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Supporting Mechanistic Reasoning in Domain-Specific Contexts

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Abstract

Mechanistic reasoning is an epistemic practice central within science, technology, engineering, and mathematics disciplines. Although there has been some work on mechanistic reasoning in the research literature and standards documents, much of this work targets domain-general characterizations of mechanistic reasoning; this study provides domain-specific illustrations of mechanistic reasoning. The data in this study comes from the Assessment of Mechanistic Reasoning Project (AMRP) (Weinberg, 2012), designed using item response theory modeling to diagnose individuals' mechanistic reasoning about systems of levers. Such a characterization of mechanistic reasoning illuminates what is easy and difficult about this form of reasoning, within the subdomain of simple machines. Moreover, this work indicates how domain-general principles may be limited. The study participants included elementary, middle, and high school students as well as college undergraduates and adults without higher education. Although the majority of participants responded to the AMRP by diagnosing at least one mechanistic element (elements inherent to the working of systems of levers) as they predicted its motion, such reasoning was not trivial. In fact, the diverse reasoning by participants shows how systems of levers support elements of mechanistic reasoning. Moreover, this study provides evidence that the development of mechanistic reasoning is dependent on domain-specific experience.

Keywords: science education, engineering education, cognition, assessment development

Introduction

Reasoning about mechanisms is central to disciplined inquiry in science and engineering and should therefore be one of the foundations of a STEM (science, technology, engineering, and mathematics) education (Bolger, Kobiela, Weinberg, & Lehrer, 2012; National Research Council, 2001; Russ, Scherr, Hammer, & Mikeska, 2008; Weinberg, 2017). Mechanistic reasoning is one of the core competencies listed in the Next Generation Science Standards Engineering Concepts and Practices (NGSS Lead States, 2013). Although the nation seems to be orienting toward a new emphasis on engineering education for K–12 students, there is not one single definition or orientation towards what that should entail. Moreover, while some significant assessment work has been accomplished in engineering education to date (Guzey, Moore, & Harwell, 2016; Marra & Bogue, 2006; Marra, Rodgers, Shen, & Bogue, 2009, 2012; National Research Council, 2001; Olds, Moskell, & Miller, 2005; Purzer, Douglas, Folkerts, & Williams, 2017; Wertz, Ross, Fosmire, Cardella, & Purzer, 2011; Wertz, Ross, Purzer, Fosmire, & Cardella, 2011), there are still many opportunities for assessments to be developed for pre-college populations, and many states have begun to adopt the NGSS. In particular, mechanistic reasoning is an area where limited assessment work has been accomplished to date.

Mechanistic explanations focus on the processes that underlie cause–effect relationships and thereby take into account how the activities of the constituent system components affect one another. Machamer, Darden, and Craver (2000, p. 3) note that "[c]omplete descriptions of mechanisms exhibit productive continuity without gaps from the set up to terminal

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conditions." Given the centrality of this form of cognition to STEM professions, educators should design learning environments that help learners to develop and appropriate mechanistic reasoning. However, doing so requires considering the nature of the resources that students may bring to a variety of contexts.

Russ and colleagues (2008) presented a domain-general framework and discourse analysis tool for characterizing mechanistic reasoning within student explanations of scientific phenomena. This framework presents nine coding categories informed by work from Machamer et al. (2000). These coding categories characterize student explanations according to their scientific sophistication. This coding scheme describes diverse forms of student explanation; for example, these explanations may include verbal descriptions during class or small-group discussion as well as written explanations on classwork or homework. The codes are applied to individual student conversational turns. Although this framework and discourse analysis tool focus on domain-general competencies within mechanistic reasoning, Russ and colleagues (2008) would agree that learners do not simply apply these general processes algorithmically; their use is tuned to and affected by the qualities of the devices they are diagnosing. Therefore, it is sensible to understand how these processes play out in specific cases that have a set of desirable properties. In this regard, the utility of systems of levers is not just their ubiquity, but their open and inspectable nature which suggests that individuals of all ages and educational backgrounds are likely to have the proclivity to reason about them. Novices and experts can reason about how they operate in logical ways, even though the characteristic ways of reasoning that these two groups adopt may look quite different. Systems of levers are well positioned to evoke many forms of reasoning, from naïve and perceptual-based to mathematical and principle-based. In addition, because this study investigates how mechanistic reasoning varies according to domain-specific experience, it is important that the systems under investigation are sufficiently accessible to all participants. Similarly, because systems of levers work via the transmission of force, these simple systems are less likely to seem "magical" or unexplainable to novices than are devices that are primarily electrical, computational, or whose workings are otherwise unfamiliar or hidden from view—that is, reasoning about them relies less on specific prior knowledge. Thus, these are good systems for understanding how people representing a variety of ages and education actually apply the general principles of mechanistic reasoning elaborated by Russ and colleagues (2008) within specific contexts.

Bolger et al. (2012) engaged elementary and middle school students in flexible interviews (Ginsburg, Jacobs, & Lopez, 1998) over three or four days in which students investigated systems of linkages. Accordingly, Bolger and colleagues developed and verified mechanistic elements that were specific to systems of levers, from children's explanations of their motion and function, to those of professionals in engineering and physics (Table 1, p. 180). The elements were (a) *related direction* (i.e., attention to the coordinated direction of the input and output of a linkage, "When you move [the input] up, [the output] goes up; when you move [the input] down, [the output] goes down"), (b) *rotation* (i.e., attention to the rotary motion of the levers, "[The output lever] only moves around [child gestures in a circle]"), (c) *lever arms* (i.e., attention to the coordinated opposite motion of the two lever arms, "This one [points to right side of output link] goes up like that and this one [points to left side of output link] goes down"), and (d) *constraint via the fixed pivot* (i.e., attention to the causal relation between the pivot being fixed to the board and the resultant motion, "this part is attached and that makes this one [the left side of the output link], this side to move up and down."). Finally, *tracing* was determined according to the following criteria: first, it was ascertained that participants referred sequentially, in talk or gesture, to each lever within a system; second, it was determined that a correct determination was expressed for the direction of motion for each component in the sequence. Thus, within a tracing episode participants must have diagnosed all mechanistic elements.

While Russ and colleagues (2008) and Bolger and colleagues (2012) report on mechanistic reasoning from student verbal and written explanations during classroom activities and flexible interviews, this study reports on data from the Assessment of Mechanistic Reasoning Project (AMRP) (Weinberg, 2012), an assessment developed using item response theory (IRT) modeling that leverages children's early capacities to reason mechanistically about properties of mechanical objects. Specifically, the AMRP tracks individuals' propensities to mechanistically parse systems of simple machines, characterizing their forms of reasoning as they are observed. This assessment leverages individuals' early capacities to make sense of forces such as pushes and pulls, force vectors, and geometry by providing them with an opportunity to develop their mechanical knowledge. From this perspective, introducing students to general mechanical principles through the mechanistic tracing of these simple systems may provide a foundation for the building of important knowledge about mechanical systems.

Research Questions

The development of this assessment is described in Weinberg (2012). Accordingly, this study reports on the following research questions using data from the AMRP: (1) how readily can mechanistic reasoning be applied, (2) how do features of mechanical systems impact the propensity to reason mechanistically, and (3) how does age and domain-specific experience impact the development of mechanistic reasoning? This paper focuses on these aspects

of domain-specific mechanistic reasoning across diverse participant populations.

Method

Participants

The participant groups that comprise the sample are presented in Table 1. The elementary, middle, and high school students come from public and private schools in the southeastern United States. The university undergraduates come from three universities, two in the southeastern and one in the mid-western United States. Of the two universities in the southeastern United States, one is a highly ranked private university and the other is a large public university. The university in the mid-western United States is a highly ranked private liberal arts college. The public elementary, middle, and high schools belong to the Centennial Public School District (a pseudonym). The percent of children attending these three schools who qualify for free or reduced lunch ranges between 60 to 90 from year to year. The adults without college degrees ($n = 10$) are 10% Caucasian and 90% African-American. Study participants represent various ethnic backgrounds and life experiences. The diverse sample was chosen in order to investigate mechanistic reasoning across age, socio-economic status, and experience.

Procedure

The assessment administrations were completed during one day and lasted an average of 37.5 minutes (ranging from 17 minutes to 78 minutes). These sessions were recorded using one camera, with a table microphone, and were digitally rendered for further analysis. First, participants were presented with a survey that inquired about their participation within academic and extracurricular programs that focused on engineering design. If participants had participated in such programs, the researcher followed up with questions about when they had participated in these programs, how long the programs had lasted, and what aspects of engineering design and content were targeted. Next, the researcher showed participants how a system of levers could be built with brads and linkages made from a pegboard (with researcher assistance). Participants were provided with two links, a pegboard, and brads, and then guided through the process of making a fixed and floating pivot (Appendix A). This was done to ensure that participants were familiar with the relevant materials and vocabulary (e.g., fixed pivot, floating pivot) before proceeding to the next phase of the assessment, in which they responded to paper and pencil items that were based on the pegboard linkages.

The paper and pencil items were presented to participants across seven forms. Elementary and middle school students completed ten items per form, while high school students, undergraduates, and non-college educated adults completed fifteen items per form. Elementary and middle school students were instructed to skip five items, indicated in each form. These younger participants were asked to skip these items to avoid interview fatigue. A *t*-test was conducted, comparing item difficulty estimates from a previous study (Weinberg, 2012). This *t*-test showed that those items that were skipped by younger students did not have different mean item difficulty estimates ($M = -0.03$ logits) from those that were not skipped ($M = -0.08$, one-tailed *t*-test). Excluding the items that the younger participants skipped, the assessment was identical for all different age groups. Moreover, the assessment was developed to be accessible to participants across a wide age range.

This AMRP relies upon IRT modeling. In psychometrics, IRT is a paradigm for the design, analysis, and scoring of tests, questionnaires, and similar instruments measuring abilities, attitudes, or other variables. It is based on the application of related mathematical models to testing data.

Item format

Short-answer (e.g., items that require respondents to draw predicted motion) responses were used on the AMRP.

Scoring items

There are 21 items in which *related direction* and *rotation* could be scored. In addition, there were 11 items in which *lever arms*, *constraint via the fixed pivot*, and *tracing* could be scored. The items were scored according to an item exemplar, a scoring guide that is specific to the item and assessable mechanistic elements (Appendix A, Table A).

Conduct of the Interview

While participants responded to each item, a clinical interview was conducted. The clinical interview is a technique

Table 1.
Participants.

Participants	Number included in analysis
Elementary school students	28 (female = 17)
Middle school students	25 (female = 16)
High school students	20 (female = 4)
University undergraduates (non-science majors)	16 (female = 13)
University undergraduates (engineering majors)	13 (female = 5)
Adults (without college education)	10 (female = 8)

developed by Piaget (1951) to study individuals' knowledge structures and reasoning processes. Participants were asked to: (1) read the problem aloud and (2) think aloud as they responded to each item. When the participant completed the item, s/he was asked to explain again, if necessary, the rationale for the observed item response.

Analysis

Scoring items

Each item was scored according to its exemplar (item scoring guide; Appendix A, Table A). Participants were scored at the highest level where they achieved competency. For example, if a participant was scored at both the levels of *rotation* and *related direction* on an item, they were assessed at the level of *rotation*. An outside researcher scored 10% of the total items. The agreement was 85%.

Coding the clinical interview

In order to probe participant thinking during the AMRP administration, participant talk and gesture were coded according to an analytic framework used in a previous study (Bolger et al., 2012).

A participant's work on one item is defined as a "performance." Participants were coded at the highest level where they achieved competency within each performance. For example, if a participant was coded at both the levels of *constraint via the fixed pivot* and *tracing* during the interview, they were reported at the level of *tracing*. All performances were coded using NVivo 10.0 software. An outside researcher coded 10% of the total instances. The agreement was 82%.

Item Response Theory Modeling

To model the data from respondents, IRT was considered. Two Wright maps were generated: (1) the Item Wright Map and (2) the Item-step Wright Map. The Item Wright Map presents the person ability scores on the same scale as the average item location for each item; the Item-step Wright Map presents the person ability score on the same scale as the difficulty estimate for each mechanistic reasoning element, for each item.

Results

This section begins with an analysis of participant propensity to reason mechanistically, including a description of the mechanistic reasoning of two participants. Next, results from the Item Wright Map are presented in order to consider what participants find difficult about mechanistic reasoning, within and across items. After that, an Item-step Wright Map is described in order to consider what mechanistic elements participants found difficult to reason about, within and across items. Then, the differences between participants who scored many items at the construct map's top two levels (i.e., *constraint via the fixed pivot* and *tracing*) are reviewed. Finally, the differences in reasoning about specific mechanisms, across participant subgroups, are discussed. This section concludes with an investigation of characteristics of and differences between participants assessed at the top construct level (i.e., *tracing*).

Assessing Mechanistic Reasoning

In general, participants showed competency with mechanistic reasoning. Although 77% (n = 86) of participants were scored at the level of *no mechanistic elements* on at least one item, 71% (n = 80) of participants were scored at the level of *related direction* on at least one item. In addition, 65% (n = 73) of participants were scored at the level of *lever arms* on at least one item. This is consistent with Weinberg's (2012) indication that *related direction* and *lever arms* were the two easiest mechanistic elements. Moreover, we also see that *rotation* (30%, n = 34), *constraint via the fixed pivot* (44%, n = 49), and *tracing* (23%, n = 26) are the most difficult mechanistic elements to diagnose; a minority of the sample was able to diagnose these mechanistic elements. Overall, 89% (n = 100) of participants diagnosed at least one mechanistic element on at least one item.

Participant means of diagnosing these machines and mechanistic elements were varied. The mechanistic explanations of two participants, Lance and Brian, are presented in order to see how they explained the machines as well as diagnosed their mechanisms. Lance connects three mechanistic elements, while Brian applies *tracing* across all mechanistic elements.

Lance begins diagnosing item Sequential Tracing A3 (STA3) by notating the direction of lever movement with arrows. The interviewer then poses the following question: "Why is it going to move like that?" Lance responds by identifying the fixed pivot as the source of the machine's motion (Figure 1). He then employs forward and backward chaining (reasoning about subsequent mechanistic elements based on what is known about previous mechanistic elements) as he describes the motion of the system as a consequence of fixed pivot constraint. Next, Lance describes the relationship between the motion of the input and output levers, thus, causally linking the identification of the fixed pivot with the resultant input–output motion (*constraint via the fixed pivot*, *related direction*). Finally, Lance gestures to the rotary path of the output link with his pencil (*rotation*). Hence, Lance has causally connected three of the four mechanistic elements (i.e., *constraint via the fixed pivot*, *related direction*, and *rotation*).

Brian was coded as causally tracing all of the mechanistic elements from input to output on item Sequential

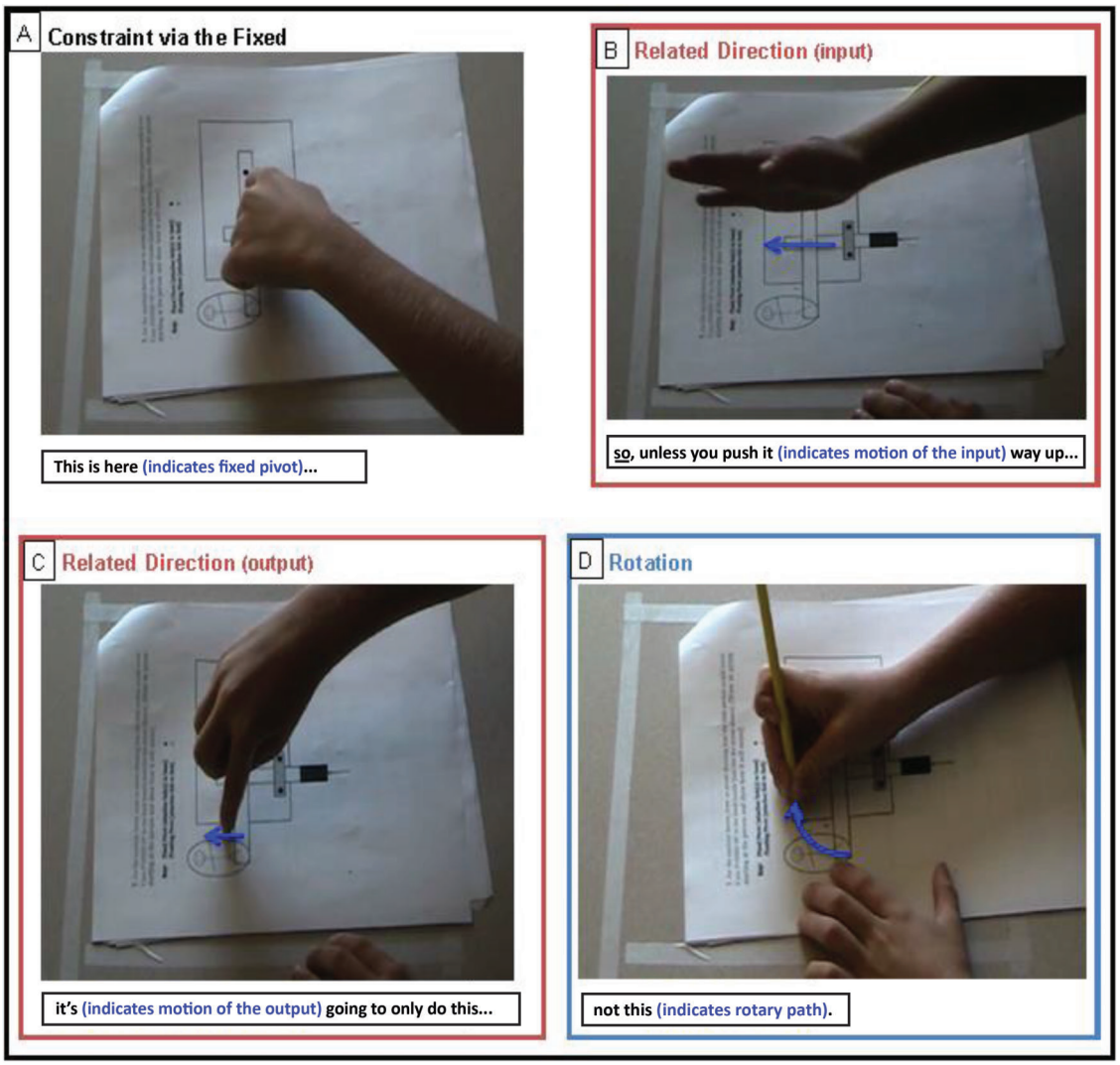

Figure 1. Coding an excerpt from Lance's explanation of the motion of this system of levers. He causally connects *constraint via the fixed pivot*, *related direction*, and *rotation*. The arrows represent the paths indicated by participants. Underlined text indicates linking words (Bolger et al., 2012) that causally connect mechanistic elements across the explanation. In the transcript, mechanistic elements coded through talk are red, while those coded through gesture are indicated in blue.

Tracing D1 (STD1). The interviewer posed the question, "So, how is it going to move?" Brian first noted (and indicated with his middle finger) that the output would go up (*related direction*, *output*; Figure 2). Next, he noted that the input would move up by causally coordinating the motion of the output and input (*related direction*, *input*; Figure 2); Brian comments: "output go[es] up and that's (indicates input) going up." Here, he is coded as diagnosing *related direction*. Next, Brian notices the fixed pivot: "and that fixed pivot (indicates fixed pivot) is on that side" (*constraint via the fixed pivot*, *identification*; Figure 2) and links it to the opposite coordinated motion of the lever arms: "and since that (indicates right lever arm) is going down (*constraint via the fixed pivot*, *subsequent motion*) and that (indicates left lever arm) will just go up" (*lever arms*; Figure 2).

Item Analysis

Item Wright Map

The Item Wright Map makes it possible to compare the mean difficulty of each item across the sample. For example, Sequential Tracing E1 (STE1) is the most difficult item, with a mean item difficulty of 0.92 logits. The easiest item is Sequential Tracing A3 (STA3), with a mean item difficulty of −0.76 logits. All item estimates and their corresponding standard errors are presented in Table 2. The standard errors indicate the precision of each estimate.

This Item Wright Map helps us consider the specific properties of these items and their represented machines that make causally tracing from input to output more or less difficult. This section reports how the following machine characteristics impact participants' diagnosis and causal

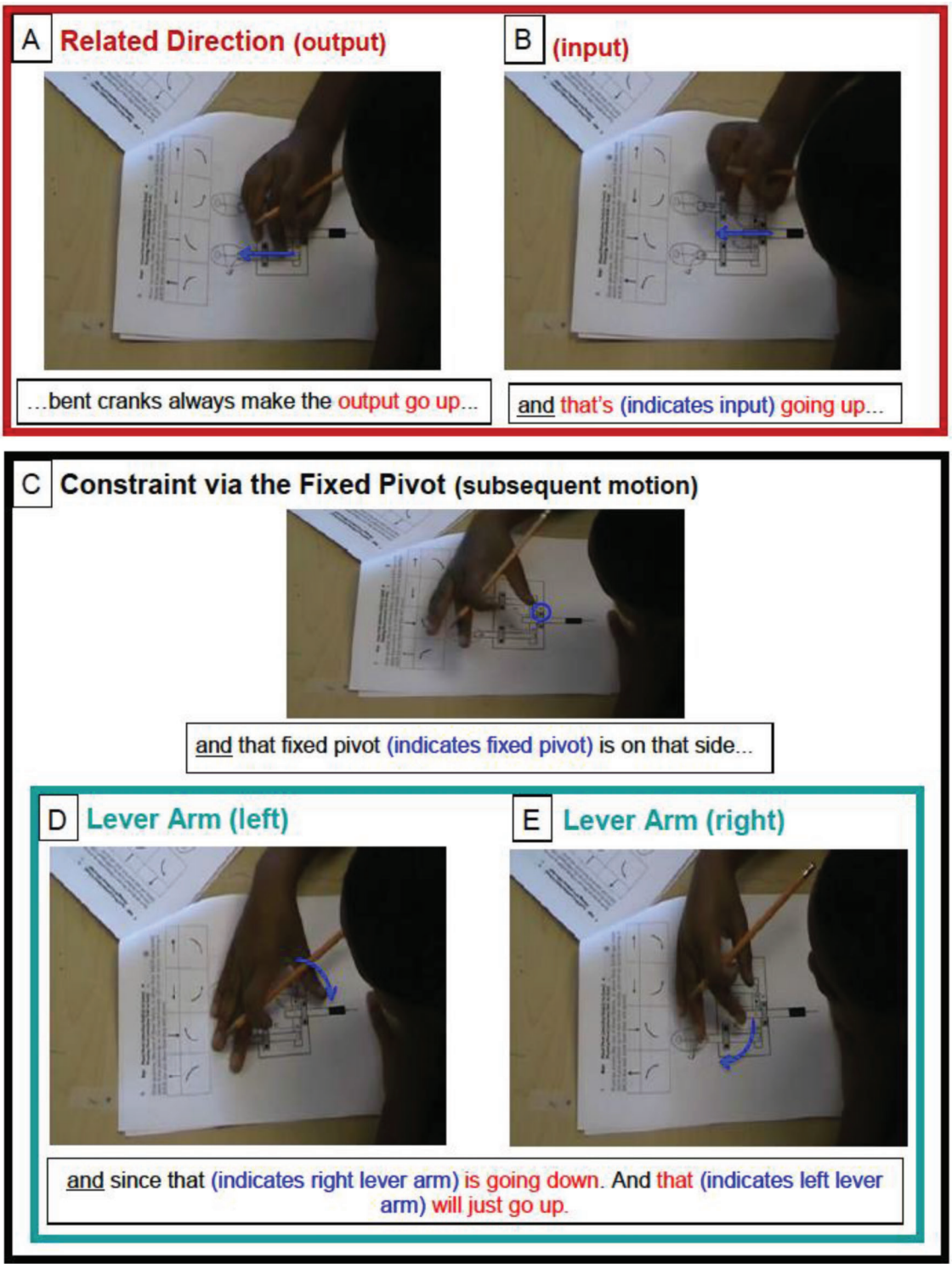

Figure 2. Coding an excerpt from Brian's explanation of the motion of this system of levers. He causally connects (*traces*) all the mechanistic elements from input to output. The arrows represent the paths indicated by participants. Underlined text indicates linking words (Bolger et al., 2012) that causally connect mechanistic elements across the explanation. In the transcript, mechanistic elements coded through talk are red, while those coded through gesture are indicated in blue.

connection of a machine's mechanisms: (1) number of levers, (2) arrangement of levers, (3) lever type (e.g., class 1 levers), and (4) presence of specialized and unfamiliar levers (e.g., a bent crank). The "number of levers," "arrangement of levers," and inclusion of a "bent crank" are not independent machine characteristics. However, each is included in this analysis in order to determine the effect each singularly has on mechanistic tracing.

Table 2.
Item difficulty estimates, standard errors, and mechanistic elements assessed.

Item	Item difficulty estimate (logits)	Standard error	Mechanistic elements assessed
Hands Fixed Pivot-Opposite	0.587	0.115	RD, R
Machine Prediction-A2	−0.426	0.114	RD, R
Sequential Tracing-D1	0.171	0.079	RD, R, LA, CFP, T
Sequential Tracing-E2	0.323	0.109	RD, R, LA, CFP, T
Hands Fixed Pivot-Same	0.008	0.128	RD, R
Machine Prediction-A1	−0.547	0.133	RD, R
Machine Prediction-A3	−0.319	0.133	RD, R
Machine Prediction-A3′	0.259	0.133	RD, R
Machine Prediction-B2	0.286	0.131	RD, R
Machine Prediction-B2′	−0.391	0.135	RD, R
Machine Prediction-D1	0.711	0.144	RD, R
Machine Prediction-D1′	0.543	0.142	RD, R
Sequential Tracing-A1	−0.700	0.117	RD, R, LA, CFP, T
Sequential Tracing-A3	−0.760	0.115	RD, R, LA, CFP, T
Sequential Tracing-A3′	−0.169	0.120	RD, R, LA, CFP, T
Sequential Tracing-B1	−0.519	0.117	RD, R, LA, CFP, T
Sequential Tracing-B1′	0.134	0.105	RD, R, LA, CFP, T
Sequential Tracing-B2	−0.487	0.114	RD, R, LA, CFP, T
Sequential Tracing-D1′	0.578	0.113	RD, R, LA, CFP, T
Sequential Tracing-E1	0.923	0.113	RD, R, LA, CFP, T
Sequential Tracing-CMT	−0.205[a]		RD, R, LA, CFP, T

Note. RD = related direction, R = rotation, LA = lever arms, CFP = constraint via the fixed pivot, and T = tracing.
[a]Estimate is constrained.

Item type

There were two item types used on the AMRP: machine prediction items and sequential tracing items. Machine prediction items ask respondents to predict the motion of machine outputs, whereas sequential tracing items ask respondents to predict the motion of all the different machine parts from input to output. There was no difference in item difficulty estimates between these two item types.

Number of levers

Participants had greater difficulty diagnosing machines composed of three or more levers ($M = 0.19$ logits) than those with two or fewer ($M = -0.38$ logits; $p = 0.003$, one-tailed).

Lever type

Five items included machines composed of class 1 levers; five items featured machines composed of class 3 levers. In class 1 levers, the input and output move in the same direction; whereas in class 3 levers, the input and output move in the opposite direction. Participants had greater difficulty with class 3 levers ($M = -0.03$ logits) than class 1 levers ($M = -0.41$ logits; $p = 0.08$, one-tailed).

Arrangement of levers

Of the twenty-one items, seven were constructed with one or more intermediate link(s) between the input and output. These seven items were more difficult ($M = 0.43$ logits) than the remaining fourteen ($M = -0.22$ logits; $p = 0.001$, one-tailed).

Bent crank

Participants had difficulty diagnosing machines that used intermediate links that were not standard levers. One such intermediate lever was a bent crank. The most difficult item was Sequential Tracing E1 (STE1) (Table 2). Sequential Tracing E2 (STE2) was another item with a bent crank as the intermediate link; this was also one of the most difficult items on the AMRP.

Domain-specific engineering experience

There are few differences in mechanistic reasoning across age groups. However, those participants who have attended K–16 academic institutions with programs in engineering, with some focus on mechanical systems, deployed mechanistic reasoning more adeptly and had higher person ability scores ($M = 1.12$ logits) than those who had not ($M = -0.91$ logits). For example, Josh, an elementary school student whose school offered an elective semester-long engineering course, had a higher ability estimate (0.51 logits) than the mean ability estimates for those who had not taken any courses with an engineering focus.

The Item-step Wright Map

The Item-step Wright Map (Table 3) places respondent ability and the difficulty for each mechanistic element, by item, on the same continuum. For instance, the element *tracing* has an item difficulty estimate of 3.04 logits on the item STE1 (the item with a bent crank, above). This indicates that those respondents who have person ability estimates of 3.04 logits will have a 0.5 probability of being scored at this level for this item.

Table 3.
Item-step Wright Map: item thresholds.

Item	Related direction	Rotation	Lever arms	Constraint via the fixed pivot	Tracing
Hands Fixed Pivot-Opposite	−0.41	1.59			
Machine Prediction-A2	−1.55	0.70			
Sequential Tracing-D1	0.25	−0.45	−0.59	−0.36	1.83
Hands Fixed Pivot-Same	0.38	−0.37			
Machine Prediction-A1	−1.17	−0.08			
Machine Prediction-A3	−0.84	0.20			
Machine Prediction-A3′	−0.98	1.49			
Machine Prediction-B2	−0.20	0.77			
Machine Prediction-B2′	−1.59	0.80			
Machine Prediction-D1	0.71				
Machine Prediction-D1′	0.55				
Sequential Tracing-A1	−1.79	−1.68	−2.12	1.51	0.61
Sequential Tracing-A3	−1.73	−2.41	−1.07	1.04	0.38
Sequential Tracing-A3′	−1.22	0.38	−1.44	1.54	
Sequential Tracing-B1	−2.18	−1.52	−1.00	0.20	1.89
Sequential Tracing-B1′	−0.07	−0.69	−0.83	−0.55	2.65
Sequential Tracing-B2	−1.11	−1.46	−1.87	0.50	1.48
Sequential Tracing- D1′	0.95	−0.27	−0.37	−0.08	2.48
Sequential Tracing-E1	0.96	−0.60	1.19	0.01	3.04
Sequential Tracing-E2	−0.46	−0.29	0.35	1.57	
Sequential Tracing-CMT	−1.00	−1.07	−1.24	0.33	1.86
Mean	−0.60	−0.36	−0.82	0.52*	1.80**

Note. Machine Prediction and Hands items can only assess *related direction* and *rotation*.
$^{**}p < 0.01$, $^{*}p < 0.1$.

This section describes those machine characteristics that seem to disrupt a participant's ability to trace all of a machine's mechanistic elements from input to output. Twenty-five participants showed the propensity to causally connect all four mechanistic elements (i.e., *tracing*) on at least one item. However, two of the machine characteristics (lever type and the inclusion of a bent crank) made a difference in these participants' propensities to consistently apply *tracing*. There were a total of 11 items in which *tracing* could be assessed. The number of items per form where this level could be assessed ranged from 3 to 8, with a mean of 6 (median = 6).

Lever type

Of those participants who had scored at the level of *tracing*, 0% did so on items with machines with class 3 levers; whereas 80% had scored at the level of *tracing* for items with class 1 levers (Table 4). Moreover, there is a difference in the proportion of participants who were able to apply *tracing* on machines with class 1, compared with class 3 levers ($p = 0.0005$, sign test).

Bent cranks

Of those participants who had scored at the level of *tracing*, 26% did so on items with machines with bent cranks; whereas 71% scored at the level of *tracing* for items with machines without bent cranks (Table 4). There is a difference in the proportion of participants who were able to apply *tracing* on machines with bent cranks, compared with those without bent cranks ($p = 0.01$, sign test).

Table 4.
Tracing by machine characteristics.

Machine characteristics		Scored at the level of *tracing* (%)
Lever type	Class 3 lever(s)	0
	Class 1 lever(s)	80**
Bent crank	With bent crank	26
	Without bent crank	71*

$^{**}p < 0.001$, $^{*}p < 0.01$ (sign test).

Domain-specific engineering experience

A participant's proclivity to reason about and trace simple systems of levers was not dependent on age, but rather experience with engineering, focusing on simple machines. When controlling for these engineering experiences, there is no difference in mean person ability scores across age groups (Table 5). Those participants who have taken at least one course with a focus on engineering design and content, including simple mechanical systems, were able to trace more systems ($M = 2.32$) than those who had not had such experiences ($M = 0.20$, $p = 0.00001$). In addition, of those participants who had diagnosed *constraint via the fixed pivot* or *tracing* on at least one item, those with experience in engineering had higher mean person ability estimates ($M = 1.15$ logits) than those

Table 5.
Mean ability estimates across age categories for participants with engineering training.

Age category	Mean ability estimate (logits)
Elementary/middle school (n = 5)	1.79
High school (n = 10)	1.13
University undergraduates (n = 12)	1.21
Adults (n = 1)	0.95

Note. The mean differences are not statistically significant.

without such experience (M = 0.42 logits; p = 0.004, one-tailed t-test).

Discussion

Reasoning about mechanisms is a cornerstone of disciplined inquiry in STEM fields. The AMRP has characterized this form of reasoning about simple levered systems across age and life experiences. In addition, it has helped to explain why this form of reasoning is difficult and what accounts for this difficulty. This study shows that machine characteristics such as number of levers, lever type, arrangement of levers, and inclusion of a bent crank can affect the difficulty of mechanistic reasoning. In addition, these machine characteristics specifically impact the proclivity for participants to diagnose mechanistic elements. Moreover, even when participants do, on at least one occasion, trace pushes and pulls through a machine, inclusion of class 3 levers or bent cranks can disrupt their propensity to do so on others.

This study extends the work of Bolger and colleagues (2012), Metz (1985), and Lehrer and Schauble (1998), who did not explicitly address the extent to which mechanistic reasoning can be applied across machines (e.g., gears, systems of levers). For example, some questions that were not previously addressed were: To what extent does a participant's proclivity to reason mechanistically about one system of levers generalize to other similar systems? What supports or disrupts the ability of an individual to see multiple systems of levers as variants of those that they can diagnose and causally trace? For instance, in this study some items disrupted participants' abilities to diagnose and causally trace a machine's mechanisms from input to output, when these participants had previously exhibited this ability on other items. All individuals who were assessed at least once at the level of *tracing* showed a decrease in their propensity to perform at this level when diagnosing machines with class 3 levers and bent cranks. diSessa (1993) provides an example of how Newton's third law of motion can be understood differently across two contexts. He notes that students are more likely to cite the relevant "equal and opposite forces" when a book is supported by a person's hand, rather than by a table. In this study, what mechanistic elements are cued (and causally connected) seems dependent on elements of mechanistic reasoning that could be further investigated in subsequent research.

This study shows that the ability to reason mechanistically is not age dependent; rather, the development of mechanistic reasoning is dependent on the accumulation of domain-specific knowledge. In this study, this knowledge was related to ideas within K–16 engineering education. For instance, participants with experiences in engineering showed greater capacities to reason about and coordinate mechanistic elements. Because mechanistic reasoning depends on the development of domain-specific principles and processes, it is important that these are taught and learned across K–12 education. Many researchers and educators (Brophy, Klein, Portsmore, & Rogers, 2008; Coyle, Jamieson, & Oaks, 2005; Cunningham, 2009; Hynes et al., 2011; Lachapelle & Cunningham, 2014; Marshall & Berland, 2012; Moore et al., 2014; Moore, Tank, Glancy, & Kersten, 2015; Roehrig, Moore, Wang, & Park, 2012) have taken important steps toward reconceptualization learning within the STEM disciplines, across the grades. Their attempts to develop a program for K–12 STEM education align well with previous efforts to identify core engineering concepts, skills, and dispositions for K–12 education (Committee on a Conceptual Framework for New K–12 Science Education Standards, 2011; National Academy of Engineering Committee on Standards in K–12 Engineering Education, 2010). Such a program could benefit from content that can support the development of mechanistic reasoning (as well as other important practices within STEM disciplines). In this study, systems of levers provided access to content that was sufficiently simple and transparent (but not trivially so) to allow students entrée into mechanistic reasoning.

This study showed that in order to diagnose simple systems of levers, individuals must recognize the push–pull interactions of various components as they trace the transmission of force. This form of system tracing is productive when diagnosing mechanisms in systems where forces are transmitted through visible components. Simple systems of levers make good candidates for content in which individuals can gain access to mechanistic reasoning. Moreover, this form of system tracing is also fundamental to diagnosing mechanisms in other similar mechanical systems.

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Appendix A

Item and Exemplar

Draw an arrow, like one of those in Figure 3, to show how each star would move if you pushed up on the black handle. (Draw an arrow starting at EACH star and show how they will move.)

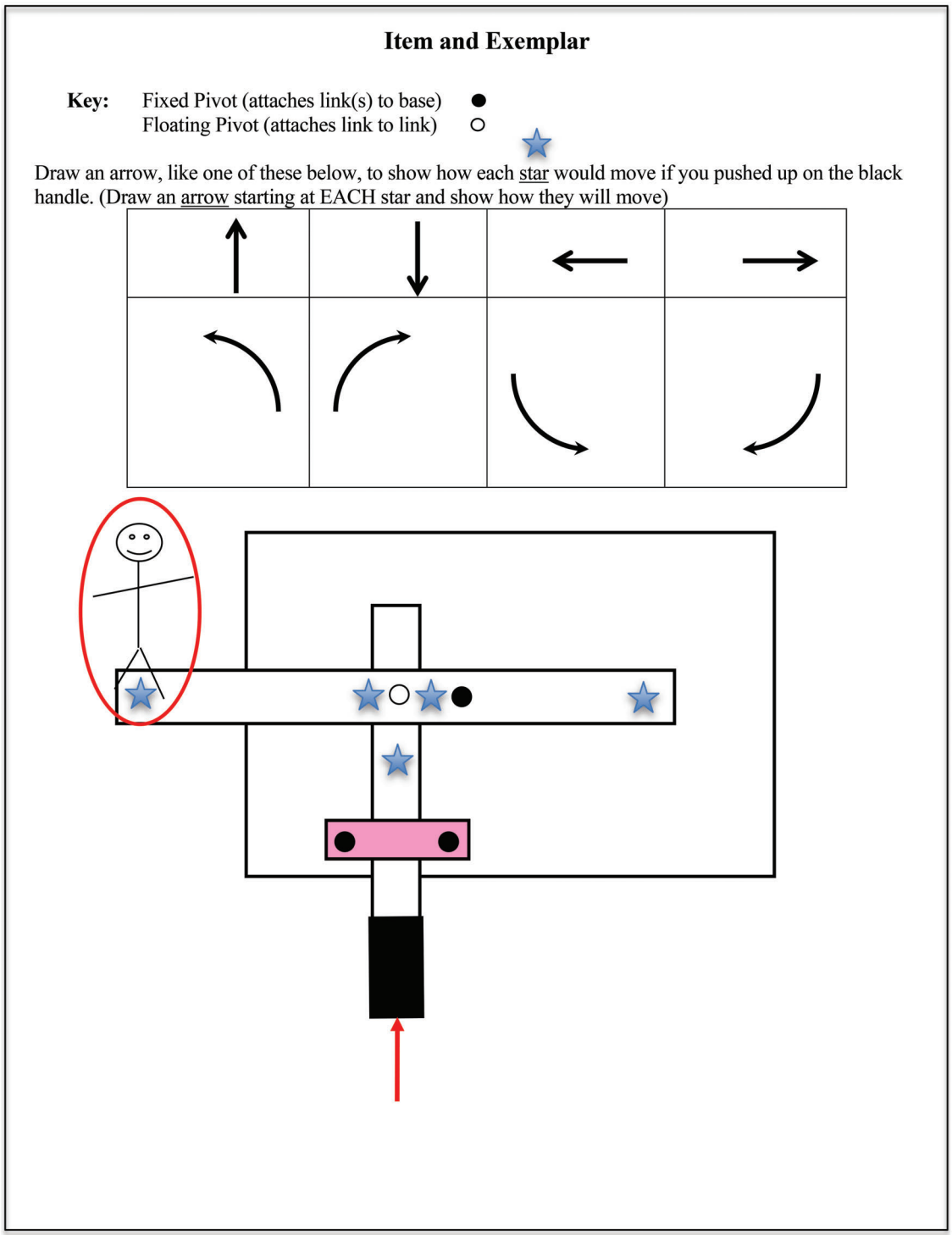


Figure 3. Item STA1.

Table *A*.
Item exemplar for STA1.

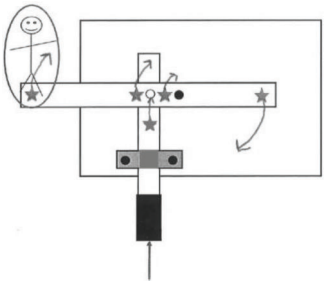
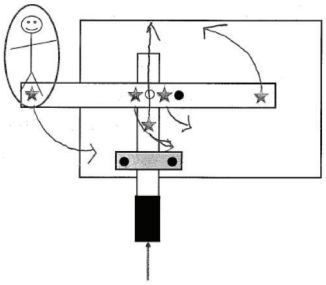
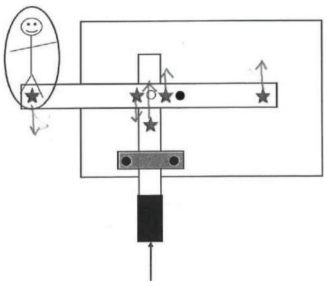
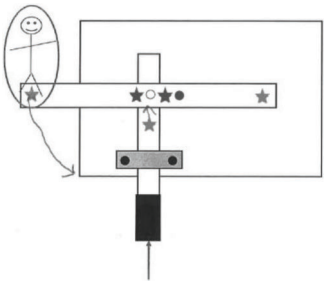
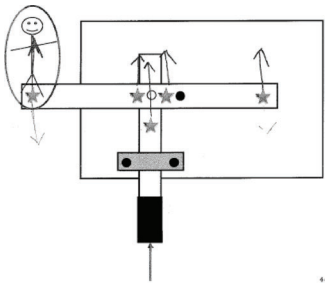
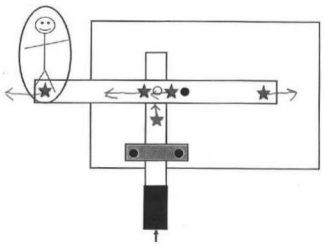
Level	Mechanistic element	Mechanistic element descriptions	Mechanistic element example
5	Tracing	Student is assessed at the level of *constraint via the fixed pivot* and diagnoses motion correctly (and without gaps) on all stars from input to output.	
4	Constraint via the fixed pivot	Participant correctly draws the opposite and/or rotary motion of the two closest points on opposite sides of the fixed pivot.	
3	Lever arms	Student draws arrows with opposite directions from stars on opposite sides of a lever's arms. *To code lever arms alone the direction must be incorrect.*	
2	Rotation	Student draws arced paths (they may show the incorrect direction). However, the location of these paths must reasonably approximate fractions of circles either centered around the fixed or floating pivot. *Note: Although these paths are centered around the fixed pivot, this element of mechanistic reasoning does not make this distinction.*	

TABLE
(Continued)

Level	Mechanistic element	Mechanistic element descriptions	Mechanistic element example
1	Related direction	Student draws the correct input motion; the correct output motion is drawn at least once.	
0	Student diagnoses no mechanistic elements	No mechanistic elements are shown.	
NL	No link	It is not clear if the student understood the nature of the task.	"I don't know"
Missing		Missing response.	

Note. This item assesses students' ability to diagnose the mechanistic elements of *related direction*, *rotation*, *lever arms*, *constraint via the fixed pivot*, and *tracing*. No link (NL) indicates an item response that does not provide any evidence of mechanistic reasoning (i.e., diagnosis of no mechanistic elements). "Missing" indicates that the item was left completely blank.