are salient, which can in turn influence the activation of individual resources.

A. Historical foundations of resource theory

Resource theory [3] grew out of a family of related learning theories known as knowledge in pieces (KiP, see Ref. [7] for the establishing monograph and Ref. [1] for a historical overview). KiP began as a framework for understanding the intuitive sense of mechanism that accounts for common explanations of natural phenomena, as well as how those intuitions develop into a more robust physics understanding over time. A major focus of diSessa's early work was in describing one class of resource called "phenomenological primitives," or "p-prims." These fine-grain knowledge elements are self-explanatory intuitions about how the world works (such as *closer is stronger*, mentioned earlier). diSessa's monograph defined the characteristics of p-prims, provided a list of heuristics for their identification (which we utilize throughout this article), and cataloged a series of p-prims relating to force and motion. This rigorous scaffolding laid the foundation for KiP's development in the coming decades.

Resource theory shares KiP's fundamental assumptions, viewing the knowledge of an individual as a complex system of smaller elements that are activated variously depending on the sensemaking demands of a given context. As well, both theories view naive knowledge as potentially productive raw material for the construction of scientific knowledge. The primary difference between the two theories is the grain size and level of detail in the constructs they feature. That is, p-prims are often fine-grained abstractions from physical experience. Their structures are described more precisely than the range of grain sizes represented by resources, which may be drawn from physical experience as well as social interaction, including classroom learning. A further difference between the two theories is that KiP includes larger constructs, such as coordination classes, which can be used to model knowledge systems underlying experts' concepts of measurable quantities such as force and velocity. These differences grant the theories different affordances. While KiP may be used for building computationally explicit models of human cognition, resource theory's comparative simplicity makes it more accessible and applicable to physics instruction. Importantly, the qualitative methods used during data collection and analysis are remarkably similar between the two theories.

Resource theory contrasts with other theories of mind along several dimensions. First, it is an antideficit perspective, which views naive knowledge as containing potentially productive raw materials for constructing scientific understanding. This contrasts with misconceptions perspectives, which view naive knowledge as consisting of incorrect ideas that must be identified and replaced through instruction. Resource theory is a complex systems perspective on cognition, which views knowledge as networks of elements. This contrasts with unitary perspectives, which assume that naive knowledge systems are largely coherent, rigid structures [14,15]. These assumptions about the structure of knowledge impact how one interprets and analyzes data and can inadvertently limit subsequent research directions. For example, Farlow *et al.* [16] initially analyzed their students' written response data through the lens of identifying student difficulties [17] but found that the framework "did not disentangle specific and consistent difficulties with sufficient clarity" (p. 4). Instead, the researchers pivoted to resource theory and found that it "affords the opportunity to dissect student reasoning into pieces that can be identified, understood, labeled, and described; increasing opportunities for the development of targeted curricular materials" (p. 4). As another empirical example comparing these perspectives, Scherr [2] examined both resource theory and the misconceptions perspective on student thinking about special relativity and concluded by identifying strengths of both while recognizing the importance of theoretical orientation to instruction. In our experience, resource theory and KiP provide advantageous perspectives for identifying the productive aspects of student reasoning.

B. Resource theory in physics education research

Within PER, resource theory has proven to be generative in a myriad of contexts. A significant body of early work focused on physics students' naive epistemologies [4]. Related work used a framing and transfer lens to examine the activation of resources across contexts [18]. Many PER scholars have used resource theory to characterize knowledge systems across a variety of physics topics, including coordinate systems [6], kinematics [19], force [20], momentum [21], mechanical waves [22], fluid mechanics [23], thermodynamics [24,25], optics [26], electromagnetism [27], inertial forces [28,29], energy [30], and quantum mechanics [31]. Other studies have emphasized the dynamics of resources, including the process of activation [32] and the connections and development of resources [6]. Some research has explored how physics students conceptualize equations [33] and utilize mathematical skills such as the separation of variables [34]. The perspective afforded by resource theory has been utilized to assess interventions [23], explore the long-term results of instruction [25], and inform instructional design and pedagogical strategies [13]. As an ontology of mind, resource theory has allowed PER scholars to describe knowledge systems in a variety of settings and has provided important insights into practical issues, such as instructional design, assessment, and curriculum.

C. Identifying resources

When approaching PER from a resource theory perspective, identifying and describing resources is a necessary first step; this provides fuel for iterative research endeavors which may examine learning over longer timescales or compare cases of learning to synthesize a broader understanding, eventually leading to instructional implications. Thus, it is fundamental for the PER community to develop a robust, reliable methodology for collecting and analyzing data to identify and describe student resources. In essence, how does a researcher start with an interview transcript and end with the identification of a resource, and how can they be confident that two similar moments of student reasoning are expressions of the same underlying resource? Answering these questions necessitates a strong research method, especially for researchers who are new to resource theory, be they graduate students or experienced scholars. Our goal in this paper is to articulate a systematic method for identifying knowledge resources, rooted in the foundational assumptions of resource theory.

Identifying resources is not only useful for researchers interested in answering questions about knowledge and learning but also helpful for instructors. Ideally, instructors would elicit and then strategically build on student resources by guiding them along pathways leading from productive informal ideas to scientific understanding. With the goal of helping instructors respond to student reasoning about energy, Sabo *et al.* [30] identified resources about energy. Similarly, Young and Meredith [23] identified resources to help guide the design of instruction and assessment in the domain of fluid dynamics. Perhaps most simply, instructors would be encouraged to value students' everyday ideas. Instead of seeing students as empty vessels that need to be filled or vessels filled with incorrect ideas that need to be replaced, they would recognize the rich landscape of ideas their students bring to the classroom and think about how those ideas might be productive in their scientific reasoning and learning. Thus, an additional goal of research within the resources paradigm can be to provide "perspectives that expand, refine, and support instructors' perceptions and judgment" (Ref. [35], p. 1316).

Whether for the sake of research or teaching, the identification of student resources is a valuable endeavor. Over the last two decades, scholars in the domain of PER have come to recognize the benefits of the theory, primarily its emphasis on the everyday "good stuff" in students' science reasoning [13]. The perspective has been used to explicate the range of productive ways of thinking that both novice and expert physicists draw on when conceptualizing physical phenomena. Physics instructors and curriculum designers have used this perspective to shape the development of new materials and techniques that intentionally leverage the productive ideas that students bring to their learning [36,37]. However, in spite of these successes, the analytical process of identifying resources remains

TABLE I. Principles for identifying resources [7].

Strong vocabulary	Resources tend to cluster in areas of strong and similar vocabulary, as the words are familiar to the participant
Coverage	Resources should cover the breadth of human experience. Resources should be seen across contexts
Diverse evidence	Multiple problem-solving contexts can aid in the triangulation of resource properties.
Unproblematic genesis	Resources are often abstracted from learners' everyday experience.
Scavenging data	Rather than gathering new empirical data, existing data may be reinterpreted to identify resources.
Discrepancy	When students give "nonphysics" answers, it may indicate the use of an intuitive resource.
Dynamic	The reasoning path taken between a participant's initial and final thinking may reveal the cuing priority and reliability of the invoked resources.
Redescription	Tuning and competitive argumentation can optimize characterizations of resources.
Diversity	Resources should display a great deal of variance. Stay close to the data, attend to nuances, and avoid merging resources that may be distinct.
Invariance	If a resource is not being used in all of the contexts where it is expected, it may indicate issues with its description.

undefined. The motivation for this current manuscript is to provide a coherent outline detailing how to engage in research design and analysis to identify knowledge resources. To achieve this goal, we are synthesizing existing PER literature on resource theory, expanding on the connections with KiP by refining and incorporating original principles [7] (summarized in Table I), and drawing on key ideas about qualitative educational research.

II. DATA COLLECTION

To begin, we consider the decisions that must be made in preparation for and during data collection, which will enable the identification of resources. These include decisions about the environment in which to collect data, the ways to foster participants' comfort during data collection, the amount of data to collect, and the domain of data collection. While making these decisions, it is important to keep the assumptions and goals of resource theory in mind. This means being considerate of participants' prior knowledge and experience, their relation to the domain and the learning environment in which the data collection will occur, and how their knowledge resources might be leveraged in their learning. In this section, we discuss key topics within the data collection process, which require thoughtful planning. While the choices made in any individual research endeavor will depend on the specifics of the research question and goal, we attempt to provide broad guidance that will inform decisions across a variety of research contexts.

A. Data sources: Availability and utility

A number of methods can be used for collecting data rich with resources. What is important is that the methods generate data that present students' thinking in as much detail as possible. Thus, the focus of data collection should be to capture the richness and variety of students' verbal explanations and articulations. Other modes of communication (e.g., gestures, body language, and artifact creation) can be helpful to corroborate interpretations, but utterances will often be the most direct manifestation of student sensemaking. KiP researchers have advocated for clinical interviews as a methodology for retrieving data of this nature [38], but there are other reasonable approaches. Classroom observational studies and surveys can all elicit the same rich data when designed and implemented with this goal in mind. Often, the selection of the method will depend on the constraints of the context of implementation, but a variety of methods can be used successfully to identify resources so long as they provide sufficient material to inform data interpretation.

The learning environment will usually determine available data sources. Large classroom implementations might yield whole-class video data that is too chaotic or indistinct to be discernible as compared to the rich details that can be captured in interviews. Conversely, the context of the wider classroom might be critical for understanding how students' everyday thinking plays a role in their reasoning during whole-class activities or discussions. A large population could also provide a wealth of written data from assignments, surveys, or other artifacts, but that data might be limited in its level of detail. One-on-one interviews will often provide the greatest opportunity for rich student descriptions and follow-up questions, but researchers' time constraints may preclude these as an option. Given these options, researchers should carefully consider the limitations and opportunities provided by large classrooms, interview settings, and other learning environments in data collection.

In addition to the learning environment, the specific aims of the research question will inform what data collection methods will be most useful. Resource theory research often aims to characterize the function, structure, or dynamics of resources. Studies focusing on function—perhaps by identifying resources activated during an instructional intervention—would want to collect data encompassing the entirety of the intervention in rich detail, as this would help reveal how the resource functions in students' explanations. An investigation of the structure and connection of resources within a particular physics domain would necessitate gathering data covering a variety of problems and contexts within the domain to provide dimensionality to the analysis. For instance, if one was looking at resources related to forces, it would make sense to gather data about student reasoning related to both contact and noncontact forces and explore both real-world settings and idealized settings. Research that attempts to chart changes in resource use and structure over time will need to consider longitudinal data collection techniques, perhaps by collecting data before, during, and after the learning. In any case, the nature of the research goal (be it function, structure, or dynamics) should be foregrounded when making decisions during the data collection process.

Guided by resource theory, prior work has relied on a myriad of data sources: interview data, group work data, whole class data, or written data. Often, multiple streams of data are collected simultaneously. Sayre and Wittmann [6] collected video data from informal group help sessions, weekly small-group short interviews, and class discussions along with written data from ungraded pretests, homework assignments, and exams. Their analysis focused primarily on video data from group interviews as it provided a clear look at students articulating their thinking in real time. For similar reasons, research using resource theory most commonly collects interviews or small group work data due to the combination of richness and variety these methods afford. An important advantage of interviews is the researcher's ability to ask follow-up questions or provide opportunities on the fly for the learner to expand and clarify their thinking. For example, Shar *et al.* [39] constructed think-aloud interviews that were designed to replicate the context of a summative assessment in order to examine what information the assessments communicated to students about what it means to "do physics" (for additional examples, see Refs. [16,40]). Other analyses have opted to collect group work from lab classes, preferring the more authentic learning environment provided by the classroom over the limitations associated with standard interviews [23,40]. Technology can also provide novel means to collect student data; Wood *et al.* [32] used smartpens to collect students' written data in a discreet, unobtrusive manner. Given the large variety of interview types and ways to organize classrooms and group work, there are numerous instructional settings in which relevant data can be collected.

B. Cultivating an environment for eliciting student ideas

In order for data to be useful for uncovering student resources, it is crucial to collect data in settings where learners have both the ability and the opportunity to express their ideas. Situations where subjects are nervous, hesitant, or uncomfortable may hinder the data collection process, especially if the subjects feel constrained in expressing their ideas or perceive expectations regarding what their responses "should" be. One way to minimize these risks is to situate data collection in authentic learning environments where students have ample experience and comfort in sharing and discussing their thoughts [40]. Another strategy is to directly state the expectations and goals of data collection so students can feel at ease; Goodhew *et al.* [22] included an excerpt in their questionnaire which read "we're trying to understand your intuition, not whether you can remember particular equations. In other words, we want to know how you make sense of this phenomenon." More generally, we find that communicating the research goals to learners increases their comfort and minimizes fears of judgment, allowing them to express more openness and vulnerability about their ideas [41].

When planning data collection, the context as viewed by the learner is paramount; their beliefs about the goals and priorities of the learning experience will frame how they engage with the learning environment. This concept of framing (i.e., the response to the question "what is going on here?") [42], may help one conceptualize the learner's point of view during data collection. At times, the framing of learners and instructors may disagree. To illustrate this idea, Berland and Hammer [43] discussed a 6th-grade classroom in which students framed a classroom discussion as a playful intellectual conversation while the teacher aimed to shift the class toward a more traditional teacher-as-authority-figure frame. When confronted with competing frames, the research goals will determine to which frame the research should attend. In the case of resource theory research, the students' knowledge systems are the primary focus. As such, student framing of the learning environment should generally be regarded as the most informative.

When students feel secure in the learning environment, we expect they will be able to articulate their reasoning using language that is familiar to them. This expectation builds on heuristics outlined by diSessa [7], namely, the principle of *strong vocabulary*. diSessa expected knowledge pieces (specifically, p-prims) to "cluster in areas of strong descriptive (representational) capability" (p. 122). We expand on this, believing that learners know the words they want to use to describe their own thinking. Often the relevant words are easily accessible to learners. Importantly, these words may not have technical precision, especially for learners, and thus it becomes important to understand what the learner means by a particular word or phrase. Researchers should be cautious about applying their own understanding of language to descriptions provided by learners. Follow-up questions and prompts which invite further explanation can provide clarity and specificity on the meaning encoded in participants' language choices. When researchers elicit rich articulations from students, the data can shed light on the resources beneath them. Crossette *et al.* [24] found that the language graduate students use when discussing entropy diverged from that seen in undergraduates; terms relating to "disorder," which were common in introductory courses, were rare among the advanced students, indicating that their understanding of the concept had deepened. The graduate students replaced the term "disorder" with "connections between entropy and volume or spreading out, the number of microstates, [and] information" (p. 6). Given the opportunities afforded by rich student responses, resource theory research should prioritize crafting data collection environments which ensure that learners can articulate their thinking using familiar language.

C. Data collection quantity

Another important data collection decision centers on the quantity of data to collect. As a general guideline, the qualitative research rule of thumb is to achieve data saturation; one hits saturation when new data no longer spark new insights [44] (p. 61). Collecting to saturation should ensure that any relevant resources are seen multiple times across multiple individuals or across the same individual in multiple contexts. This is done in order to support systematizing the description of that resource (a process we will discuss later alongside data analysis). Practically, this means that it might be hasty to decide *a priori* to collect a specific number of interviews or hours of group work. Instead, a PER scholar might need to make decisions about when to continue or cease data collection on the fly, based on the preliminary analysis that accompanies data collection. Commonly, resource theory papers collect many hours of video data, interviews, or group work. In instances where logistical constraints limit the amount of data that can be collected, we urge researchers to be prudent when extrapolating from sparse data; single occurrences of a potential resource are generally insufficient to draw solid inferences about its function or properties, especially when arguing for the existence of new resources. When analyses and claims are rooted in only a few utterances across a handful of students or within a limited range of contexts, we recommend erring on the side of caution and avoiding claims that extend beyond what can be reasonably supported by the data. When a logistical constraint (e.g., a semester course schedule) limits data collection, it may be wise to complement the dataset with additional sources, such as scavenging data from published work or pairing classroom data with interview data.

D. Data collection contexts and domains

Although resource theory was originally developed to describe student reasoning within Newtonian mechanics, this should not constrain the domains to which the theory is applied; diSessa's [7] principle of *coverage* suggests that intuitions should cover "the breadth of common experience." When exploring resource use in a particular domain, it is important to cast a wide net and gather data from a variety of problems and sensemaking activities within the domain. diSessa notes how the use of multiple problem-solving contexts can aid in the triangulation of resource properties in his principle of *diverse evidence*. As an example of a study collecting data from multiple problems, Robertson *et al.* [20] presented students with five conceptual questions related to forces, but varied the contexts across airplanes, tossing coins, pushing furniture, lifting boxes, and dropping a ball while walking. As a result, the study was able to identify six resources that represent intuitive formulations of Newton's laws. Importantly, each resource was seen in at least two of the conceptual contexts, and each question saw students using multiple resources. Similarly, Young and Meredith [23] compared student responses to two questions: one about swapping out one kind of gas for another and one about drinking from two straws when only one is submerged in liquid. Although both would fall under the topic of "fluid mechanics," the students activated vastly different resource clusters when reasoning about the problems. In these cases, the researchers were afforded a multiplicity of perspectives due to the diversity of contexts in their data collection, which allowed them to compare and contrast their data and reveal subtle patterns in student responses.

Even the problem setup or phrasing of a question can drastically affect the resources that students activate to make sense of it. Goodhew *et al.* [22] found that predict-style questions (where the prompt outlines an initial state of a system and asks for a description of what will occur) elicited resources that include if-then statements, algebraic expressions, and mathematical procedures. In contrast, when the authors used questions eliciting an explanation (where an observation or measurement is described and the students are asked to explain why the behavior occurred), students were much more likely to resort to fundamental principles such as force, motion, and energy to explain the phenomenon. By diversifying the questions and prompts used during data collection, researchers can increase the likelihood that the data will contain sufficient opportunities to observe resources in their many contexts, which in turn can increase one's confidence in the existence of the resource and the details of its application.

It is also often useful to collect data from learners with different backgrounds and life experiences. Research in PER has tended to focus on students enrolled in introductory calculus-based courses or students at institutions where the incoming students have strong math preparation. Meanwhile, such research has given minimal focus to K-12 students, students at 2-year colleges, and students at minority-serving institutions [45]. Gathering data from learners across academic levels, institutions, and types of courses should add further depth to our understanding of the range of resources students bring to their learning and the applicability of the theory across participant groups in different settings. Diversity in participants' cultural and social backgrounds can also provide important details about the range of life experiences that impact intuitive resources.

E. Reinterpreting existing data

As has been mentioned previously, there are occasionally strategic reasons to reinterpret existing data rather than gathering new empirical data, as discussed in diSessa's [7] principle of *scavenging data*. For instance, Harrer *et al.* [46] analyzed published transcripts from Watts [47] to argue for the productiveness of student responses. Watts believed student intuition to be coherent, stable, and at odds with normative science understanding. However, Harrer and colleagues argued that the transcripts of student responses showed evidence for context-dependent activations of small-grain knowledge elements, as assumed by resource theory. Smith and Wittmann [48] performed a reanalysis of data from the Force Concept Inventory and the force and motion conceptual evaluation to show how seemingly straightforward test results could be obfuscating deeper analyses. They argued that clusters of similar incorrect answers could provide useful insights into students' mental models and that some of the responses graded as correct could be "false positives" which mask student misunderstandings. Modir *et al.* [49] used the KiP theory of epistemological framing to provide an alternative explanation for a set of student difficulties in the domain of quantum mechanics which had been previously documented in PER literature. Through these examples, we see that a strength afforded by scavenging data is the opportunity for competitive argumentation, comparing analyses from opposing theoretical lenses to facilitate theory development and community discussion. Additionally, scavenging data can be used at times when traditional data collection is hindered, as was the case during several months of the COVID lockdown in 2020. Similarly, if the collected empirical data are sparse, scavenging can allow researchers to "double up" on data collection by reusing existing datasets for multiple purposes. Scavenging is not without its drawbacks; the limited knowledge of the data collection context and learner's history, the inability to ask follow-up questions or seek clarification, and the possible omission of pertinent details when working with incomplete data can diminish the validity of subsequent analyses. Scavenging data is at its best when researchers have direct access to original transcripts, videos, and artifacts (preferably in their entirety), affording them a comparable level of reliability as traditionally collected data. When done carefully, scavenging data can be a helpful tool for furthering resource theory research.

To summarize, identifying student resources requires that researchers have a rich, detailed dataset in which students express their ideas, ideally in real time during problem-solving or sensemaking. We expect resources to be abundant in the realm of physics, and we generally advise researchers to gather data from a variety of contexts and sensemaking activities. Scholars interested in this endeavor should consider how the setting and logistics of common data collection methods will impact the experience of the students and, in turn, the usefulness of their anticipated data. Allowing students to comfortably express themselves at length, uninterrupted, and in authentic settings will likely grant the most reliable window to explore their knowledge structures. Collecting data that accurately capture the cognition of students can be a challenging task. Thoughtful planning is necessary to prevent data that are indistinct, indecipherable, or insufficient.

III. DATA ANALYSIS

Next, we consider how the goal of identifying resources shapes the process of data analysis. Within the KiP community, a number of researchers have begun to use *knowledge analysis* (KA) to refer to a family of methodological strategies for studying the structure, function, and dynamics of knowledge. diSessa *et al.* [50] presented a detailed description of KA, including a review of its history and theoretical foundations, a list of basic principles and counterprinciples, a general framework organizing the steps of knowledge analysis, regimes of study to classify KA works and prototypical examples, and theories that have been developed using KA. Drawing from that work, we present an overview of KA methodology while remarking on the choices and components that are most relevant when attempting to identify resources. Despite our focus on the identification of resources, KA is a flexible qualitative methodology that can attend to a variety of research questions that pertain to knowledge and learning in PER research.

Prototypically, KA is implemented as an iterative process in which one goes back and forth between data analysis and theory building [51]. The data are examined with respect to the theoretical topic of interest, key episodes or issues are identified and examined, an initial theory is constructed, and the data are reexamined using the new framework to test the theory. This movement between data and theory can occur as many times as needed to refine the theory to satisfaction. The central steps of this process share many important features with grounded theory [52] and its goal of allowing theories to emerge organically from the data without imposing rigid preconceived notions or expectations.

To operationalize the analysis portion of KA processes, we turn to the *observe, schematize,* and *systematize* cycle (OSS; Refs. [53–56]), which splits the core data analysis loop into three distinct stages: (i) the identification of notable episodes within the data where resources might be present, (ii) the characterization of data to build and refine a rough schema of resources, and (iii) the organization, generalization, and broadening of the developed theory. We unpack this cycle below.

A. Observing the data

The first step in the OSS cycle is to observe data and to identify notable events, utterances, or written responses that could prove useful or interesting with respect to the focus of the inquiry [56], specifically, the existence of new or previously identified resources. During this phase, the researcher might ask themselves questions, such as: What patterns of learning or struggles do I see in the data? What is interesting or puzzling in the data? Creating a catalog of such interactions provides a focused set of data to analyze. For instance, Parnafes [54] studied students' conceptual understanding of simple harmonic motion through pair interviews with high school students. The research questions focused on describing instances of conceptual change and how they related to the representations (paper and simulation) used in the interviews. During this phase, the author noted whenever students expressed surprise at something in the simulation that was not aligned with their expectations [56]. The techniques employed in this identification process will depend on the affordances and limitations of the collected data. A physical transcript or artifact can be marked with a highlighter, margin notes, or other flags for later analysis. When studying visual data such as video files, memos or narrations can be written in tandem with the video transcription [44,52]. Having thinking partners who are able to offer constructive feedback during observation can provide additional perspectives for catching subtle or nuanced events. The observation step itself may be iterative when repeat passes continue to yield new events or later analysis steps provide insights expanding on noteworthy episodes.

When attempting a grounded approach as described here, selections should be made with minimal preconceptions. It is important to avoid assigning meaning during the selection process itself, which would alter later analyses. Shubert and Meredith [40] used "noninterpretive" descriptions (such as "reacting" instead of "surprised") when labeling time stamps in their video data to avoid casting initial judgments on chosen events. When attempting to identify resources, we recommend describing the data using language that is similar to that used by the learner, rather than existing theoretical constructs. Though, if the research is focused on confirming or elaborating preexisting resources rather than characterizing new resources, it may make sense to select episodes where the known resources are likely to be found.

During observation, any instances of rich student articulation should be considered (e.g., written or spoken explanations, as opposed to "yes," "no," or multiple-choice responses). Responses that deviate from researcher expectations can be especially fruitful for discovering resources. diSessa [7] notes in his principle of *discrepancy* that "nonphysics" explanations often given by naive learners include intuitive resources. In general, incorrect answers can be as useful as correct answers. Young and Meredith [23] took note of one student's flawed explanation when reasoning about drinking through a straw. The student's explanation was full of productive ideas, such as identifying the relevant agents and properties in the system and realizing that pressure differences could cause motion in the fluid. Such observations exemplify the asset-based perspective that resource theory affords.

The foremost objective of the observation phase should be to cull the wider dataset down to a more manageable collection of episodes (in video data) or key written responses that are potentially useful or interesting with respect to the focus of the inquiry. Toward this, it is important to keep in mind that the distribution of selections made during observation can unintentionally skew analysis if there are wide disparities in episode density across the data. Here, diSessa's [7] principle of *diverse evidence* continues to provide guidance; just as data collection should cast a wide net to increase the likelihood of capturing resources in their entirety, episode selection should be spread across participants and contexts to maximize the researcher's viewpoints on any potential resources.

B. Schematizing the observed occurrences

The second step in the OSS cycle is to schematize the observed occurrences [56]. During this phase, descriptions for the selected excerpts are generated. These can (and often do) focus on the explicit language used by the students, using an *in vivo* coding strategy in which the name of the code is derived from the data itself [57]. This is especially useful when working with video data, which is widely used in resource theory research. As an example, Tuminaro and Redish [58] discussed how they assessed their codes while refining their proposed theoretical construct (p. 10). Descriptions written in the language of the participants leverage the principle of *strong vocabulary* [7] by remaining close to the natural or intuitive language most readily used by learners. Focusing on language can also detect subtle patterns, such as the order in which students activate resources. diSessa's [7] principle of *dynamic* suggests that the reasoning path taken between a participant's initial and final thinking may reveal important features of the invoked resources. Students' quickest responses will often reflect the resources that are most easily cued, what might be considered a "knee-jerk" response. Later responses, by contrast, indicate resources with higher contextual sensitivity, meaning they have proven to be productive in previous attempts at making sense of similar phenomena. An example of high-priority cuing can be seen in Cvenic *et al.* [26], where students' in-the-moment explanations of polarized light often began by referencing the diagrams and schematics found in textbooks, demonstrating that "the figures used in teaching were a strong visual cue" (p. 13). Moving beyond language, descriptions can also attend to the actions, affect, body language, or social interactions represented in the data. Once an account has been made for each selection, the explanations can be compared to reveal larger patterns in student thinking and behavior. As connections are discovered, new or previously identified resources can be used to organize subsequent analyses. We find it useful to begin this organization by assigning a temporary label to each resource and constructing a table with their basic properties, examples, and relationships to other resources.

Constructing these resources may require returning to the observation step to identify additional instantiations in the dataset or even to data collection if the dataset does not provide sufficient examples. If additional data collection is required, the principle of *unproblematic genesis* [7] can prove useful in suggesting that data may be found in common everyday experiences. Specifically, preliminary characteristics of the resource under consideration may provide clues as to the everyday experiences from which intuitive resources originate. For example, if one is considering a resource related to buoyancy and more data are needed, it may be prudent to gather more data about learners' reasoning about relevant everyday experiences (e.g., floating toys in the bathtub).

Researchers should remain flexible as the schematized resources take shape. We advocate for the principle of *redescription* [7], which acknowledges the difficulty in creating precise descriptions and advocates for "tuning and competitive argumentation" (p. 124) to slowly and recursively develop each resource. By "tuning," we mean iteratively refining the name and characterization of the resource. By "competitive argumentation," we mean comparing emerging resources with existing ones (or other constructs existing in the literature) and constructing arguments as to why the new resource is needed (i.e., how can it help us predict and explain thinking and learning in ways that existing constructs cannot). As the resources become more concrete, it may be necessary to combine similar categories or divide broad categories. When making these decisions, we follow the principle of *diversity* [7], expecting that resources will display a great deal of variance and our delineations should reflect this nuance. Once reasonably stable expressions of the categories are reached, attention can be shifted toward formalization or systematization.

C. Systematizing the results

The third step in the OSS cycle is to systematize the descriptions, aggregating the preliminary results of data analysis into a starter theory [56]. The systematizing step can be challenging to outline as the shape of one's theory will largely depend on the specifics of their research questions and the results of their data analysis. When identifying resources, systematizing will often involve turning a rough coding scheme of observed resources into a more rigorous scheme. This can be done by drawing on other coding approaches, such as concept codes or holistic coding [59], or by implementing interrater reliability. Just as they did during schematization, the principles of *redescription* and *diversity* [7] should inform the finer details of any revisions that occur at this phase. Systematizing also involves organizing the resources into clusters or themes. This part of the process of systematization can be aided by the use of epistemic forms [60], such as matrices or hierarchical lists. These representational tools can serve as templates for guiding the organization of documented resources and for motivating the identification of others in the data.

When one has a solid description of the resource scheme, it becomes important to reapply it widely across the data to test, thereby generalizing the theory. In particular, characterizations of resources (i.e., codes) should identify the resource's activation in all of its expected contexts, as described in the principle of *invariance* [7]. If a relevant context does not seem to activate the resource, the description may need to be amended or it may warrant deeper investigation. Likewise, an unexpected indicator of a successful description could be witnessing the resource used in a relevant context even without the researcher's expectation. Young and Meredith [23] observed such an instance when students used a "lighter is faster" resource both in the expected context of swapping out different types of gas and in the unexpected context of fluids being sucked up a straw. By repeatedly describing, applying, and refining code systems, theories can be developed which are soundly rooted in data and are useful across a range of empirical domains.

The three-staged loop of the OSS cycle is a versatile tool for analyzing data about learning and knowledge in PER. Within existing empirical work, many authors employ a similar iterative approach to data analysis without necessarily connecting the process to KA or the OSS cycle. Crossette *et al.* [24], Cvenic *et al.* [26], Robertson *et al.* [20], Shubert and Meredith [40], Tuminaro and Redish [58], and Young and Meredith [23] all utilize iterative data analysis processes which involve identifying key moments in the dataset, grouping similar instances together to form broad categories, and refining those categories to formalize a system that describes the data as a whole. We advise those using resource theory in PER to explicitly connect their work to KA and the OSS cycle. We believe this will greatly improve our field's methodological alignment, as well as provide a universal lexicon for communicating about and referring to the central ideas of data collection and analysis found within resource theory.

Researchers should conceptualize data collection and analysis not as two uniquely distinct and sequential steps, but as one interconnected, iterative process. The eventual goals of the anticipated data analysis inform the target and scope of initial data collection methods. Likewise, if data analysis reveals a gap that may provide pivotal information if explored further, additional data collection may be justified. We encourage PER scholars engaging in resource theory research to attend to the aims of the research questions when navigating this iterative procedure. Keeping sight of overarching guiding ideas (like resource identification heuristics) can preempt issues and ease decision-making. With careful planning and foresight, researchers can collect and analyze meaningful data.

IV. STRENGTHENING CONCLUSIONS

Throughout data collection and analysis, it is important to consider how the intended audience will judge the quality of the research in light of its theoretical and methodological foundations. Resource theory research is primarily a qualitative endeavor, seeking to describe students' science sensemaking when conceptualizing physical phenomena by characterizing the function, structure, connections, or dynamics of resources. This goal is often in contrast with those in quantitative works, which illuminate statistical patterns across large datasets. The criteria used to judge the merit of qualitative work are vastly different from that used for quantitative work [61]. Qualitative research relies on a variety of checks and procedures to ensure its conclusions are accurate, sound, and replicable, rather than notions of credibility and dependability, which are more common in quantitative work.

For qualitative researchers, it is important to clarify and be explicit about positionality. A growing strategy is to include statements of positionality in one's published articles where the authors explicitly discuss how their experiences and identities might have impacted the research (see Refs. [62–64] for examples of such statements). For PER scholars, these statements may include details about their role in data collection, such as cases where the researcher is also an instructor at the site of data collection. More broadly, PER scholars may wish to mention their personal knowledge and experiences about the topic or domain of the study, any interventions or assessments found in the work, the student population participating in the research, or the institution through which the research is being performed. With respect to resource theory in particular, it is important for researchers to recognize the bias inherent in their identification and description of particular resources, as we tend to recognize in students' thinking those ideas we have already thought. Transparency is important for preserving rigor in research. Rather than struggling to uphold the quantitative presumptions of objectivity and a lack of bias, qualitative researchers should accept the subjectivity inherent in their research. Explicit conversations about the role of the researcher are integral to achieving a depth of understanding in qualitative settings [65].

A. Validity

One metric often used to assess the trustworthiness of data analysis in qualitative research is validity, which is "an attempt to assess the 'accuracy' of the findings, as best described by the researcher, the participants, and the readers (or reviewers)" (Ref. [66], p. 259). There are many perspectives on how best to judge the accuracy of qualitative work and how the notion of validity fits into a project (see Refs. [66–68] for more details on this topic). In the context of KiP research, validity has two important dimensions: the authenticity of the learning environment where data were collected and the proximity of the researcher's interpretation of data to the participants' experiences [40]. As a general rule, maximizing these two dimensions will improve the likelihood that conclusions drawn from the research are truthful representations of genuine learning.

Many generic strategies for improving validity in qualitative education research are also applicable to resource theory research. First, when possible during data collection, data should be collected directly from environments where learning takes place, such as classrooms and labs. If cameras are used to collect video data, they should be as inconspicuous as possible to minimize intrusion. Authenticity can also be preserved by collecting student work after the fact. If students are invited to participate in controlled research environments, one strategy for improving validity is to have prolonged engagement with the students, such as systemic data collection over a semester or a series of interviews. These sorts of interactions can reduce the novelty of the research endeavor, improving the students' comfort and promoting relaxed, genuine behavior. Second, it is useful to look for disconfirming evidence during data analysis to avoid confirmation bias, such as examples of students not invoking resources in contexts we would expect. This strategy is practiced in KiP research and fits well within the paradigm, given its emphasis on theory development and options for scavenging data. Another commonly enacted strategy is the triangulation of multiple lines of evidence, such as comparing video data with students' written work. As an innovative example, Wood *et al.* [32] triangulated smartpen data that captured sound and written notes with student's votes on multiple-choice physics questions. Among resource theory analyses, it is also common to improve the accuracy of findings through informal peer reviews with critical friends who can offer an outside perspective. The inclusion of peer input can be helpful at any stage in the analysis process, even when planning for data collection [69]. A final strategy we recommend is to present sufficiently rich descriptions of the results so that the reader has ample information to make a judgment themselves about the conclusions presented in the work [70]. Such rich descriptions are vitally important for communicating key discoveries, especially as novel empirical works build new pieces of resource theory.

When interpreting data, researchers should strive to reduce the risk of injecting their own meanings and interpretations into data. At one extreme, where direct interaction with participants is impractical, data collection methods should direct participants to give as complete an account of their thinking as possible to minimize gaps in the data. More commonly, researchers will be able to interact with students in classroom settings or interviews. In these environments, researchers can use open-ended questions and follow-ups to gather rich student accounts. Going deeper, some qualitative studies use member checking [71], where researchers give participants additional opportunities to validate their narratives. Birt *et al.* [72] discussed the many ways this process can take place, from simply returning interview transcripts to participants for review to sharing the results of data analysis with participants to verify the accuracy of the conclusions. Finally, it may even be possible to include the participants in the data analysis process itself, inviting them to collaborate with the researchers and expound on their own data and thereby increasing the strength of the interpretations. When participants are integrated into the data analysis process, we advise researchers to be cautious and considerate of the additional strain such activities place on participants, the power dynamics which exist between researcher and participant, and the ethical considerations around data privacy [72].

B. Reliability

Another helpful criterion for assessing qualitative research is reliability (also referred to as *dependability*, see Ref. [73]), which is the likelihood that the study and its findings are replicable [74]. As with validity, reliability can be approached in several ways, including the likelihood that the methodology could produce meaningful data if repeated and the likelihood that other researchers would have arrived at similar conclusions if presented with the same data [40]. Methodological reliability is at its best when researchers describe their procedures in great detail and triangulate their results. To that end, we echo our previous call to utilize KA and the OSS cycle as a shared template for resource theory research. We believe this would demonstrate that independent researchers can arrive at complementary conclusions when following the same procedure.

Within a single study, improving the reliability of data interpretation presents a greater challenge; while there is a systematic process one can implement, different researchers will make different interpretations based on the nuances of their research questions, theoretical framing, and assumptions. The most common method for assuring replicability in coding is to have multiple individuals participate in coding and measure the interrater reliability (IRR), a practice that can be found in many resource theory studies (see Refs. [19,21,23,40]). Several different approaches are used to calculate IRR, but the most widely accepted method within educational research is Cohen's Kappa [75]. A numerical calculation of IRR is not strictly necessary, but it can be a useful way to demonstrate to the reader that the coding scheme does not represent the idiosyncrasies of a single coder and that it is transparent enough to be interpreted across multiple coders. Implementing IRR can be especially productive during the systematization step of the OSS cycle. Shubert and Meredith [40] described the general steps of IRR as beginning with defining the codes, then communicating them to independent researchers (possibly through a code book) and having them implement the codes, compare their results, and resolve any discrepancies. This process should be a habitual inclusion for studies with multiple coders, but it can prove useful for single coders as well. Verifying a lone coder's interpretations by demonstrating consistency with an independent collaborator can solidify the reliability of the study's findings. As another approach, the development of theoretical constructs and their systematic identification in the data can be made more reliable through multiple individuals discussing the constructs and their substantiations to reach a consensus where possible [76].

C. Worthiness, coherence, and generalization

Beyond validity and reliability, there are other considerations to make when judging the quality of resource theory research. One consideration is the "worthiness" of the topic, which can be based on PER priorities, societal or personal events (e.g., studying online learning during COVID-19 lockdowns), or whether or not the study is theoretically compelling. Simply, it is best when the topic of study is not chosen merely to be convenient [61,77]. Another consideration is the study's level of coherence, where the purpose, literature review, methods, analysis, and results of the study are intimately connected [61]. While worthiness and coherence are important general goals in qualitative research, it is helpful to consider how these notions apply to resource theory research. If a study claims to espouse resource theory and its assumptions of productivity, but then focuses only on errors and incorrect reasoning in its analyses, the reader should be concerned about the incongruity between the study's stated priorities and its practices. Additionally, if a resource theory paper reports only the frequency of resource use without deeper examinations of the way those resources emerge, function, and interact, it would demonstrate a lack of coherence between its central theory and reported findings. For a positive example, Sherin's [33] work investigated how students understand physics equations. This work was motivated by existing models of physics problem-solving and the disjoint between research on physics problem-solving and research on naive physics. The data came from pairs of university physics students solving problems, the analysis captured different episodes where symbolic forms were utilized to navigate mathematical expressions, and the final discussion focused on the range of symbolic forms uncovered. Across the article, there was clear worthiness in the purpose and motivating literature, as well as strong coherence across the research design, data collection, and data analysis.

Finally, it is important to recognize the manner in which results from qualitative research can be extended. A rule of thumb for qualitative work is to generalize the theory, not the population; this means that the range of applicability of a developing theory may expand to new content topics, settings, and phenomena as research continues, but that results seen within one population do not necessarily mean that a demographically similar population will respond in kind. This is especially relevant for PER, where the average classroom will likely be an inaccurate representation of larger population demographics [22]. For example, using resource theory, one may identify new or existing resources in a different STEM domain or type of learning environment or one might find new ways that previously identified resources are activated, thereby extending the range of applicability of the theory.

Maxwell [69] discussed external generalization, which goes beyond the case to other settings. In resource theory, this sort of generalization is expressed as applying new theories of learning to other cases in different circumstances, like searching for resources found in one content area in another domain. Barth-Cohen [78] documented the activation of p-prims in complex systems, which went beyond prior work that had documented them in Newtonian mechanics. We refer to this as small-scale generalization in which particular resources identified in one setting were also found in another setting that was different in numerous ways. As another example, Barth-Cohen and Wittmann [10] showed that the theoretical machinery of a related theory within KiP, called coordination class theory (originally developed to capture learning in interview settings), can also capture learning in classroom settings where students are building ideas off of each other during group conversations. This can be viewed as a larger generalization of the entire theory from one setting to another. External generalization can also occur when a category of data is examined which might not have seemed relevant, such as Smith and Wittmann [48] repurposing FCI data that were collected under different theoretical assumptions and purposes. When generalizing the theory, it is important to examine the nuances of the context and how it impacts all aspects of the process in order to understand the likelihood that the theory will generalize across contexts. Importantly, generalizing theory in these ways forwards momentum as we aim to triangulate results across empirical studies to build a more robust body of new knowledge.

We have discussed a multitude of strategies that can be employed at various stages of the research process to increase the quality of the research findings. As with risk mitigation in the physical world, the layering of multiple strategies tends to be the most effective implementation for ensuring high-quality research. Often called the "Swiss cheese model," each layer of quality assurance is conceptualized as a barrier with a few holes. While any one barrier would be insufficient on its own, the combination of techniques allows for the strengths of one layer to counteract the weaknesses in another, limiting the possibility of unforeseen issues going unchecked. Wherever time and resources allow, we encourage researchers to include as many strategies for validity and reliability as is pragmatic within their research procedure.

V. CONCLUSION: CHALLENGES, TENSIONS, AND OPPORTUNITIES

Resource theory is proving itself to be an increasingly popular and sustained perspective in PER as it uncovers new insights and perspectives for analyzing and understanding learning. We have attempted to give an overview of the underlying assumptions of the theory, the methodological steps that comprise data collection and analysis, and a selection of techniques for improving the overall quality of such work. Our main focus was to consider how the theory could be used to identify knowledge resources, as it is the first step toward synthesizing deeper and more complex understandings about the development of knowledge systems. We hope that our work can encourage PER scholars who were previously unfamiliar with the theory to contemplate its utility for their own work. We also hope our discussions can bring unification and solidarity to the method being used by a diverse body of scholars.

Despite its power and productivity, resource theory is not without its limitations and challenges. To start, resource theory is not a comprehensive "theory of everything." It is an ontology of mind and can shed light on adjacent issues such as curriculum development or assessment, but there are limitations to its versatility. Within learning contexts, resource theory and KiP have already begun to proliferate beyond physics research to yield constructive insights about learning in other domains. Such developments have informed research in mathematics [5,79], chemistry [80], and geology [81]. The influence of KiP has even extended beyond STEM conceptual learning to inform sensemaking in other areas. For example, Philip [82] drew on KiP to examine teachers' ideological sensemaking about racism and social justice. Moving forward, it may be fruitful to examine resources in less explored terrain, such as climate science, biology, engineering, sociology, psychology, and teacher education. However, beyond examining learning and instruction, it is unclear how far the utility of resource theory may extend. Important issues, such as the role of identity or beliefs in learning, may extend beyond the scope of resource theory. More work is needed to better unpack the limits of the domains and contexts in which resource theory can be a helpful lens for uncovering the "good stuff" in subjects' reasoning.

Within PER, there exist many questions about how resource theory may be applied and adapted for future research. Resource theory is at its strongest in areas where learners have innate "gut feelings" that originate from everyday experience. Some research has used resource theory to examine how the intuitive resources from classical physics can impact conceptualization and instruction in less intuitive domains such as quantum mechanics [31], but these studies remain few and far between. Similarly, the transition between intuitive resources and those acquired through instruction requires teasing out. Very few studies have explored the ways that intuitive knowledge becomes co-opted or repurposed as students venture into more abstract topics in physics [83]. There have also been challenges in communicating this work to physicists who are not PER scholars or whose experience focuses on quantitative analysis. For example, Robertson *et al.* [20] examined students' resources about force through data from the written work of five conceptual questions. In their write-up, they mentioned making choices to craft an intellectual argument that would be accessible to quantitative PER scholars. Future resource theory work in PER has a wealth of topic areas to explore, but those who engage in it may need to grapple with the divide between the qualitative and quantitative sides of PER.

Resource theory is a pocket knife; it is an ostensibly simple implement which harbors a powerful set of tools that invite creative and explorative implementations, but it has limitations to its power, reach, and applicability. PER has recognized the utility which resource theory provides with respect to characterizing knowledge and learning. The application of resource theory has already made great strides in recontextualizing student difficulties and suggesting avenues for advancement or refinement in instructional paradigms. Resource theory's potential can only be determined through application, by engaging with the theory to see if its use yields productive, replicable, and defensible results. These applications will be aided by thoughtful data collection and analysis methods along with careful arguments about the quality of the results. By explicating the tenets of resource theory research design, we strive to increase the accessibility and rigor of the theory and its associated methods for both new and established researchers. In turn, we hope this will encourage the extension and contribution of resource theory within the domain of PER and beyond.

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