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Developing a Coding Framework to Analyze Student-to-Student Reasoning Based on Mental Models Theory*

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The use of active learning pedagogies, as well as research into their effectiveness, has increased greatly the past few decades. These pedagogies typically depend on student-to-student interactions to facilitate learning. Video recordings of student interactions provide excellent observational data from which to study the dynamics of these pedagogies in a naturalistic setting. However, these data are typically voluminous, include many potential features to follow, and as such make analysis difficult. One way to decrease the difficulty in analysis is to use a robust coding framework. This study develops such a coding framework using a well-established Mental Models theory of reasoning as a theoretical lens. Each element within the coding framework is analogous to an element in the mental models theory. This coding framework was applied to video recorded data of six student teams reviewing a peer team's prototype design in a classroom setting. The coding resulted in 567 transcription segments of which 68% related to the prototype review. All elements of the mental models theory are evident and code-able in the data and the general structure of the verbalized reasoning is identified. A rich description of the verbalized reasoning is provided. Furthermore, this reasoning structure appears constant across changes in student engagement and interaction purposes. As such, the identified structure of student reasoning, based on the mental models theory, provides a robust coding framework.

Keywords: mental models; coding framework; student reasoning

1. Introduction

The call to use active learning pedagogies has increased greatly in recent years [1, 2]. Many of these pedagogies rely on student-to-student interactions as the vehicle for learning. Research into the effectiveness of these pedagogies has greatly increased as well [3]. Both quantitative and qualitative research methods have been used based on a variety of data types. One particular data type, video-recorded student interactions, offers an opportunity to view an active learning pedagogy in use. This observational data allows a researcher to follow the development of ideas and reasoning between students. Such questions as, "How are the students collectively processing a learning task?," "How well is the student reasoning based on evidence?," or "How well are students integrating various tradeoffs in a complex problem?," can be readily informed. Informing questions of this sort is potentially a strong tool to improving the pedagogy being used. The starting premise of this study is twofold. First, analyzing verbalized student-to-student reasoning is a useful window to understand how the pedagogy facilitates learning. Presumably, the better the collective student reasoning is, the greater opportunity there is for student learning. Second, the expressed reasoning can be directly observed in their dialog and video recorded for analysis.

Recorded student-to-student reasoning is naturalistic data. It includes statements, utterances, gestures, manipulations of learning materials, and a variety of other communication and actions by the students. Since the students are already speaking with each other during active learning sessions, recorded data avoids the problems that some protocols (such as "talk-aloud") create by interfering with other cognitive processes that may be at work during the naturalistic setting [4–6]. One difficulty, however, with recorded observational data is that it creates voluminous amounts of *messy* data [7]. The data usually contains a wide variety of potential features to observe. The subsequent analysis of the "sheer quantity [of qualitative data] can be daunting, if not overwhelming . . ." [8]. Thus, the very data that provides an excellent view into the dynamic functioning of pedagogy is encumbered with a large overhead in analysis.

One way to streamline analysis of observational data is to use a standard coding frame which prescribes how to segment and structure the data. Since the basic steps following recording are prescribed, they can be completed in a more methodical method. However, such a coding frame needs to be grounded in a theory of reasoning that describes the reasoning being analyzed, otherwise the coding frame could systematically obscure relevant features in the data.

The goal of this study is to develop a coding frame based on the *mental models* theory of reasoning [9–12]. This theory is used as a lens to identify the *structure* of expressed student reasoning within the data in this study. This structure can then be used as

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a coding frame in subsequent studies to diagnose the specific *content* of student reasoning. One clarification is necessary at this point: the coding frame elucidates the expressed reasoning, not the underlying cognitive reasoning processes.

This study analyzed video recorded student team dialogues within a class setting. The students reason with each other about a prototype machine constructed by a peer team. These data are analyzed with the methodology of *content analysis* [13]. The root question that informs developing the coding frame is:

> What is the structure of the students' reasoning, as expressed in their dialog, while reviewing a physical prototype?

The intent is twofold. The first intent is to determine if the verbally expressed reasoning displays a consistent structural pattern. If the reasoning displays a clear structure, then that structure can be used as a coding frame to analyze the data. The second intent is to assess how consistent the structure of the reasoning is. Presumably, coding data will be more streamlined and faithful if the underlying reasoning structure is very consistent.

To these ends the paper is structured as follows. First, a well-established cognitive theory of how people make quick inferences is reviewed. This theory forms a lens for investigating the study data. A coding frame is developed from the theoretical lens, where each part of the theory forms an element in the coding frame. How to appropriately apply the coding frame within the methodology of content analysis is discussed. The study data is then coded to determine if a structure of reasoning emerges. A structure of reasoning does emerge, as will be discussed, and a variety of descriptive statistics are gathered to characterize the structural content of the data. The major elements of the structure are then richly described including examples from the data. Finally, the major elements of the structure are summarized into a general pattern.

2. Developing the theoretical lens

A theory of *mental models* was first proposed by Craik [14]. Since then, theories of mental models have developed in two distinct ways [15] where the term mental models have distinct meanings. In the first context, *a* mental model (usually stated as singular) describes a person's mental representation of a knowledge-rich domain to support reasoning, such as how to solve physics problems [16] or use a calculator [17]. In this context, mental models are stored in long-term memory and provide a framework from which to solve problems. In the second context, Johnson-Laird proposed that a *set* of mental model*s* (always stated as plural) are spontaneously created and manipulated in working memory to support logical reasoning [9]. These mental models are typically of short duration and are used for making quick inferences. The student dialogs in the study data were filled with quick inferences based on physical observations and so the Johnson-Laird theory was deemed more appropriate to use as a lens.

Just as there are two distinct uses for the term mental model, there are competing theories of how people make quick inferences: *Mental Models* and *Mental Logic.* The mental logic theory [18, 19] posits that people have a form of cognitive logic composed of a variety of schemas. Reasoners insert content into this natural logic to reach inferences. In contrast, the mental models theory of reasoning [9, 10] posits that inferences are obvious features in the set of models people spontaneously create and so do not require "logic." Both theories predict conditions where fallacious inferences are commonly reached.

Either the Mental Logic or the Mental Models theory potentially could be applied in this study. However, for this study Mental Models theory has the advantages of describing reasoning in a simpler and more general way. It also has the practical advantage of not being burdened with multiple logic schemas in which to map to the reasoning content. Hence the Mental Models theory was chosen.

2.1 Mental models theory

The mental models theory (hereafter referred to as *the theory*) is primarily focused on logical reasoning in tasks such as deductions and inferences [9]. The theory posits that *all* reasoning, ranging from everyday inferences to highly trained, is based on model sets acting in working memory. The theory rests on three assumptions: mental models are models of possibilities, mental models are iconic, and mental models describe truth rather than falsity [9, 10].

The first assumption is that mental models represent *possibilities* that are relevant for the reasoning context. For example, in a coin toss all possible trajectories of the coin are reduced to two possibilities: heads or tails. So the mental models associated with reasoning about coin tosses represent those two possibilities and do not represent models of all trajectories. As such, mental models track a parsimonious (least possible) amount of information while reasoning; they do not burden working memory with contextually irrelevant, but possibly true information. The theory goes even further stating that reasoning is *always* founded on possibilities.

The second assumption is that mental models are *iconic*. Parts and structures of mental models corre-

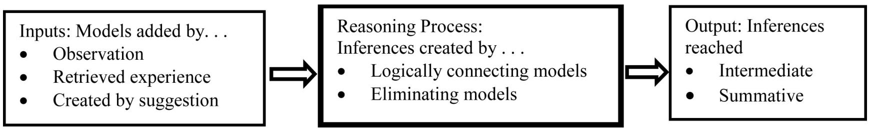

Fig. 1. The reasoning process converts inputs to outputs.

spond to parts and structures of the real world. The iconic structure of models is not necessarily visual or physical, though it may be. For example, *that* a coin is ''heads'' or ''tails'' (iconic state) is frequently more relevant than where it lands (physically iconic).

Third, mental models represent what is considered *true* and not what is false. People typically reason by tracking how the world is, not how it is not. This assumption also implies that people use a parsimonious amount of information while reasoning. When people do reason with falsity, such as with a counterexample, they must make mental footnotes to track the reputed falsity of claims in the counterexample.

A fourth assumption that is never stated, but always shown in examples of the theory, is that models are simple. The content in any one model is usually limited to one or two pieces of information with a single associating relationship.

When people reason, they create mental models representing different facets of the problem. Their conclusions are simply ''lifted off'' these models. The following example is an adaptation of one presented by Johnson-Laird [10, p. 171].

A student manipulating a prototype machine observes:

The actuator moves a coin through the machine.
The actuator sometimes sticks and has a jarring motion.
The coin jams when it is jarred.

The statements above can be denoted with the following iconic structure:

Actuator moves	Actuator sticks	Actuator jars
Coin moves		Coin jams

Where ''Actuator moves'' denotes a mental model of the actuator moving, ''coin moves'' a model of the coin moving, and so on. The left to right positions denotes sequential operating states of the machine, and the vertical position denotes actions that occur simultaneously. From this set of models you may infer,

The coin jams after the actuator sticks.

The theory posits such an inference is obvious within the model set; it is simply lifted from the models. No mental logic is needed.

The theory describes models as input to reasoning, reasoning as the process, and inferences as the output. The theory states that the cognitive process of creating mental models is unknowable, but that models are created from a variety of sources such as suggestion, observation, and from experience. The reasoning process connects these models or eliminates possibilities to produce inferences. Further, inferences themselves are mental models and can be part of subsequent reasoning; thus outputs can become inputs. Fig. 1 displays this process.

2.2 Creating a lens based on mental models theory

The contents of mental models are in working memory and thus available to speech, though the underlying cognitive processes are below awareness and are not observable [9]. In contrast, the student dialogs, which are the result of cognitive processes, are observable. Consequently the cognitive theory must be interpreted to form a lens for verbally expressed reasoning. Each characteristic of the theory defines an analogous characteristic of the lens as described below.

Models are parsimonious. Student dialog statements vary in length from single word utterances to extended statements containing multiple ideas. All dialog statements should be partitioned into the smallest phrases where each phrase conveys information representative of a single mental model.

Models are iconic. Only dialog statements that have one-to-one correspondence with aspects relating to the reasoning task are statements of models. Student statements that are unrelated to the reasoning task, such as moderating the discussion, are excluded because they do not express models used in the reasoning task.

Models are stated from a truthful perspective. Student dialog statements that use counter-examples should be separately tracked.

Models represent possibilities. Student dialog statements that express what may be possible, or possibly important, in the reasoning context are statements of models.

Reasoning combines or eliminates models. Words or phrases (e.g., ''because,'' ''if,'' ''so that,'' etc.) that establish relationships between models are expressed acts of reasoning.

Reasoning creates inferences. Student dialog statements create inferences. Inferences are embedded in the relational elements that express elements of reasoning; they are not separate statements.

3. Applying the lens in the methodology of content analysis

Content Analysis is a methodology for examining the content and meaning in texts [13]. The term *text* is used broadly to include written documents or any communication "produced by someone to have meanings for someone else" [13, p. 19]. In this study, the transcription of the student dialog is the text being analyzed.

Content analysis can be either *inductive* (sometimes called *conventional*) or *deductive* (sometimes called *direct*) [8, 20]. Inductive content analysis seeks to identify themes that emerge within the text, code the text within those themes, and then interpret the text based on those themes. In contrast, deductive content analysis begins with themes identified in prior studies or by theory [8]. This current study employs deductive content analysis because the theory of Mental Models informs the coding categories. Unlike typical content analysis, this study does not seek to interpret the themes, but rather to identify the structure of the reasoning for use as a coding scheme.

One practical concern in content analysis is the size of a *meaning unit* [21]. If the text is analyzed in units as large as a paragraph, several different meanings could reside in the single unit. Conversely, if single words are analyzed as units, the interpretation becomes fragmented [21]. To appropriately apply the lens developed above, each meaning unit needs to be representative of a single mental model. This implies that single phrases that state an iconic possibility within the reasoning context are the correct size of meaning units.

There is precedence in other studies of using this *size* of unit. Christensen [22] described a methodology for "studying design cognition in the real world." His methodology, termed *in-vivo*, [22–24], employed a verbal protocol analysis [25]. In his studies he recorded design discussions and then segmented the transcripts into verb phrases (the verb phrase being the meaning unit) to analyze the reasoning. A verb phrase is the part of a sentence that includes the verb and its object such as, ". . . *push* the *actuator*," where push is the verb and actuator is the object. This method made it possible to "monitor thinking and reasoning" [22–24] in a design context at a grain size of a verb phrase. A verb phrase is similar in size to a parsimonious statement of a model, though a model is not necessarily limited to only verbs and their objects.

3.1 Coding Steps Using the Theoretical Lens

A key differentiation in the coding was to separate verbalized models from verbalized reasoning. Fig. 2 shows this differentiation as a vertical dark line between verbalized models (inputs) and verbalized relationships (reasoning). Student statements that did not go beyond stating observations, constraints, or possibilities within the reasoning context were considered to be verbalized models (hereafter called *model phrases*). Statements that went beyond this boundary, such as logically connecting two observations, were considered to be verbalized reasoning (hereafter called *reasoning phrases*). Verbalized models suggest the presence of actual mental models, but should not be collapsed to a one-to-one correspondence with mental models, because actual mental models are unknowable [9]. Likewise, verbalized reasoning should not be collapsed to the cognitive process of reasoning.

Coding steps using the lens were as follows. Corresponding characteristics of the mental models theory are highlighted in bold.

<u>Step 1: Segmenting the transcription</u>. The video recording was transcribed and included notes of student physical actions and gestures. The transcript was then segmented to isolate each student verbalized model. In general, most students' statements were single segments. Longer statements typically segmented into two or three shorter segments. This step isolated the one-to-one correspondence between the statement and the reasoning context, which is necessary for the statement to be **iconic**. Student statements that moderated discussion or were off-topic were segmented into separate segments.

<u>Step 2: Writing model phrases</u>. A *model phrase* was written for each segment to express the content in simplified verbiage. Segments that expressed the same thought were reduced to repetition of the same model phrase. This step helped explicate the content. Actions and gestures were included in the

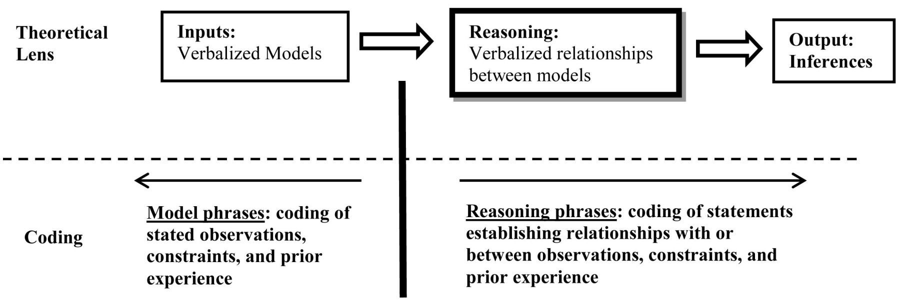

Fig. 2. Relation between coding phrases and the process of reasoning.

model phrases as warranted by context. For example, a model phrase such as "[during normal operation] the chip didn't flip," expresses the action as well as the student statement of, "the chip didn't flip." This step presented the content in a **parsimonious** way. Model phrases were not written for segments unrelated to the reasoning task so that all model phrases expressed **possibilities** in the reasoning context.

Step 3: Writing reasoning phrases. A *reasoning phrase* was written for every sequence of model phrases that student dialog connected with logical connectives. Such connectives as *instead, because, and, so that,* or equivalents were used as identifiers of reasoning. Since communication is broader than the syntax of uttered words, the video was reviewed phrase by phrase for implicit connectives. When warranted, the implicit connectives were annotated in the transcript. These reasoning phrases explicated how **relationships were established** between model phrases.

Step 4: Creating a visual tree of verbalized reasoning. The above steps yielded a set of verbalized model and reasoning phrases. To aid in identifying patterns, these model and reasoning phrases were structured in a chronological table. Each reasoning phrase could then be examined for where its supporting model phrases had originated and how it subsequently was incorporated into further reasoning phrases. Table 1 shows seven segments from the study data coded as model and reasoning phrases.

3.2 Study context, data, and coding

This study was conducted in a mechanical engineering design class of 30 students. The students worked in teams of three or four. The first project involved creating a machine to flip poker chips individually from an input stack into an output stack. A first prototype was designed, constructed, and tested by each team. A few days later each team redesigned their machine and constructed a second prototype. The prototypes were made of corrugated cardboard and the project lasted one and a half weeks. After the second prototypes were constructed, the teams conducted design reviews of peer teams' second prototypes. Each team was given a machine to review, instructed to evaluate the machine and make a list of strengths (positive attributes) and weaknesses (negative attributes). After conducting their first review, each team moved to another machine to review, and then another, until they had reviewed six machines.

A video recording was made of six teams sequentially reviewing the same machine. Thus, the first recorded team reviewed the prototype before reviewing other machines, the second recorded team had reviewed one prior machine, the third team two prior machines, and so forth. The video recording was transcribed and coded using the lens. Throughout the coding, the video was reviewed segment by segment to insure fidelity to the context. After the coding was completed, the video and coding were reviewed a final time.

4. Data analysis and description

Subsequent to coding, the transcription segments, model phrases, and reasoning phrases were classified by emergent characteristics, that is, themes that repeatedly appear in the coded data. Frequency

Table 1. Example of seven transcription segments coded into model and reasoning phrases

Line	Person	Transcription segment Actions, gestures in **[bold]** Dialog in *italic*	Model Phrase	Reasoning Phrase Connectives: underlined
1	C	**[Moves another chip through machine which binds up in output stack]**		
2	C	*that one (mumble) got stuck*	[during normal operation] chip sticks in output	
3	C	**[Pokes stuck chip with a finger]**		
4	B	*So you can push it too fast*	you can push the actuator too fast	chip sticks in output if you push the actuator too fast
5	A	*However it's already past the five chips* **[pointing at output stack]**	(output stack) is past 5 chips	chip sticks in output if you push it too fast however (output stack) is past 5 chips
6	C	*Yeah*		
7	A	*So they're not falling as far*	chips are not falling as far	chip sticks in output if you push it too fast however (output stack) is past 5 chips so chips are not falling as far

counts and descriptions of these emergent characteristics are described in the following sections. These counts and descriptions provide a basic understanding of what was in the data. As will be shown, the structure of the student reasoning becomes clear, which qualitatively demonstrates that the lens brings the reasoning into focus.

The descriptions are presented in the following order. The teams are described first to provide a context for the study. Following the team descriptions, the dominant characteristics of the model phrases are richly described. The model phrases correspond to mental models in the theory and hence these descriptions provide an understanding of the basic elements used in verbalized reasoning. These model phrases are further described in terms of both their *content* and their apparent *origin of the content* relative to the context of the learning activity. The analysis concludes with rich descriptions of how model phrases are combined to form inferences: basic chains of models, redirecting chains of models, and causal chains.

4.1 Team characteristics

The six teams were recorded for a combined 32½ minutes, which generated 567 transcription segments. Sixty-eight percent of the segments (386) were related to the prototype review, which are verbalized model statements in this reasoning context (hereafter *prototype segments*) and the remaining 32% (181) moderated discussion or were off-task (hereafter *moderating segments*). The 386 prototype segments were classified into three broad categories based on conversation focus: evaluating the current prototype (277), suggesting improvements (98), and discerning the designers' original intent (11).

The six teams displayed a wide variety of focus on task and approach. The first three teams spent approximately the same amount of time in review. Team 1 spent considerable time carefully observing the functioning of the machine, whereas Team 2 made quick judgments about the functioning but spent time conjecturing on why the designers designed the parts as they did. One member on Team 2 was more dominant than the others such that a teammate had to make multiple conversational attempts to successfully contribute to the conversation. Team 3 had strong disagreements, which stalled their overall progress. The effect of these team dynamics on team reasoning are described later.

The last three teams spent less time reviewing the machine than the first three teams, but about the same amount as each other. Team 4 used a strategy of summarizing inferences to help the scribe record the lists of "strengths" and "weaknesses." Team 5 used a strategy of contrasting the current prototype with the previous four machines they had reviewed. Team 6 was fairly distracted and generated only 52% prototype segments but 48% moderating segments.

Considered together, the teams approached the review with widely different strategies and strikingly different team dynamics. Interestingly, as will be described, the structure of the verbalized reasoning was consistent across all teams, but used for different purposes. The team characteristic statistics are listed in Table 2.

4.2 Mental models: building blocks of reasoning

The theory implicitly assumes that mental models are small bites of information, each one being a parsimonious representation of a possibility. When the data is interpreted from this perspective, each transcription segment appears to express a mental model. For example the phrase, *"If they want to cut the footprint down . . . "* expresses the possibility that the designers may wish to reduce the size of the machine. Alternately, it may express the possibility that the machine could be reduced in size. Consequently reducing the transcription segments to model phrases was straightforward, though on some segments there was uncertainty concerning the nuanced meaning of the content.

Table 2. Model Phrase Characteristics of Team Discussions

		Team 1	Team 2	Team 3	Team 4	Team 5	Team 6	Total
Duration of discussion (min:sec)		6:43	8:20	7:04	3:40	3:10	3:36	32:33
Transcription Segments (Total Count)		131	151	71	82	65	67	567
Segment Count by Conversation Focus	Evaluating prototype	66	72	35	50	22	32	277
	Improving prototype	34	27	6	9	19	3	98
	Conjecture of designers' intent	1	9	1	0	0	0	11
	Off-task or moderating discussion	30	43	29	23	24	32	181

Another aspect of models being parsimonious is that they cannot be subdivided. Consequently, if one tries to reduce a mental model to subparts, it should no longer describe a possibility. This aspect provided a minimum length to each segment. For example, in the following segment the student paused mid-statement while examining the prototype.

> **[student picks up the machine to look at it]** *they added... they added like an extra ... (pause)... feel like, yeah,* [continues to move head to see features] ... *they definitely added like extra stuff...*

The first portion of the statement "they added extra" is an incomplete possibility until he finally adds "stuff." Arguably "stuff" is a very general term and yet it made the statement a complete possibility.

The theory also posits that mental models are iconic; parts and structure of the models reflect the real world. For example, *"this [part] doesn't need to be that high..."* reflects the physical structure, *"[the machine is] difficult to operate..."* is iconic of the operator's experience, and *"this part goes up down up down..."* is iconic of motion. Significantly, every prototype segment was iconic.

The theory posits that mental models represent information as truthful and that mental footnotes are engaged whenever counterfactual information is tracked. Throughout the discussions the students appeared to state the information as they thought it to be, rather than counterfactually. For example, *"the slant helps the flip to be consistent..."* describes what the student thought to be true, though he may have had the facts or inferences wrong. In the case of this example, the team did not evaluate the dynamics of the machine in enough detail to know with certainty that the slant did help the chips to flip consistently.

Verbal footnoting of counterfactual information was not evident (e.g. "this slope works but if it didn't work then..."); however another truth-preserving tactic was evident. The students occasionally entered cycles to refine their statements, with each statement being a better approximation of truth:

> A: "... that's about..."
> B: "seven, eight inches,"
> A: "I'd say closer to ten,"
> B: "that's a foot, almost..."

This approach sidesteps the need for mental footnotes while preserving the truth of the models.

4.2.1 Content of prototype segments

Six broad categories describing the content of the prototype segments emerged during coding. Thirty-nine percent of the segments described the dynamic functioning of the machine, *"... when the chips fell I think they'd rotate faster."* Since function was a major goal for the machine this result was not surprising. As the students discussed how the machine worked and possible improvements, their statements described the relative physical position of machine parts accounting for 23% of the prototype segments, *"if this (ramp) were shortened and this were made steeper...."* The project emphasized manufacturability where students calculated an assembly and manufacturability cost. Correspondingly, 16% of the prototype segments related to construction costs, *"actually they could probably do it all in like two pieces, this whole thing...."*

Prototype segments related to constraints came in two forms. First, required specifications for the machine would be cited, *"... it's over the (allowed) footprint."* Second, physical constraints would be stated, *"There has to be room for the, the pusher...."* Constraints were evident in 13% of the segments. Segments that conjectured the designers' original intent accounted for 2% of the segments which were primarily clustered in a single episode in one team's discussion. All other prototype segments accounted for the remaining 7%.

4.2.2 Model origins

The cognitive mechanisms for generating mental models are not known [26, 9]. However, six broad categories of apparent origins for the prototype segments emerged during coding. Observations made during testing accounted for 42% of all segments. Repeating a previously verbalized model was also common at 25%. Sixteen percent of the segments were spontaneous proposals of design improvements, some of which likely originated in prior experience of designing and building their own machine. Together, these three categories accounted for the large majority of segments.

Eight percent of segments were summary statements of previous inferences. These summaries usually came about as the students were scribing the comments on their lists of strengths and weaknesses. Another 6% related to prior experience, usually when contrasting the prototype being reviewed with the students' own design. The final 3% of segments did not include verbal or contextual clues that suggested their origin.

In summary, the prototype segments express the essence of mental models per the theory. The segments stated possibilities, were iconic, and stated what was thought to be true. Though some teams were more engaged than others, the structure and size of the segments did not noticeably vary across the teams. Rather, what appeared to vary was the total number of segments, where team 3 (with open disagreements) and team 6 (off topic) verbalized models at a slower pace. The prototype segment counts are listed in Table 3.

Table 3. Prototype segment counts

		Team 1	Team 2	Team 3	Team 4	Team 5	Team 6	Total
Prototype Segment Count by Content	Description of dynamic function	37	40	20	20	10	22	149
	Relative physical positions of parts	34	14	8	21	6	7	90
	Manufacturability and assemblability	4	30	8	8	12	1	63
	Descriptions of designers' intent	2	6	1	0	0	0	9
	Statement of constraint	20	6	6	6	9	2	49
	Other	4	12	0	3	4	3	26
Prototype Segment Count by Apparent Origin	Testing and observing prototype	31	40	25	26	16	22	160
	Proposing improvements	17	22	6	8	6	2	61
	Retrieving specific prior experience	4	6	3	4	5	1	23
	Summary of multiple inferences	12	5	0	14	0	0	31
	Repetition of previous statement	32	29	8	6	14	9	98
	Other	5	6	1	0	0	1	13
Prototype Segments (Total Count)		101	108	43	58	41	35	386

4.3 Come let us reason together, or not

4.3.1 Building inference chains

The most dominant characteristic of the reasoning was how fluently the discussions connected one prototype segment to another. Students would make inferential connections (identified with underlining) within their own statements, *"You have to use the cardboard though <u>because</u> the paperclip would not be that long. . . ."* They would also make connections to statements of fellow students:

A: *". . . the design is kind of wobbly,"*
B: *"[<u>so</u>] . . . base . . . put a base on the bottom. . . "*

More than a third (43%) of the segments included relational connectives to other segments. In total the students connected prototype segments within their own statements 91 times and to another student's segments 74 times.

These connections usually created inferences that went beyond the information jointly contained in the verbalized models being connected (induction). The example above contains the two segments "the design is wobbly" and "put a base on the bottom." However, when the student joined them with the implicit "so" the joining induces that adding a base will solve the problem of being wobbly. This inference goes beyond the given information to provide a likely, though not guaranteed, outcome.

The connections were also used to restate important inferences that did not go beyond what was in the verbalized models (deduction). These restatements typically collapsed an inference chain to its final piece.

A: *"yeah but this is. . . I like this 'cause it's all one piece of"*
B: *"cardboard. . . yeah <u>so</u> this* **[facing the scribe]** *we'll just say. . . ah. . . we like it <u>because</u> it is cheap. . . "*

After discussing the number of parts and part complexity, the final statement by "B" collapses the reasoning chain into a single inference to the student scribing the list, *". . . it is cheap. . . ."*

Roughly half of initial connections were followed by a connection to a third segment. These chains of inferences were common and basically built one idea onto another and then onto another. Table 4 shows two sequential transcription statements which subdivide into three segments. The resulting three model phrases and two reasoning phrases are shown to make it easier to recognize the linking. This example was classified as a chain length of "3" to match the number of segments that are linked. Table 6 displays the count of the various chain lengths in each team.

Another interesting facet of the example above is the change of segment types within the single chain. The first segment described a physical part, the second a constraint, and the third the dynamic functioning of the machine. The logical linking of the segments relies on the segment type that is linked each time. In this way physical parts are related to constraints which are related to the dynamic function. This connecting of a segment type to another segment type was common in the expressed reason-

Table 4. Example of student dialog showing a chain of connectives

	Transcription Actions, gestures in **[bold]** Dialog in *italic*	**Model Phrase**	**Model Type**	**Reasoning Phrase** Connectives: underlined
A:	*So if there was some kind of guide* **[pointing]** *for the shover* **[gesture]**. . .	If there was a shover guide	Physical parts and position	
C:	*A guide so it wouldn't come out. . .*	Shover wouldn't come out	Constraint Dynamic function	If there was a shover guide so the shover wouldn't come out
	. . . *and* so you know, know when **[gesturing with arm in air]**. . . [you] *are all the way. . . it was over the edge.*	You know (feel) when it was over the edge		If there was a shover guide so the shover wouldn't come out and so you know when it was over the edge

ing and appeared to happen fluently without a "grinding of cognitive gears" [10].

4.3.2 Redirecting inference chains

Most of the connectives simply appended another prototype segment; however some of the connectives replaced or challenged a previous segment (substitutive connection) within the chain. Substitutive connectives were used 42 times while additive connectives were used 123 times. An example of a substitutive connective is shown in Table 5.

In the example in Table 5 person "B" substituted that being hard to push is an advantage rather than a small problem as stated by person "A." Substitutive connectives were common in the first four teams, but operated in different ways. In Teams 1 and 4, the substitutive connections were used primarily to refine and clarify ideas. In Team 2 one member dominated the conversation and a teammate used a few careful substitutions to rejoin the conversation and redirect the ideas. In Team 4 two members frequently disagreed and substitutions were typically brief ways to express those disagreements. On average, additive connectives outnumbered substitutive connectives 3 to 1. However, in the team with frequent disagreements the opposite was true; substitutive connectives outnumbered additive connectives 2 to 1. Group 5 and 6 had few substitutions, most of which were used to refine ideas. Table 6 lists the number and type of connectives used in each team.

In summary, connectives followed more than a third of all prototype segments to create chains of reasoning. These connectives were used nearly equally to link between a person's own ideas or to another's ideas. About three quarters of the connectives appended segments and the remaining quarter modified existing inference chains. The substitutionary connectives were used for refining ideas, though at times they appeared to be used for simply disagreeing. Across all teams the connective reasoning had the same characteristics; one segment would be connected to another with apparent fluency from segment type to segment type.

4.3.3 Causal reasoning

Causal reasoning was also evident within the transcripts. Reasoning connectives were coded as causal if they described physical motion or interaction of parts. Causal reasoning was further coded as "forward" when stated cause to effect and "backward" when stated effect to cause. Forty-one percent of all reasoning statements (67 of 165) were causal. Reasoning connectives that used causal terms or syntax but were not related to physical causes were excluded from these counts.

Table 5. Example of substitutive connectives used to redirect an inference chain

	Transcription Actions, gestures: **[bold]** Dialog: *italic*	**Model Phrase**	**Reasoning Phrase** Connectives: underlined
A:	*Also it's a little tough to, to push it. . .* . . . not that that's a big deal. . . . . . but it could be easier.	It is difficult to push	
		Difficult to push is not a big deal	It is difficult to push but difficult to push is not a big deal
		It could be easier to push	It is difficult to push but difficult to push is not a big deal but it could be easier
B:	[However] *I think the advantage of having it, this hard to push. . .*	Hard to push is an advantage	It is difficult to push but hard to push is an advantage
	. . . *though, is that you can keep this* **[points at top edge]** *lower.*	The top edge can be lower	It is difficult to push but hard to push is an advantage because the top edge can be lower

Table 6. Reasoning phrase counts

		Team 1	Team 2	Team 3	Team 4	Team 5	Team 6	Total
Person Making Inference	Building on own statements	31	27	16	5	6	6	91
	Building on peer's statements	23	13	4	18	10	6	74
Inference Chain Length Count	= "2"	22	25	10	10	7	6	80
	= "3"	19	10	6	5	2	2	44
	= "4"	10	4	3	4	2	2	25
	= "5"	3	1	1	2	2	1	10
	= "6"	0	0	0	2	1	1	4
	= "7"	0	0	0	0	2	0	2
Inference Type Count	Additive	40	34	13	16	10	10	123
	Substitutive	14	6	7	7	6	2	42
Causal Reasoning Phrase Count	Stated cause to effect	15	12	7	7	2	3	46
	Stated effect to cause	10	4	5	1	0	1	21
	Non-causal statement	29	24	8	15	14	8	98
Reasoning Phrase (Total Count)		54	40	20	23	16	12	165

The prominent characteristic of the causal reasoning was that the cause and effect were nearly always "adjacent" as in this example:

A: *"well you want it to slant up. . . "*
B: *". . . because it puts the weight in the back. . . "*

In this example the students had been discussing the inclined ramp and "B" makes the observation that slanting the ramp shifts the center of gravity of a stack of chips rearward. Both the cause and effect were immediately observable in the prototype. The students did not construct long causal chains that led from one inference to a distant target. Nor did the students use physics to "insert" potential causal reasoning into chains of observations. Rather there was the occasional reference to a dynamic concept, *"the momentum will carry it. . . ,"* or *"cause it to flip faster. . . ."*

Reasoning from effect to cause is more difficult than from cause to effect because a single effect could have several potential causes [10]. Further, inferences seem more plausible when stated cause to effect [27]. Similarly, the forward causal statements outnumbered the backward statements 46 to 21. However, the backward causal statements merely seemed to be syntactically constructed to more easily fit the flow of the conversation. For example in the statement:

". . .right there it wasn't flipping but maybe that's because I messed it up. . ."

The effect, "it wasn't flipping," is mentioned first and the cause, ". . .I messed it up. . ." is mentioned second. Hence though stated in reverse order, it is still cause to affect reasoning. Nevertheless, it was very evident that the causal reasoning was structured identically to the other reasoning. Prototype segments were linked to other segments with inferential connectives; the only difference was that the inferential connectives were causal. Counts of causal and non-causal inferences are listed in Table 6.

5. Discussion

Johnson-Laird's mental model theory was developed in the distant context of word problems, and yet when used as a lens, it brought the design reasoning with physical artifacts into clear focus. The natural discourse segmented intelligibly into statements that had all the characteristics of mental models. They were statements of possibilities, iconic, and stated as truthful rather than counterfactually. The reasoning also exhibited characteristics of the theory; students' inferences were directly based on their models [9].

Perhaps the most striking feature of the data was how "quantized" the reasoning appeared. Students would logically connect from one verbalized model statement to the next much as stepping from one stone to another; the model statements forming the stepping stones and the logical connectives forming the steps between them. When they stopped their line of reasoning, they would stop on a model statement. This quantized aspect of their reasoning is shown in the following example figures.

In Fig. 3, student "A" states an aspect concerning the physical prototype. This statement distills down to a model phrase (MP 1), which the person joins to another model phrase (MP 2) using a logical connective (LC). The joining of the two model phrases creates an inference. In the example shown, the person continues with another logical connective joining another model phrase (MP 3). The *content* of the reasoning resides in the model phrases and the *relationships* reside in the logical connectives. The figure includes example model phrases and logical connectives that display the structure.

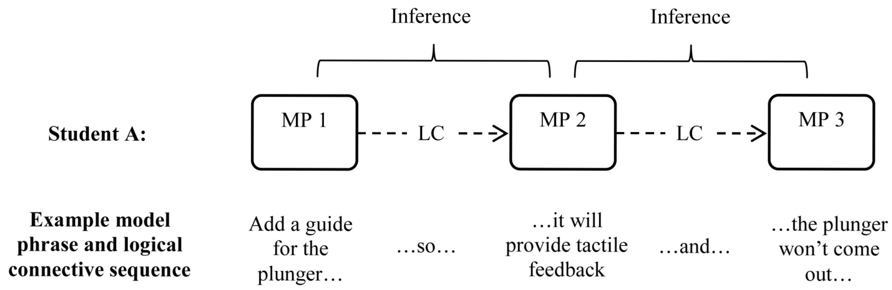

Fig. 3. The basic structure of the verbalized reasoning.

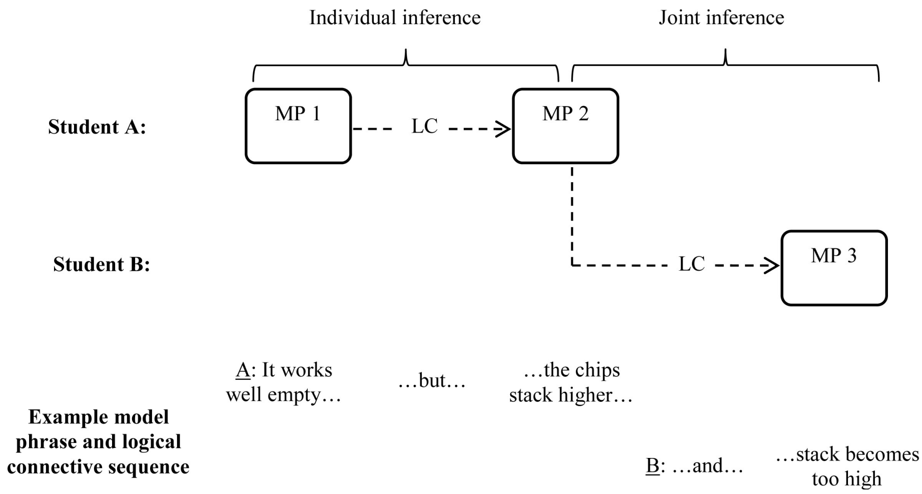

Fig. 4. The structure of joint reasoning.

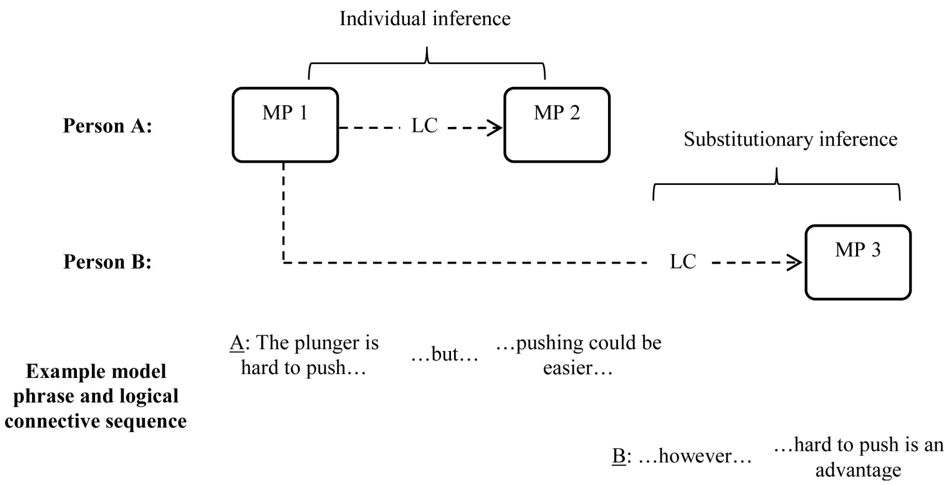

Fig. 5. The structure of substitutive inferences.

The same structure was present when the students reasoned together. With joint reasoning, each student would contribute model phrases and the logical connectives would span each other's models. In Fig. 4 student "A" states a model phrase (MP 1) and then logically connects a second model phrase (MP 2). Student "B" then adds a logical connective in the dialogue and appends another model phrase (MP 3).

The same structure again appears with substitutive inferences. In Fig. 5 "A" begins with two model phrases and a logical connective to make an inference. Student "B" begins with the original model phrase (MP 1) but logically connects it to a different model phrase (MP 3 instead of MP 2). Approximately one quarter of inferences were substitutive.

The three basic structures of inferences described above, individual, joint, and substitutive, were evident throughout the transcriptions. Furthermore, these inferences structures were woven together in combination and longer chains than shown in the above examples. Finally, not all model phrases were structured into inferences; approximately half were left unconneted in the dialogues. These structures emerge whether the students seemed to be in full agreement or strongly disagreeing, whether they appeared engaged or disengaged, or whether their reasoning seemed sound or naïve. Stenning and Monaghan [28, p. 146] stated that "deductive reasoning is as commonplace as language," and that, "we are constantly, almost effortlessly, forging mappings between. . . people/place/things. . ." The students' reasoning likewise seemed to effortlessly forge mappings between aspects of the prototype.

5.1 *The structure of reasoning in other contexts*

This study examined student reasoning in a prototype review, consequently the data does not inform what reasoning structures might exist in other contexts. However, there are three reasons why the identified structure could be expected in other contexts. First, the Mental Models theory is a general theory of reasoning and a theoretical lens built upon it would likewise be general. Second, the contextual information, that is the comments *about* the prototype, was imbedded in the verbalized models and not the overall structure. There was no evidence that the reasoning structure actually depended on the context. Third, the students used the same reasoning structure for widely different ends. If the reasoning structure depended on the context, then the contextual shift from agreeing or disagreeing, or from being engaged to disengaged, could have displayed a shift in structure. However, these local contextual shifts did not display a shift in reasoning structure.

This study identified the structure of the student reasoning based on the Mental Models theory. This structure provides a direct means to code the observational data in the study, and hence an approach to understanding and improving the pedagogy used in the study. If the student reasoning structure proves similar in other contexts, which the data suggests but cannot confirm, then the identified structure is a potential methodological tool in contexts broader than the study data.

6. Trustworthiness and limitations

6.1 *Establishing trustworthiness*

Trustworthiness has three aspects: dependability, transferability, and credibility [21]. Credibility concerns whether the data and analysis directly address the research question or study focus. To be credible the data must be sufficiently large to surface the phenomenon and the meaning unit (coding size) must be an appropriate size. In this study the data included 32 minutes of dialog, where approximately 22 minutes were students reasoning about the prototype. If measured in terms of meaning units, the data was 386 units long. The structure of the reasoning was apparent throughout the dialogs and across sections as short as a few consecutive meaning units. Consequently, the data was sufficiently large to establish patterns and the meaning unit was of proper size to identify those patterns.

Credibility also requires the coding categories to span the content of the data [8]. If not, then data may be inadvertently or systematically excluded. The coding categories completely span the data if all data can be reasonably coded into a defined category. Furthermore, it is important to strictly adhere to a clear coding scheme [21, 29]. This study adhered to coding scheme prescribed by the theoretical lens. Additionally, all student reasoning phrases coded directly into the chosen categories. Consequently, the coding categories spanned the data.

The aspect of dependability concerns whether the data changes over time and context. Similar studies conducted at other times should yield the same result. The data in this study is limited to one context and time, and so this study cannot make a dependability claim beyond the immediate context of the data. However, since the lens was based on a theory tested in many contexts, it is likely the results span time and contexts.

The aspect of transferability refers to whether the findings of one study may be applied in another context. Transferability is not established by the study itself, but rather by a thorough description of the study. The description gives readers a clear understanding of the study context, analysis process, and multiple examples from the data. This understanding allows the reader sufficient insight to determine if it is reasonable to transfer the findings to a new context [8, 29]. This current study provides a full description of the study context, analysis process, and examples from the data.

One final trustworthiness concern is errors introduced by the coder [29]. Data may be coded for *manifest content* or *latent content*. Manifest content refers to physically identifiable elements in the text such as specific words, phrases, or references. Latent content refers to interpretive elements where nuanced meaning may change how data are coded. Manifest content typically does not need dual coding because the content is obvious whereas latent content always involves dual coding [29]. The structure of the student reasoning in this study was manifest content, and hence dual coding was not required. Furthermore, the descriptive statistics developed in this study identified the structure of reasoning, and were not used to generate statistical inferences [29].

6.2 Limitations

The primary limitation of this study is the assumption that mental models are evident in common dialog. The theory posits that the cognitive processes of mental models are below conscious awareness [9], though their content is consciously available. This study assumes that the presence of mental models naturally flows into the student discussions and can be coded to some level in the transcript. Since mental models theory is a working memory construct [15] and speech is also formulated in working memory [30] this assumption is not a large step. Further, determining the precise content of mental models is impossible because people "are not always able to fully articulate their knowledge" [15, p. 9685]. This limitation implies that coding would lack precision concerning the exact content of the mental models (which it did as noted previously) and would reduce the certainty of the listed descriptive statistics. However, the previous analysis and discussion do not rely on interpreting the exact content of the mental models, nor on precise descriptive statistics. Rather, the analysis relies on identifying the content of the models well enough to describe the structure of the reasoning.

Another potential limitation regards whether the theory can be directly applied in this context. The mental models theory has extensive evidence for its own validity [9–12]. However, the theory's strongest support relies on experiments using verbally stated reasoning problems by individuals [31]. Changing the context to a student design review with a physically manifested reasoning problem could likely affect the reasoning. That said, the theory led to a coherent picture of the everyday reasoning in the design reviews. This coherent picture should be considered evidence, but certainly not sufficient, to rule out other possible cognitive models.

Finally, any theoretical lens can also act as a filter such that characteristics of the data are systematically overlooked. Hence, the lens informs aspects of the data that come into focus, but not aspects of the data that are not detected. However, the coding framework in this study represented all reasoning content in model phrases and all verbal connectives in reasoning phrases. Consequently, this theoretical lens did not systematically exclude relevant data.

7. Conclusions

Recorded student dialogue in active learning pedagogies provides a window to understand the dynamic workings of the pedagogy. However, these recordings create a voluminous amount of messy data that can be daunting to analyze. One way to streamline the analysis of such data is to use a standard coding frame which prescribes how to segment and structure the data.

This study developed and tested a coding frame based on a well-established mental models theory of reasoning. Each aspect of the reasoning theory was recast as an aspect of the coding frame. This coding frame was then used to identify the structure of expressed reasoning as students critiqued a peer team's prototype. The coding frame clearly identified the underlying structure of the expressed student reasoning and supports three direct conclusions:

1. The structure of the students' expressed reasoning consisted of parsimonious statements about the prototype chained together with logical connectives to form inferences. This structure was consistent across all team dialogs and across a variety of team dynamics.
2. Logical connectives were used in two ways: additive connectives extended chains of inference and substitutive connectives rerouted chains of inference.
3. All characteristic elements of mental models, and the basic reasoning with mental models, as described in this established theory, were evident and code-able, throughout the dialog. As such, this reasoning theory formed an effective coding frame from which to analyze the student reasoning.

The findings of the study suggest avenues for future work. First, similar studies could be conducted in other contexts to inform whether the same structure of reasoning emerges. The theoretical lens for this study is a general theory of reasoning which suggests that the reasoning structure in other these contexts should be quite similar. If so, then the coding framework could become a significant tool from which to examine many active learning pedagogies.

Second, this study developed and verified an analysis tool, but did not employ that tool to analyze or improve the specific learning session recorded to gather the data. Studies that identify relationships between how an active learning pedagogy is structured and how the ensuing student reasoning develops could inform how to best design active learning exercises.

Finally, as mentioned earlier, the theoretical lens is based on a very general theory of reasoning. It is not confined to engineering education, and so these findings could be applied to many disciplines across the academy.

References

1. ASEE: National Effective Teaching Institute, http://www.asee.org/conferences-and-events/conferences/neti, Accessed 27 February 2015.
2. R. M. Felder, D. R. Woods, J. E. Stice and A. Rugarcia, The future of engineering education II. Teaching methods that work, *Chemical Engineering Education*, **34**(1), 2000, pp. 26–39.
3. M. Prince, Does active learning work? A review of the research, *Journal of Engineering Education*, **93**(3), 2004, pp. 223–231.
4. S. P. Davies, Effects of concurrent verbalization on design problem solving, *Design Studies*, **16**(1), 1995, pp. 102–116.
5. P. Lloyd, B. Lawson and P. Scott, Can concurrent verbalization reveal design cognition?, *Design Studies*, **16**(2), 1995, pp. 237–259.
6. J. W. Schooler, S. Ohlsson and K. Brooks, Thoughts beyond words: When language overshadows insight, *Journal of Experimental Psychology General*, **122**, 1993, pp. 166–166.
7. M. TH. Chi, Quantifying qualitative analyses of verbal data: A practical guide, *The Journal of the Learning Sciences*, **6**(3), 1997, pp. 271–315.
8. S. Elo and H Kyngäs, The qualitative content analysis process, *Journal of Advanced Nursing*, **62**(1), 2008, pp. 107–115.
9. P. N. Johnson-Laird, *How we reason*, Oxford University Press, USA, 2006.
10. P. N. Johnson-Laird, Mental models and reasoning, in J. P. Leighton and R. J. Sternberg (eds), *The nature of reasoning*, Cambridge University Press, Cambridge, 2004, pp. 169–204.
11. P. N. Johnson-Laird and R. M. Byrne, *Deduction,* Lawrence Erlbaum Associates, New York, 1991.
12. P. N. Johnson-Laird, *Mental models: Towards a cognitive science of language, inference, and consciousness*, Harvard University Press, USA, 1986.
13. K. Krippendorff, *Content analysis: An introduction to its methodology*, Sage, USA, 2004.
14. K. Craik, *The nature of explanation,* Cambridge University Press, Cambridge, UK, 1943.
15. D. Gentner, Psychology of mental models, in N. H. Smelser and P. B. Bates (eds), *International Encyclopedia of the Social and Behavioral Sciences*, **11**, Elsevier Science Publishers, 2002, pp. 9683–9687.
16. A. A. DiSessa, Toward an epistemology of physics, *Cognition and instruction*, **10**(2–3), 1993, pp. 105–225.
17. D. Norman, Some observations on mental models, in D. Gentner and A. L. Stevens (eds), *Mental Models*, Laurence Erlbaum Associates, New York, 1983, pp. 7–14. 1983.
18. M. D. Braine and D. P. O'Brien, (Eds.), *Mental logic*, Psychology Press, 1998.
19. D. P. O'Brien, Mental-logic theory: What it proposes, and reasons to take this proposal seriously, in J. P. Leighton and R. J. Sternberg (eds), *The Nature of Reasoning*, Cambridge University Press, Cambridge, 2004, pp. 205–233.
20. H. F. Hsieh and S. E. Shannon, Three approaches to qualitative content analysis, *Qualitative Health Research*, **15**(9), 2005, pp. 1277–1288.
21. U. H. Graneheim and B. Lundman, Qualitative content analysis in nursing research: concepts, procedures and measures to achieve trustworthiness, *Nurse Education Today*, **24**(2), 2004, pp. 105–112.
22. B. T. Christensen, A methodology for studying design cognition in the real world, *Nordes*, (1), 2009.
23. K. Dunbar, Understanding the role of cognition in science: The science as category framework, in P. Carruthers, S. Stich, and M. Siegal (eds), *The cognitive basis of science*, Cambridge University Press, Cambridge, 2002, pp. 154–170.
24. K. Dunbar, How scientists build models in vivo science as a window on the scientific mind, in L. Magnani, N. Nersessian, and P. Thagard (eds), *Model-based reasoning in scientific discovery,* Springer Science & Business Media, US, 1999, pp. 85–99.
25. K. A. Ericsson and H. A. Simon, *Protocol analysis*, MIT Press, 1985.
26. N. J. Nersessian, The cognitive basis of model-based reasoning in science, in P. Carruthers, S. Stich, and M. Siegal (eds), *The cognitive basis of science*, Cambridge University Press, Cambridge, 2002, pp. 133–153.
27. A. Tversky and D. Kahneman, Causal schemas in judgments under uncertainty, in D. Kahneman, P. Slovic, and A. Tversky (eds), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press, Cambridge, 1982, pp. 117–128.
28. K. Stenning and P. Monaghan, Strategies and knowledge representation. In J. P. Leighton and R. J. Sternberg (eds), *The Nature of Reasoning*, Cambridge University Press, Cambridge, 2004, pp. 129–168.
29. B. L. Berg and H. Lune, *Qualitative Research Methods for the Social Sciences,* **4**, Pearson, Boston, 2001.
30. S. E. Gathercole and A. D. Baddeley, *Working Memory and Language Processing*, Psychology Press, 2014.
31. B. T. Christensen and C. D. Schunn, The role and impact of mental simulation in design, *Applied Cognitive Psychology*, **23**(3), 2009, pp. 327–344.

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