Patterns of Understanding with Open-ended Learning Environments: A Qualitative Study

☐ Susan M. Land
Michael J. Hannafin

This study examined patterns of scientific understanding using an open-ended learning environment (OELE). Four seventh-graders were drawn from a general science class and were studied as separate cases. The OELE was the ErgoMotion program on mechanical physics, which combines computer-generated graphics, computer simulations, video, and print-based materials. Primary data collection techniques included think-aloud protocols and interviews. The results indicated that learners perceived information from the system, derived interpretations to explain observations, and used system features to test interpretations. Learners also, however, tended to perceive and interpret information inaccurately. While learners built and formalized scientific theories, they often failed to use system data to evaluate the limitations of their understanding. In some cases, they assimilated new data into existing theories, ignored inconsistent data, or derived independent theories to account for contradictory evidence. This study indicated that powerful intuitive theories, which are highly resistant to change, influence the interpretation of system events.

☐ Recently, researchers and educators have developed technology-based environments that promote active, student-centered learning (see, for example, Cognition and Technology Group at Vanderbilt, 1992; Spiro, Feltovich, Jacobson, & Coulson, 1991; Tobin & Dawson, 1992). Accordingly, new visions regarding the relationship among technology, the learner, and the learning process have been conceptualized (Hannafin, 1992; Kozma, 1987; Jonassen, 1984). Technological advances have enabled the development of powerful tools and resources to represent and construct meaning (Perkins, 1991). Accompanying perspectives have guided the use of technology through powerful theoretical frameworks of student-centered learning *processes* (see for example, Brown, Collins, & Duguid, 1989; Spiro et al., 1991). When used to enable student-centered learning, technological tools can redefine both the experiences available to learners and the processes required to engage them (Salomon, 1986; Salomon, Globerson, & Guterman, 1989).

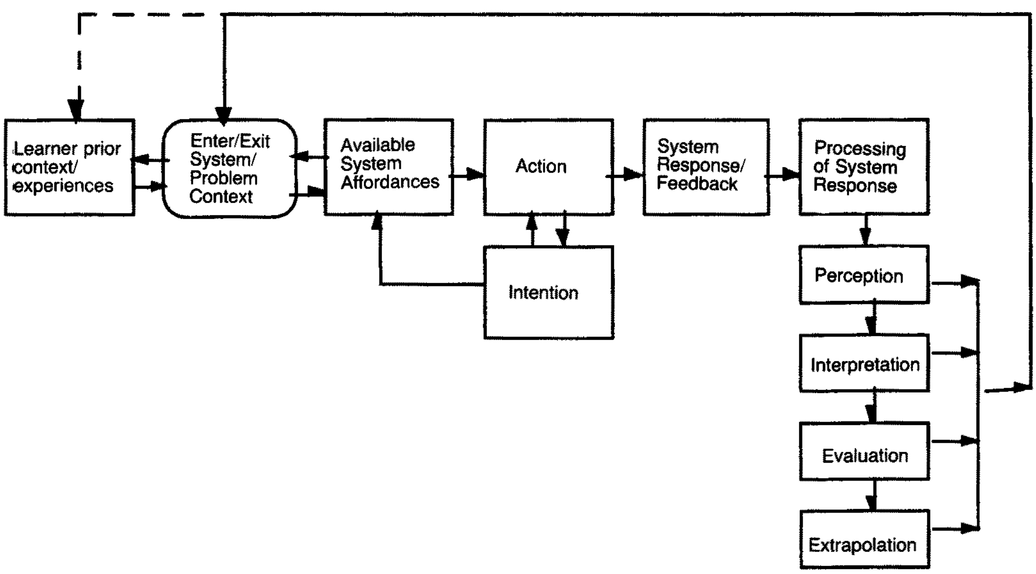
Open-ended learning environments (OELEs) utilize technology to support student-centered inquiry. Tools for manipulation and experimentation are provided to promote discovery and evolution of personal beliefs (Papert, 1993b). Using OELE tools, learners typically construct physical models of a concept and receive real-time, dynamic feedback about the effects of their actions (Perkins, 1991). For example, open-ended physics microworlds enable learners to alter the force and direction of an object in space and note the results (Rieber, 1992). In thermodynamics, learners can alter surface area and insulation properties of an object, and chart subsequent changes in temperature (Lewis, Stern, & Linn, 1993). Understanding evolves continuously and dynamically, as ideas are generated, tested, and revised.

OELEs employ contexts that anchor new information and skills within familiar experiences. In situated environments, learners reference contextually-relevant prior knowledge, manipulate system features, and derive conclusions about observations by applying informal conceptions to interpret the events (see Cognition and Technology Group at Vanderbilt, 1992; Schön, 1983). Learners' theories are often simplistic and naive, but they permit progressive refinement through manipulation and experimentation using the system's tools and resources. For instance, when learning about force and motion, learners will likely have experienced force and motion concepts related to increasing/decreasing speed or changing direction; accordingly, the contexts and activities posed by OELEs are often problem-based, exploratory, and designed to stimulate connections to learner prior knowledge.

According to OELE proponents, understanding evolves as underlying theories are established, confirmed, and/or refuted. Figure 1 illustrates several elements that influence the evolution of understanding in OELEs: (a) learner and system context; (b) available system tools and resources; (c) learner intentions and actions; (d) system feedback based on learner actions; and (e) learner processing of system feedback (see Land & Hannafin, 1996, for a detailed description of the model). The nature and quality of learning depends upon the extent to which these elements emerge, evolve, and support progressive levels of understanding.

Learners use OELE tools and resources to refine their understanding of events depicted in the system. Presumably, learners construct initial formative models of concepts under study, use system tools and resources to represent and test them, and progressively refine them based upon system feedback. Strategies and intentions may take the form of unsystematic explorations, such as browsing, or thought-based actions that are guided by the learners' intentions to test their understanding. The system provides feedback which is subsequently processed at varying levels, ranging from simply perceiving a general consequence to extrapolating interpretations to, or from, other contexts. Information about the consequences of actions, as well as the limita-

Figure 1 □ A conceptual model for developing theories-in-action with OELEs (from Land & Hannafin, 1996)



tions of their thinking, is then used to refine understanding and to guide further action. Once limitations in thinking have been perceived, new goals and actions emerge that result from the revised conceptual model. As understanding evolves, intentions and actions become more systematic and processing deepens through the testing and refining of formative theories.

Yet, the manner in which open learning environments promote understanding has been questioned. Some have suggested that available tools are not used or do not support user goals, intentions, or expectations. Atkins and Blissett (1992), for instance, found that learners rarely used the manipulation features of a videodisc environment to learn; rather, they used random strategies and rarely refined either their initial strategies or understanding. Similar observations were reported by Hill (1995) who noted that learners frequently failed to establish and refine their goals using system tools; in some cases, the available tools did not enable users to pursue their interests. OELEs are designed to support problem-solving via intentional, thought-based action; the learner's intentions, however, are often unclear or not supported by available tools. As a result, understanding often fails to evolve.

The purpose of this research was to *describe* the processes through which learners develop understanding while using an OELE; and to *explain* how understanding developed. Consistent with Hashweh's (1988) approach to the study of science learning, the descriptive component emphasized learner actions and processes, while the explanatory aspects focused on characterizing patterns according to an explanatory framework. Three learner activities were emphasized: (a) processing of feedback/information; (b) intentions for actions; and (c) use of system features.

METHOD

Participants and Design

Prior to the study, the first author spent several months serving as a teacher's aide in the class from which participants were selected. This helped to ensure that she was viewed as a natural everyday participant in classroom activities. The participants were 4 seventh-graders drawn from an intact general science class. Each was in the 11–13 year age range, Caucasian, and from a middle-class socioeconomic background. The students were average to above-average ability based on a prestudy assessment of physics knowledge. Low-achieving students did not participate because of restrictions regarding removal from classroom activities. Participant selection was made to ensure representative gender (two males and two females), verbal levels (two quiet and two verbal), and computer experience (two skilled and two moderately skilled). All students were told that they would not receive a grade for their work, but that they would serve as group leaders or "experts" for the class who would participate at a later date—a common classroom practice.

A qualitative approach was selected because of its sensitivity to process (Guba & Lincoln, 1982) and suitability for describing phenomena from a learner's perspective; interpretations and themes regarding *why* and *how* learners generated meaning could be readily identified (Driscoll, 1995; Jacob, 1987; Robinson, 1995). The students were studied as separate cases and analyzed for similarity and differences by referencing an existing theory-based pattern. Case results were compared against, and explained according to, a previously developed theoretical model depicting how learners build and revise theories-in-action (Yin, 1994).

Materials

The open-ended, computer-based environment was *ErgoMotion,* a mechanical physics program in the *Science Vision* series. The materials were developed by the *Interactive Media Science Project* at The Florida State University and funded by the National Science Foundation and Houghton Mifflin Company. *ErgoMotion* incorporates features such as computer-generated graphics, computer simulations, video, direct-manipulation interfaces, and print-based materials into a microworld that supports the process of open-ended learning (Bowen, 1992; Litchfield & Mattson, 1989; Tobin & Dawson, 1992).

The situational context for *ErgoMotion* is the learning of physics concepts using the metaphor of a roller coaster. Participants are oriented to the environment with a video scenario of teenagers riding a roller coaster accompanied by voice-over narrative speculating about what makes the ride thrilling. The focus of activity is the experimentation site—a virtual roller coaster track that supports manipulation of three major parameters: sizes of three hills (3 sizes each), motor size and mass of the coaster cars (3 options each), and radius of a series of horizontal curves (small, medium, and large). Learners adjust a button to make the hills higher or lower, the curves wider or narrower, or the mass and motor size larger or smaller. After setting parameters, learners run a computer simulation to observe via a video clip the effects on the coaster. Figure 2 illustrates an overview of the coaster experimental site screen.

If the selected parameters result in too much inertia or acceleration, the coaster will crash, simulating real-life consequences. Resources are available with which to collect information related to physics concepts and simulated coaster performance, which can be accessed from any screen or selected from menus or help buttons. For instance, students may receive video instruction from a *videopedia*—a comprehensive resource of physics concepts (e.g., Newton's Laws, acceleration, potential energy) which provides brief video vignettes, examples, and explanations of physics concepts. Scaffolding is available in the form of opinions and advice from on-line experts who serve as consultants. Participants who seek procedural or conceptual support can be guided through an *inquiry menu* of related questions, which provide probing questions and generic procedural support for problem solving. Finally, learners can be quizzed on their physics knowledge through a *Radio Quiz Show* game in which they listen to two experts discuss a problem under study and judge which opinion seems more reasonable.

Students can also collect quantitative data and interpret their meaning for each available parameter. For instance, they can access numerical data points along the coaster track to gain additional information about inertia, potential/kinetic energy, and acceleration of

Figure 2 ☐ The coaster experimentation site.

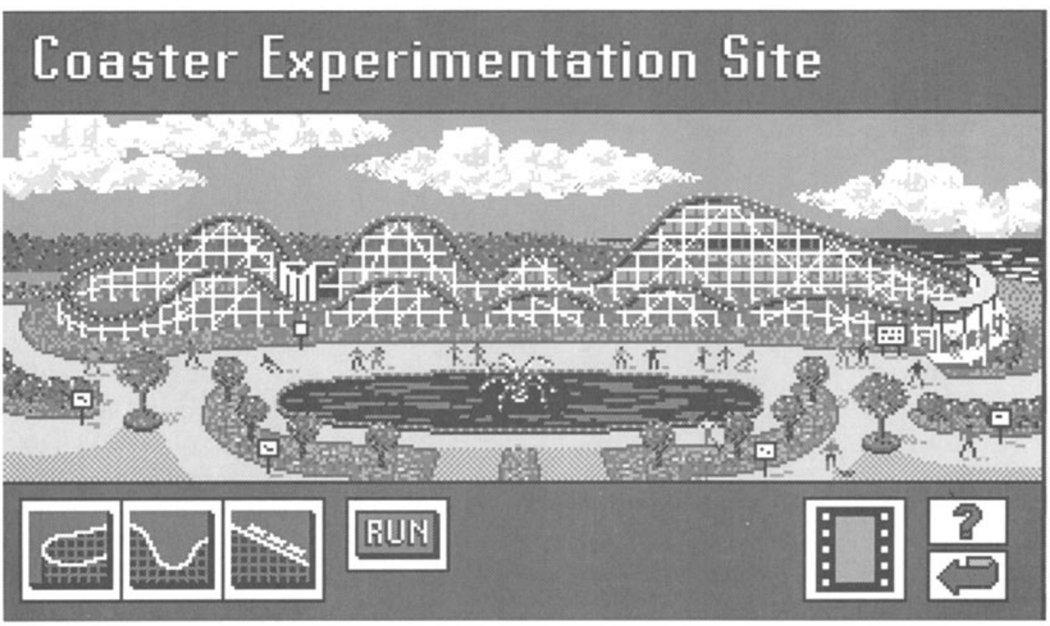
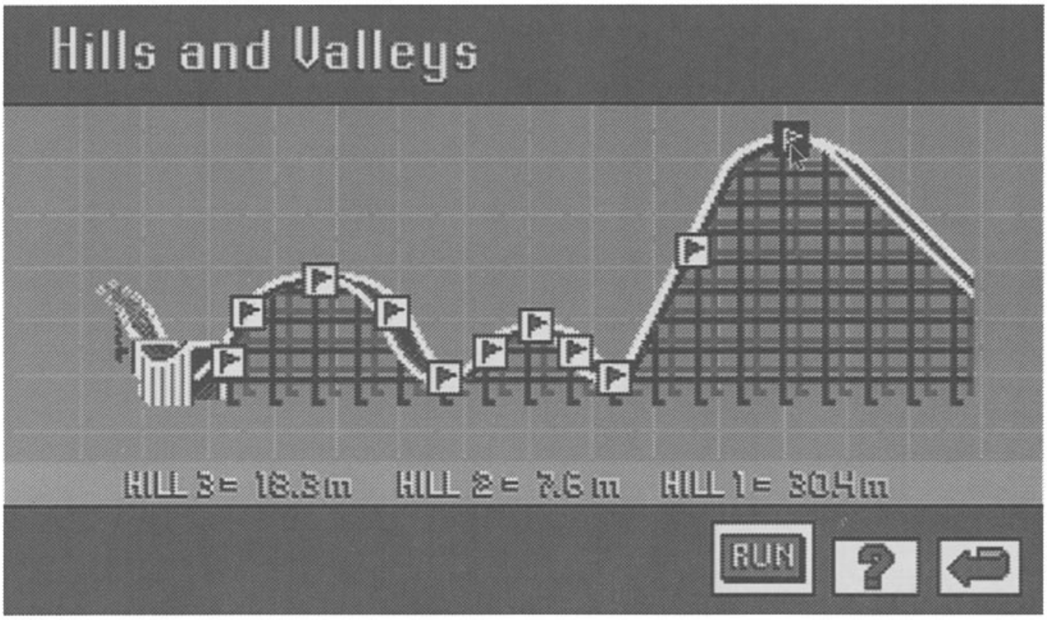


Figure 3 □ Data points at the hills and valleys section.



the coaster, following their simulated coaster run. These data can be charted in student workbooks (e.g., as mass increases, potential energy increases), and trends can be interpreted. Figure 3 shows how data points are accessible at the hills and valleys section.

Finally, learners can participate in a coaster challenge that presents specific problems (e.g., "set the size of the hills so that the coaster will come to a rest in the first valley"). These problems serve as analogs to the main coaster problem, and introduce additional variables to be manipulated (e.g., friction settings). Three analog coaster challenges of progressive complexity were available.

Techniques for Data Collection

Think aloud protocols were collected during both use of the system and postlearning (hypertext) interviews. Data collection was organized around three learner activities: processing of information, intentions for action, and use of system features. These categories were selected based on research which indicated that science learning is influenced by depth of cognitive processing (e.g., Roth & Roychoudhury, 1993), extent of intentional, constructive activity (e.g., Atkins & Blissett, 1992), and amount of informed use of system features (e.g., Lewis et al., 1993). Table 1 illustrates the data collection sources, techniques, and indicators.

Research Methods

Think-Aloud Protocols. Learners were prompted to think aloud while using the system and during the interviewing (see Ericsson & Simon, 1992 for a detailed description of the procedures). The goal of the think-aloud procedure was to document thought processes as they occurred and to increase the precision of communication between the researcher and the learner. Think-aloud verbalizations reflected the learners' thoughts as they engaged the system.

Post-Session Interviews. In order to ascertain *why* participants took an action, made a decision, or provided an interpretation during the learning process, the think-aloud procedures were augmented via a postsession interview.

Table 1 ☐ Data Collection Categories, Techniques, and Sources

Category	Techniques	Data Sources
Processing of information	• Think-aloud protocols	• Verbalizations of reflections or meaning of the results of an action
	• Interviews	• Verbalizations of interpretations of system-provided feedback
		• Self-reports of thought processes and extent of processing effort
Intentions for action	• Think-aloud protocols	• Verbalizations of a reason or intention for acting in the environment
	• Interviews	• Verbalizations of decision-making process
		• Verbalizations of strategies for taking action
		• Self-reports of reasons for actions
Use of system features	• Think-aloud protocols	• Verbalizations of reasons for using a system feature
		• Observations of system choices
	• Interviews	• Self-reports of awareness of features
		• Verbalizations and observation of purpose achieved by using feature

Interviews of approximately two hours took place on an individual basis during the final session. The interview began with a series of guided questions regarding general attitudes toward using the system, comfort level with the open-ended learning process, and awareness of system features. Video excerpts of the learning sessions were then shown to stimulate recall of participants' actions and thoughts while using the system. Explanations of processing, intentions, and actions were solicited to gather data not verbalized during the initial think-aloud process.

The interviews allowed comparisons between students' interpretations and the researcher's transcript analyses regarding their reasons, thoughts, and actions. They also helped to clarify discrepancies between researcher observations and student verbalizations, and were used to elicit missing information. Video excerpts were used if reasons were not provided initially as to *why* an action was taken, an interpretation was provided, or decision was made.

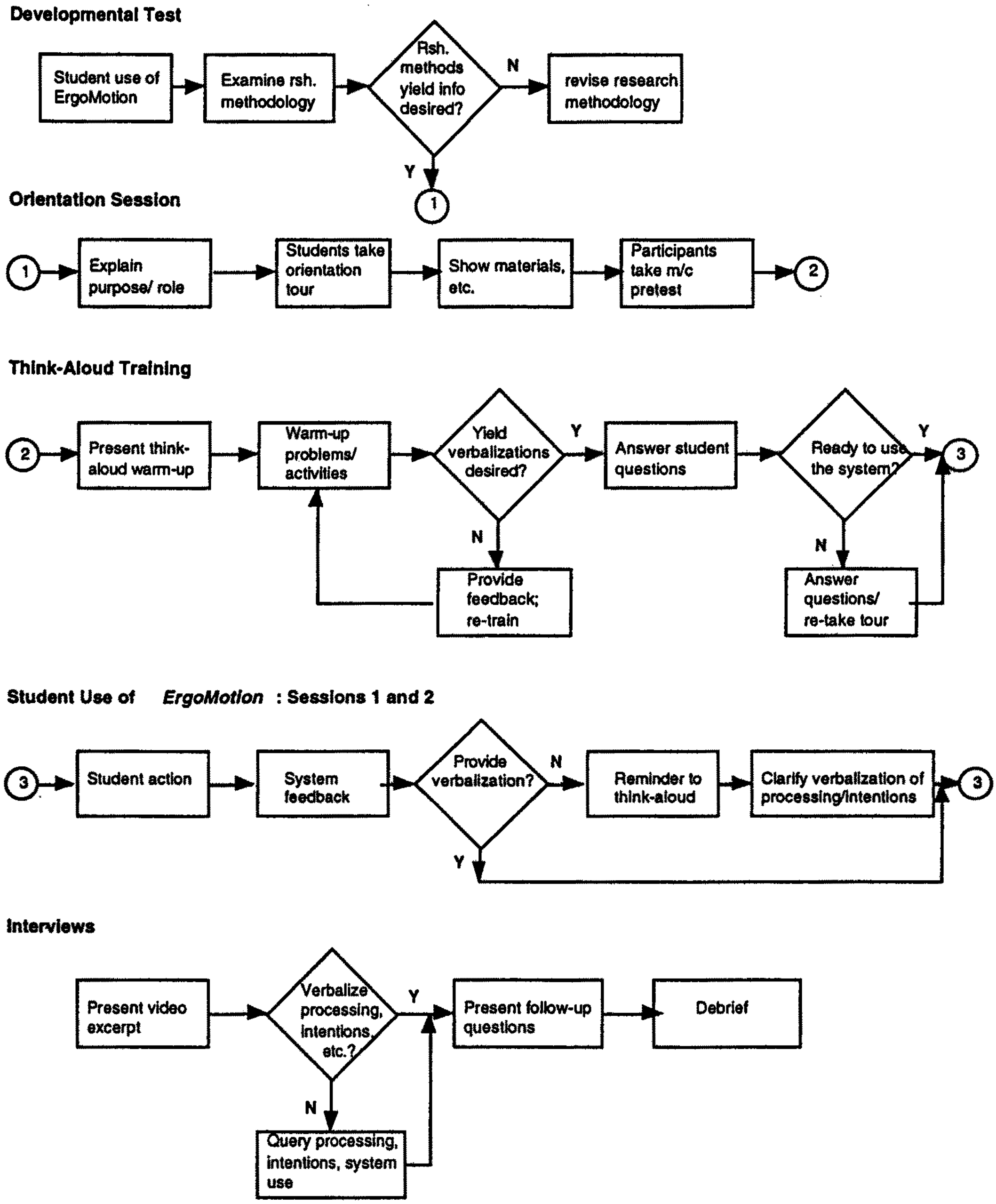
Procedures

A graphical illustration of the research procedures is provided in Figure 4. A developmental test was conducted during which research procedures were validated. Two pilot cases were studied which yielded information used to improve the research procedures. Think-aloud procedures, training procedures, general research methods, and interview techniques were implemented and refined. As a result of the developmental test, several needs were evident which were subsequently addressed: (a) to explain system features that were not covered effectively in the on-line system training; (b) to provide reminders to think-aloud without guiding or influencing participant responses; and (c) to provide a broader context for learners when showing video clips during the interview (e.g., what happened before and after the clip was shown). All sessions were videotaped for subsequent analysis.

The science teacher informed the participating students that they would go to a separate room to learn about physics principles through roller coaster design. Prior to the first session, students attended a 30-minute orientation to become familiar with the general design and features of *ErgoMotion*. They viewed an introductory movie to orient them to the problem and their goal as coaster designer—to design a roller coaster that was both ". . . thrilling and safe."

At the beginning of the next session, prac-

Figure 4 ☐ Overview of research procedures.



tice in the think-aloud procedure was provided in order for students to become familiar with the process of thinking aloud during problem-solving (Ericsson & Simon, 1992). This was done using a series of warm-up activities involving mental tasks ("multiply 24 × 12 in your head," "count the number of windows in your parents' house") which were to be vocalized aloud. After receiving feedback, they were then instructed to solve three simple force and motion problems, again thinking aloud as they completed the task. Feedback was again provided related to their think-aloud vocalizations.

After ensuring that students were familiar with the system and the think-aloud procedures, participants were instructed to use the *ErgoMotion* environment in any way they chose for the remainder of a two-hour session. A second two-hour session focused exclusively on system use to address the problem under study. Roughly four hours were devoted to learning via the system, resulting in an average of approximately 290 individual actions per participant.

The postsession interview was completed approximately two weeks later. The duration of data collection procedures, including interviews, was approximately one month.

ANALYSIS

Data from think-aloud protocols were analyzed to determine the interplay between goal-oriented actions and the changing conceptual models that underlie them (Karmiloff-Smith & Inhelder, 1975). The purpose was to identify how understanding evolved as a function of system feature use.

The Coding Scheme

Session videotapes were transcribed to reflect both system events and the verbalizations of the researcher and the learner. Think-aloud protocols, interview data, and observations of videotaped system events yielded the foundation data for the analysis. Think-aloud protocols were transcribed and matched to videotaped observations of learner actions and system events. Data were collated according to each of three predefined research categories: processing, intentions, and feature use (see for example, Atkins & Blissett, 1992; Chan, Burtis, Scardamalia, & Bereiter, 1992; Merriam, 1988). Criteria were developed for each category, which were used to assign data (see Lincoln & Guba, 1985). For instance, isolated responses such as "the coaster crashed," or "I'm going to change the horsepower" were labeled as individual units. Multi-color highlighter pens were used to mark transcript responses and label distinctions among major categories (Ericsson & Simon, 1992).

Initially, protocols were examined broadly for different examples of theory-building activity; similar instances were grouped according to major categories (Chan et al., 1992). The protocols were examined for instances of processing, intentions, and feature usage by participants (e.g., for intentions: "I don't know why I did that" versus "I want to change the horsepower, so I can slow the coaster down"). Examples were then grouped to reflect a range of simple-to-complex responses (e.g., "It crashed" [simple] versus "It crashed because I set the first hill too high, and it had too much acceleration" [complex]).

Conceptual and Operational Definitions

Based on the predefined categories, conceptual and operational definitions were developed. Subcategories were defined (conceptually and operationally) to further differentiate responses within categories and to classify instances of the similar processes or operations. Definitions for each subcategory were sufficiently broad to enable distinctions among different instances yet provide a coherent framework to illustrate a range of examples. Definitions and subcategories reflected not only instances of the process but an indication of its sophistication. The coding scheme for classifying subcategories and definitions is listed in Table 2.

Initial subcategories were further refined, discarded, and defined. Consistent with a grounded theory approach (Strauss & Corbin, 1990), similarities within and across participants were identified, and new codes or subcategories were established. The data were refined during several iterations over a three-month period. Classifications of equivocal or ambiguous data were negotiated between researchers, until a representative subcategory and/or code was agreed upon.

Category 1: Processing of Information and Events

Conceptual definition. Mayer (1989, p. 46) defined a learning process as ". . . the way in which students encode to-be-learned information." Learners *per-*

Table 2 ☐ Coding Scheme

Sub-Category	*Definitions*	*Code*
Category 1: Processing		
Perception	selection of relevant conceptual information	P
	recognition/labeling of system events	PLAB
	recognition of observed effects of actions	PACT
	selection of relevant vs. irrelevant information	PREL
	drawing conclusions about observations	PCON
Organization	infer internal connections among concepts	O
	makes inferences about observations	OINF
	elaborates and/or confirms expectations	OEXP
	draws generalized conclusions	OGEN
Integration	relate connections to prior knowledge	I
	relates personal experiences with roller coasters	IROL
	elaborates observations using personal experiences	IEXP
	draws general conclusions	IGEN
Category 2: Intentions		
Unsystematic explorations for information	trial and error/browsing	U
Goal-based intentions	intention to meet a goal	G
	attaining/setting goals	GSET
	information gathering	GINFO
Means-based intentions	intention to extend boundaries of understanding	M
Category 3: Use of System Features		
General awareness of features	acknowledge existence of feature	A
Awareness of how to use system features to meet identified goal	uses features to meet identified goal	AG
Awareness of how to use features to build, test, or evolve theory	reflects upon hypothetical problems to test theories	ATEST

ceive or *select* relevant conceptual information, *organize* the information around interpretations or explanations (infer internal connections among concepts), and *integrate* information with existing prior knowledge (transfer external connections) (adapted from Mayer, 1984; 1989).

Operational definition. Processing responses were identified if they represented reactions to information or feedback provided by the system. Processing was most readily identifiable in instances following the consequences of an event, such as affective or interpretive reactions to the coaster crashing; analysis of numerical data; answers to questions; annotation of conceptual information; and evaluation of expectancies/understanding of information. Specific levels of processing were defined for subcategories of perception, organization, and integration. Table 3 illustrates definitions and examples for *processing*.

Category 2: Intentions for Action

Conceptual definition. Intentions represent reasons for action and can mediate a learner's actions and the processing of information result-

Table 3 ☐ Definitions and Examples of Processing

Sub-Category	Definition	Example
Perception		
Reporting what was observed, heard, or otherwise recognized as related to task at hand, but not involving interpretation or inference	• recognition or reporting of system events • reporting of learner actions	• "the coaster crashed." • "I set hill 1 at its highest, hill 2 at its lowest, and hill 3 on its lowest."
	• reporting or restating what was heard or seen • reporting of visual cues • reporting of visual cues associated with success/failure	• "this [hill] is 18.4 meters and this one is 15.2 meters • "it's going slow" • "It crashed with a 25-horsepower motor"
Organization		
Inferencing that is expressed as either expectations, interpretations, or confirmation of system feedback but not referenced to prior knowledge	• simple cause-effect interpretations without reference to the reasons for their association • cause-effect interpretations that were elaborated with intuitive understanding or data-driven observations	• "The horsepower is too much." • "That wasn't enough people [mass] I guess. You've got to have a lot of weight on there with that much power, or it's going to go off around the curve—even with a wider curve."
	• theoretical or generalized conclusions about relationships among variables	• "The more mass you have, the slower it will go."
Integration		
Connecting actions, concepts, or system events to prior knowledge or relevant personal experiences, which were used to interpret, evaluate, or supplement conceptual understanding	• relating statements, observations, or events to prior knowledge	• "I was thinking about how the [crash test] dummies hit a wall . . . and get pushed forward."
	• using prior knowledge or experiences to explain events	• "They maintain the same speed because the computer won't let them go over it.'
	• elaborating a statement or observation with related prior knowledge	• "I was thinking about when you go faster [in a car], it will push you back in your seat, and when you come to a stop sign, you go forward . . . and go from side to side on curves if they are pretty sharp."

ing from them. Three predefined levels of intention, based primarily on Karmiloff-Smith and Inhelder's (1975) identification of goals and means, distinguished how learners used information to regulate future actions: unsystematic, goal-based, and means-based. In unsystematic explorations, learners browsed the system with no apparent intention either to meet a goal or to understand a relationship. With goal-based intentions, learners interpreted results of actions in terms of success or failure in meeting a specific goal. Means-based approaches focused on taking action to discover why an event occurs or what *could* happen if limits were extended. The search for means implies a goal to confirm or refute a theory.

Operational definition. Table 4 illustrates definitions and examples for intentions. Goals and means were defined operationally as reasons for actions attendant to the processing of system events. In most instances, intentions followed a stated goal, interpretation, or expectancy. Intentions were most readily identifiable in instances in which learners made statements about what they wanted to manipulate, find out, or explore.

Category 3: Use of System Features

Conceptual definition. Pea (1993, p. 51) used the term *affordances* to describe both the "perceived

Table 4 ☐ Definitions and Examples of Intentions

Sub-Category	Definition	Example
Unsystematic Explorations		
Accessing non-specified information that might be useful	• trial and error or browsing to explore system features and functions	• "I'm going to see what happens when I try this"; "I was just looking [in the videopedia] to see if anything would 'click'."
Goal-Based Intentions		
Using system tools and/or resources strategically to achieve a goal	• planned use of system manipulation tools to design a successful roller coaster	• "It kept crashing on the large curve, so I changed it to medium"; "I'm decreasing the horsepower to slow it down."
	• strategic use of an information resource to achieve a goal	• "I'm going to get out of here [coaster challenge site]. I'm going to review friction in the videopedia"; "I want to find out what [the online expert] meant about banking speed."
Means-Based Intentions		
Exploring the boundaries of successful or unsuccessful actions.	• emphasis on reasons why a coaster succeeded or failed; sparked by an unanticipated failure • focus on exploring alternative solutions and reasons for action	• "[If there were] no people on it, it wouldn't [crash]." • "The curve is too small, but I want to see if it can make it [regardless] if I lower the hills and the horsepower."

Table 5 ☐ Definitions and Examples for Use of System Features

Sub-Category	Definition	Example
General awareness of the existence of a given feature		
Awareness of features, either through exploration, use, acknowledgment, or training	• employs a feature while using system	• participant uses videopedia to look up definition of velocity
	• acknowledges awareness of features not used	• "Yeah, I knew those [data points] were there. I just didn't think I needed them."
General awareness of how to use a feature to achieve a desired goal		
Use of features to help meet an identified goal	• uses system tool to help meet an identified goal	• "I want to make the first hill higher to get more acceleration" [and change the hill height accordingly]
	• uses system resource to help meet an identified goal	• "I want to find out more about acceleration" [followed by referencing the videopedia for its definition]
Awareness of how to use features to derive goals or problems		
Constructing and testing counter-examples in order to evaluate and test a theory	• reflect upon hypothetical problems and use the system to build, challenge, or test theories	• "It would be better to have more people because you would have more speed. But then, again, let's look . . . Have the lowest [mass of] people and the lowest motor [power], does it act the same way?"

and actual properties" of a tool or resource that determine how it *can* be used. Thus, system affordances are determined by two elements: the *actual* properties of a system feature and *perceived* properties the learner believes will support him or her. Feature use was distinguished by how learners manipulated the affordances and functions of the system. It represented a *choice* for action, that is, how system features were used to act on individual intentions.

Operational definition. Table 5 illustrates the definitions and examples for *use of system features,* which was defined operationally as how learners used the system to meet a goal or intention. Feature use was most readily identifiable in instances in which learners stated their intentions and their plans to use the system to help them. Three subcategories were developed: awareness of the existence and functions of a feature; awareness of how to use a feature to achieve a desired goal; and awareness of how to use a feature to derive goals or problems.

Patterns of Understanding Analysis

Individual transcript responses were selected as the basic unit of analysis because they revealed how learners invoked processing, intentions, and actions to build theories; that is, they represented the smallest piece of data that could be interpreted in the absence of additional information (Lincoln & Guba, 1985). In order to derive an overall pattern, analysis within and across these units was conducted. This analysis equated the categories of processes, intentions, and feature use with Land and Hannafin's (1996) conceptual framework, which was the basis both for analyzing how the coded categories interacted and for organizing general patterns of understanding.

During this analysis, sets of conceptually-related responses were examined to determine their influence on understanding. For instance, if learners responded at the *organization* level that "the coaster crashed because the horsepower is too high," the events both preceding and following the response were examined to determine: (a) how learners derived this interpretation; (b) if they used system resources to subsequently test its validity (e.g., by lowering the horsepower during the next interaction); (c) if they evolved their interpretation based on new data (e.g., "when I lowered the horsepower, it still crashed. The curve must be too small"); and (d) if they continued to evolve this interpretation during later interactions (e.g., "the coaster will crash if the curve is too small and the hills are set too high"); or continued to return to the original theory during later interactions (e.g., "it crashed because the horsepower is set too high").

This approach is similar to learning paths charts which have been used to represent knowledge and strategies observed or inferred from learner-system interactions. Topics are organized sequentially, indicating how ". . . later strategies and knowledge are built upon earlier ones, but not necessarily in a strictly linear sequence" (Edwards, 1995, p. 88). This analysis was further supported by the use of an *event history matrix* that identified trends within and across categories for a given problem (Miles & Huberman, 1984). The event history matrix classified and linked system events, responses to events, assumptions or rules about responses, resultant intentions, and subsequent actions. The matrix categories corresponded to the components of the conceptual framework, and learner assumptions and theories were also represented. The matrix illustrated how actions, processing of information resulting from actions, and decisions for future action influenced strategies and understanding over a series of trials. The event history matrix focused primarily on activities at the coaster site, where learners manipulated variables and ran simulations. A sample event history matrix is shown in Table 6.

Understanding was determined using explicit statements as well as inferences. At the most direct level, understanding was identified as a result of a theory vocalized while using the system (e.g., "The heavier the object, the faster it falls"). On other occasions, no formal theory or explanation for an event was stated, but the existence of such a theory

Table 6 ☐ Sample Event History Matrix

Event	*Consequence*	*Assumption*	*Intention*	*Action*
Crash (1–36)	Reason: force/power	More weight needed if more force.	Increase mass.	Increase mass.
Crash (1–38)	Reason: force/power	Need more weight with more force. Large curve helps, but not enough.	Increase mass.	Increase mass to 6000.
Crash (1–40)	New reason: horsepower	Decrease engine to make it go slower.	Decrease engine.	Decrease horsepower to 50.
Crash (1–42)	Adds to new reason (adds mass to horsepower).	Decrease engine to make it go slower. Increase mass to increase force.	Decrease engine and increase mass to 6000 (make it stay on tracks).	Decrease horsepower; increase mass to 6000.
Crash (1–44)	Adds data to new reason (same as new reason).	Decrease engine even with no people—not a lot of force.	Decrease force (make it work).	Decrease mass.
Crash (1–46)	New reason: hills. Fits in new reason with previous.	Hills add more force; hills force greater than mass force. Decrease hills, decrease force.	Make it work—decrease hills, decrease force	Decrease middle hill to low.
Crash (1–50)	No reason.	Decrease hills, decrease force.	Take action—make it work.	Decrease all hills, low, low, low
Success (1–52)	Reports speed (too slow); recalls previous (1st hill steep)	With the first hill steep, it went faster. (data-driven)	Make it go faster.	Increase middle hill; increase last hill

was established during the interview (e.g., Question: "Why did you increase the mass in this situation?" Response: "I was trying to make the coaster go faster.") An underlying theory was *inferred* (i.e., heavier objects fall faster) based on learners' actions, reasons for action, and posthoc interpretations.

Overall patterns of understanding were inferred by examining responses and connecting them across underlying and/or stated beliefs, processes, intentions, and actions. Implicit theories were identified from an analysis of observations and verbalizations when a formal theory was not explicitly stated: "It crashed . . . I'm going to decrease the horsepower . . . It still crashed . . . Maybe it was the mass . . . I'm going to decrease the mass." Interpretations were made based on connections across an *underlying theory* (the coaster will slow down if the external force is decreased); *processing* (perceiving the crash and offering an interpretation); *intentions* (trying to make the coaster function successfully by decreasing horsepower); and *actions* (decreasing the horsepower). These events triggered subsequent interactions, building upon what had been discovered. A new interpretation about the influence of mass was inferred because of the limited applicability of the previous theory about the influence of horsepower. Using this approach (guided by the event history matrix), learner theories could be identified and analyzed for development over time.

RESULTS AND DISCUSSION

Approaches of Participants

Rene. Rene's approach focused on discovering how to make the coaster run successfully. Most of her interactions took place at the coaster site and the coaster challenge; she seldom used other system resources. Overall, her experience with the system was driven by goals to ". . . see what happens" and ". . . find a successful track." Once she designed a successful track, she attempted to ". . . try all the weights with all the horsepowers to see which one would work better." Accordingly, while many of her interactions were systematic, they focused on validating the success of the coaster.

Rene maintained this focus despite feedback that was surprising or dissonant. She systematically verified success but did not offer explanations for, or try to reconcile, discrepancies. She focused on her goal, often to the exclusion of pursuing new problems. For instance, she noted, "On the hill part, it's so shaky, [so] I think I should change it, after I finish doing what I'm doing right now." Rather than responding to perceived data and interpreting it, she single-mindedly pursued her goal of verifying success.

Rene's responses to system feedback were characterized by irrelevant judgments and observations. For instance, she frequently responded with value judgments: "I liked that one . . . That was my favorite one" and "I was most comfortable with the mass on 4000." She often used inaccurate information as the basis for interpretations: "The little places that people sit in were shaking a lot. It looked like it was having a hard time moving on the track." Accordingly, her interpretations were often based on observations that were neither tested nor, in some cases, testable.

Jason. Jason used many aspects of the system but focused mainly on manipulating the coaster site. Jason's goal was not only to make the coaster run successfully but to ". . . get it as fast as possible without it going off the track." Accordingly, he used the manipulation tools to ". . . push [the coaster] to its limits." The result of this approach was to extend understanding beyond identifying actions that lead to success. Jason quickly generated rules about the variables affecting the speed of the coaster: "I [wanted to] see how fast I [could] get it going. And then if it didn't make it, I'd just change . . . the energy loading." As a result of his goal to *increase* speed, he accessed and tested his beliefs about variables affecting speed.

Jason readily took risks, made mistakes, and tackled difficult problems: "I felt like I could [solve the problem], but I still didn't know all about it and had a little bit of trouble with it." Accordingly, he encountered data from which he derived new problems and insights: "I knew I could do it and all, but I was just trying to see how fast I could get it. I knew it would probably go off and all, but I just wanted to try it. Just to see if it would or not."

Jason's approach promoted explanation-building. Since he often encountered coaster crashes and data that conflicted with his expectations, he frequently provided and revised explanations for events. Furthermore, his goal of increasing speed appeared to divert attention from simply making the coaster function to determining *why* it functioned: "I had to think *why* isn't it working . . . I tried to figure out how can I get this . . . to work." Accordingly, Jason provided a number of explanations and built upon them through his experience. He often, however, supported his interpretations with inaccurate perceptions of speed.

Rick. Rick's approach focused on addressing the guidance questions supplied by the system. Initially, his interactions at the coaster site were minimal; instead, he used other system resources to gather background information. Most of his responses involved reporting rather than interpreting events, actions, and resulting data. Eventually, he accessed the question file, which provided a list of conceptually-based probe queries which he used to guide his exploration.

Initially, Rick used the coaster site to locate specific information to answer the system-provided questions. He remarked, "I wanted to go there to find out the answer to my question on how the motor size affects the roller coaster, and I left there because I felt like I knew the answer to it." Eventually, Rick began using system feedback to guide his own intentions and actions at the coaster site. For instance, while experimenting, he encountered an unanticipated coaster crash. He then provided an explanation for the event ("I must have done something to the horsepower") and took action to test his observation and solve the problem. Eventually, he generated and tested his own explanations of events.

Mary. Mary's approach focused on collecting information for future use. She primarily used information resources—the consultants, videopedia, and Radio Quiz Show. She characterized her initial approach: "I went in and talked to my consultants and watched the first video, figuring they'd tell me information that I'd want to know. Then I could go look at the questions, and I'd know the answers." Mary's actions were indicative of a "bottom-up" approach (i.e., looking for instruction and information prior to building her coaster), which was apparently motivated by the goal to acquire information independent of a specific problem or context.

Mary used system resources extensively to gather information about how to build her roller coaster. She relied heavily on external guidance to initiate actions and provide answers. For instance, she often returned to the workbook because she ". . . couldn't find anything else to do." Furthermore, she expressed a need for direct information: "I thought that they'd tell me something like, 'on the large curve, you're supposed to go this fast, and on the small curve, you're supposed to go this fast. If you go above it, it's bad for you.' But it didn't." Mary's success or failure was contingent upon the system's capacity to provide the specific information or answers she sought. She often became frustrated, since the system did not provide needed information.

Mary responded to system feedback with personal, and often abstract explanations. Most of her explanations were derived from prior experiences or beliefs. For instance, she often referred to the coaster's "computer" and "brakes," although they were not represented in any way in *ErgoMotion*. She used beliefs rooted in prior experience to explain events that could not be tested or verified in the system. Consequently, Mary experienced difficulty because she failed to test or elaborate ideas that *could be* represented operationally in the system.

Patterns of Understanding.

The patterns provide an overall representation of how participants used system resources, interpreted system concepts and events, and decided how to solve problems according to Land and Hannafin's (1996) model. All participants' interactions were analyzed and synthesized to generate the patterns; representative exchanges are described for each pattern.

Pattern 1: Perceptions of system events and effects of actions.

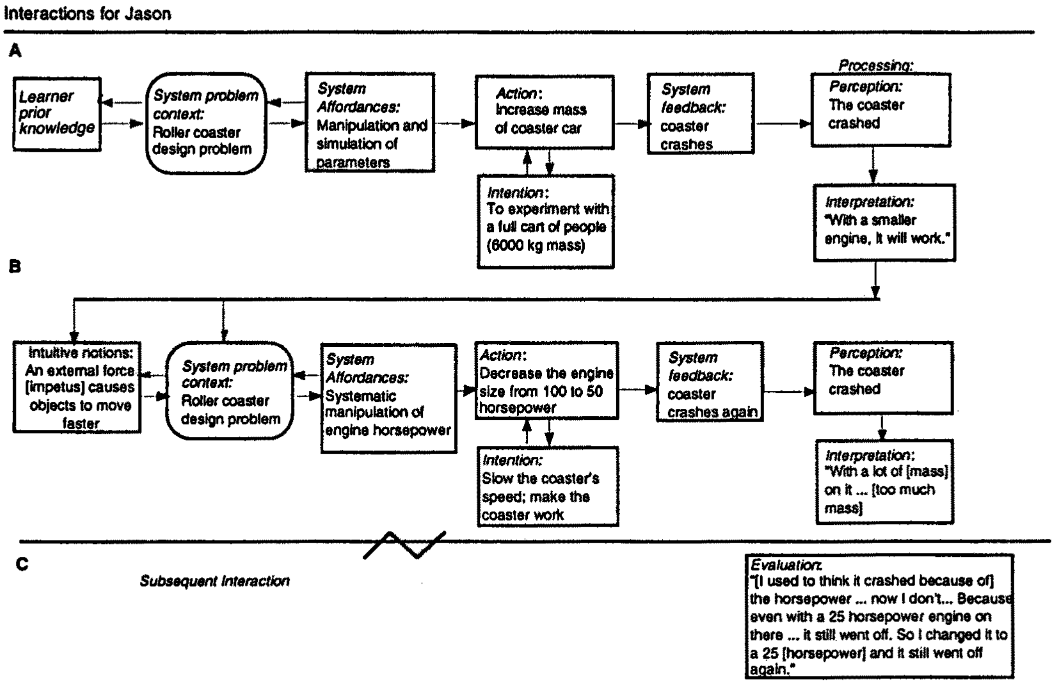
All learners perceived information and recognized the effects of their actions on system events. For instance, Rick perceived visually that variations in mass and horsepower influenced the time needed for the coaster to reach the top of the first hill:

> I thought that the more mass that was in there [with a 50- versus a 25-horsepower engine], it took it a while to get up there. So I'm now going to change the horsepower to 100.

In this case, he perceived information deemed relevant (i.e., changed the horsepower) and derived conclusions regarding its effect on the coaster.

Figure 1 details the basic model used to interpret participant's interactions. Figure 5a–5c illustrates how the model is used to interpret a series of interactions for one participant, Jason. As shown in Figure 5a and 5b, Jason perceived correctly that the coaster had crashed, providing the basis for further consideration. However, learners also voiced erroneous conclusions based upon misperceptions of the video simulations. They occasionally confounded their visual perceptions with inaccurate personal judgments, that is, they described the behavior of the coaster in inaccu-

Figure 5 ☐ Example of the conceptual framework for mapping Jason's patterns of understanding with OELEs.



rate ways based on misperceived visual cues. For instance, Rene stated, "It's gaining speed at the very end." Similarly, after setting the curve to large, Mary mistakenly concluded, "They always put a curve at the end. Is that to help slow it down? So that means curves slow them down." Learners relied heavily on the video feedback generated by the simulation for information about speed, video segments that only approximated real-time representations. Individual conclusions (i.e., the coaster crashed), consequently, were confounded by faulty observations (i.e., it went further). In this instance, perceptions resulted in erroneous assumptions about the effect of horsepower on the speed of the coaster (i.e., it went further after lowering the horsepower; therefore, horsepower must affect speed).

Pattern 2: Identifying what "works."

This pattern was typical during initial interactions with the system. Learners relied heavily on perceiving actions believed to be associated with goal attainment (e.g., stop the coaster from crashing). This phase was highly experimental, as learners manipulated variables and set goals in order to "see what happens." Through the process of setting and testing goals (e.g., "I'm going to make it go faster"), learners collected data on actions associated with success. Learners *perceived* conditions related to success and formed *intentions* to replicate them. Consistent with Karmiloff-Smith and Inhelder's (1975) findings, learners initially attempted to catalogue successful actions until a repertoire of successful actions was established. To illustrate, once Rene identified a configuration that worked (i.e., it did not crash), she began to systematically test various horsepower and mass levels to see which would run successfully. She explained during the interview, "I was trying to figure out which ones [would and] would not work." This strategy helped learners to identify key variables needed to generate subsequent explanations. Consequently, understanding evolved by progressing from *perception* of variables related to success, to *intentions* to repeat the successful actions, to *actions* that confirm or refute the initial success.

During this study, typical action sequences involved deciding how to set parameters (e.g., "set all of the hills large, the horsepower to high, and the curve small") in order to test the effects. If the coaster crashed, learners would typically respond that they needed to "slow it down" or "make the curve wider." They would then report the consequences of their actions after observing the simulation results (e.g., "it went further this time" or "it crashed again"). Once learners confirmed actions that led to success, they tended to repeat them. For instance, they found that the coaster was most likely to crash on small curves. Once they perceived this, they adjusted the curve setting to medium or large to avoid further crashes. During this phase, learners did not provide explanations for events (e.g., why the coaster crashed on the small curve); rather, they built upon and refined system experiences to guide subsequent interpretations.

Pattern 3: Constructing personal interpretations of observed events.

Learners generated predictions regarding future success after identifying successful system rules and interpretations. According to Hawkins and Pea (1987), individuals assign meaning to isolated events in order to establish predictive control. In this study, all learners attempted to assign meaning to system events by generating interpretations, expectations, or evaluations based on system feedback. They organized their observations to establish simple cause-effect relationships and expectancies. For instance, they learned quickly that, when the coaster moved rapidly during the simulation, it was likely to crash. Statements of Rene's expectancy such as "It's going to fall off," "I didn't think it would make it," and "I knew it would go over" established or confirmed rudimentary expectations about the events under study.

Once successful actions were catalogued, learners offered individual interpretations to explain regularities in, or deviations from, previously *observed* events. For example, they typically hypothesized why the coaster crashed on the small curve, and they took action to test it (change the curve to medium or large). After changing the curve size from small to medium following a coaster crash, Rick noted, "I think that 50-horsepower [engine] is too much for that small curve. Maybe a medium curve would work." They progressed from *perception* to *interpretation* as they recognized and *tested* variables associated with their observations.

Pattern 4: Consolidating and generalizing a theory.

As learners progressed, interpretations and rules became consolidated and refined. In unexpected circumstances (e.g., learners anticipated the coaster to be successful and it crashed, or vice versa), previous theories or rules were incomplete, inadequate, or insufficient. Consequently, learners tended to generate new theories to explain the event.

Eventually, participants provided an explanation or cause for a system event (e.g., ". . . it was probably too much horsepower going up . . ."). Research has indicated that learners often explain scientific events with intuitive or informal theories that often conflict with canonical views (Carey, 1986; Driver & Scanlon, 1988; Twigger et al., 1991; Vosniadou & Brewer, 1987). With force and motion, intuitive theories typically reflect an "impetus theory" of mechanics—a misconceived belief, largely based in prior experience, that an object accelerates as a result of a stronger external force acting upon it (Hawkins & Pea, 1987; Piaget, 1970; Twigger et al., 1991).

Likewise, in the present study, simple cause-effect interpretations were usually based on intuitive ideas. Learners often expected the coaster to negotiate large curves successfully because they had previously observed it crashing only on small curves. When it crashed on large curves, their rule-based theory ("the coaster crashes only on small curves") was insufficient to explain the contradictory evidence. Consequently, they *perceived* and generalized another theory ("The horsepower is too high") to explain it. The horsepower theory provided a powerful intuitive *interpretation* for events not anticipated based on prior system experience. Figure 5a illustrates that Jason believed that the coaster crashed because of excessive horsepower ("I think the engine's too [powerful]"). As shown in Figure 5b, he then acted to test this interpretation by reducing the horsepower. Learners offered explanations for events, which guided subsequent actions, but did not overtly reference their previous observations to support their interpretation.

Once interpretations were generated, learners attempted to isolate causes. Initial cause-effect relationships focused on deriving specific rules to predict specific events. These rules were strengthened or weakened depending on whether they reliably predicted success or failure. Holland, Holyoak, Nisbett, and Thargard (1986) suggested that rules are organized according to a default hierarchy of specificity and predictability. In such instances, learners prefer specific rules that confidently predict a specific situation. When these rules do not apply, however, another more general rule is invoked which competes with previous rules. In this study, Rene based her prediction on previous observations that the coaster would *not* ascend the third hill. When the coaster ascended the hill, she invoked a new theory to explain the event: "The horsepower and mass must have changed." In this instance, she generated a default theory that was based in prior experience and naive conceptions of force and motion. The horsepower interpretation was consistently used by *all* learners to account for changes in power or speed. This pattern is consistent with research on impetus theories about force and motion—the belief that objects are set in motion by the impetus of an external force (Carey, 1986). When expectations or beliefs were not supported by new evidence, dissonance resulted and learners generated intuitive interpretations. They then tested their theories by manipulating variables believed to influence the observed effects. In this study, powerful interpretive theories were tendered, based on intuitive conceptions, to explain events to which previously derived rules did not generalize.

Pattern 5: Integrating observations or conclusions with related personal experiences.

Comparatively, learners showed little evidence that they integrated system events. When integration was apparent, learners tended to explain using previous experiences riding roller coasters. For instance, in response to information at the Radio Quiz Show about where on the coaster gravity is the greatest, Mary responded:

> Oh! I knew it! I knew because you feel flattened when you're starting at the bottom and you're starting to go up, but you feel like you're going to go *up* [italics added] when you're at the top and you're starting to go down. It helps to ride roller coasters before you do the program.

When returning to this question in a later session, she added the concept of g-force to her experiences: "Oh, Yeah! When you go down, and you're starting to go up those little hills, and you go 'squoosh!' by g-forces, and then when you go to the top of the hill, [you feel] light . . ."

In response to acceleration information provided by an on-line consultant, Rick remarked: ". . . like when you hit a wall [in a car] real fast, the car just backs up and stops immediately. Then, when you're going too fast . . . and you slam on the brakes, you might keep skidding or keep [moving forward]." In this instance, he linked the system concept to prior knowledge about car accidents.

On occasion, however, prior experiences were inconsistent with system experiences. For instance, the solution to one of the coaster challenge problems was to design three hills so that the coaster would roll backwards down hill 3, roll backwards over hill 2, and come to a rest in the first valley. Mary initially wanted to attempt this but remarked:

> Oh yeah, It's got brakes, it can't roll backwards . . . They told us that because there was this one lady who was freaking out before we went on a ride. And they said, "it's got automatic brakes along the edges, and if it stops, it will clamp and you'll hang."

Mary continued to make references to brakes and clamps when addressing issues of slowing down and stopping. Prior knowledge, in this case, appeared to hamper interpretations and future actions because of inconsistencies between personal experience and the affordances of the environment.

Rene, who rarely integrated, formed an analogy and generated a rule about why the coaster crashed on the small curve: "I related it to a car. And if you are going around a real sharp curve, you have to slow down to get around it. And if it's a large curve, . . . you can keep going . . ." In this instance, Rene created an analogy by referencing prior knowledge to support a conclusion about why the coaster crashed. Such explanations were linked to prior knowledge but were often applied inaccurately. For instance, learners occasionally attempted to decrease coaster speed around a small curve by reducing horsepower, associating this action to the application of brakes to navigate a curve. The result was a powerful generalization that was not readily transferable.

Pattern 6: Expanding theory boundaries.

The limits of theories expanded as learners progressed from focusing on goals to exploring means for reaching goals. Initially, as evident in Jason's efforts (see Figure 5b), learners attempted to achieve a *goal* (usually making the coaster run successfully). Learners perceived those actions associated with success and repeated them. Their goal was to confirm that something worked, rather than to develop and test the limits of the theory.

Learners also perceived data that *could* be interpreted in ways that were consistent with prior experiences. For instance, a learner might initially derive a powerful rule that confidently predicts that a coaster which has crashed on the small curve will run successfully if the curve is widened. Rather than simply taking action to stop the coaster from crashing and confirm a known relationship, (i.e., increasing the curve size to achieve success), learners might instead decrease the hill sizes. In such instances, learners appear to change their *intention* in an effort to expand the boundaries of their theories or rules. They generate or collect new data to either strengthen the known rule (i.e., the coaster continued to crash until the curve was changed to medium) or strengthen a new rule (i.e., the coaster did not crash on the small curve *with small hills*) (Holland et al., 1986).

Means-based intentions were evident when learners explored the limits and boundaries of actions rather than focusing on what was known to solve a problem. In the following example, Rick explored to expand his repertoire of success/failure experiences:

> Put the mass at 6000, horsepower on 25 . . . I'm trying to see if it could still make it over the hills with a bunch of mass and a low horsepower. But I want to make the hills low, and I'll keep experimenting higher with the hills. I'm going to put the curve small 'cause . . . I have a low horsepower, and I think it could make it around it.

A new intention was formed to explore the limits and boundaries of a theory. The shift from goals to means was most apparent in his decision to select a small curve, even though past experiences indicated that this action would cause the coaster to crash. Instead, his intention changed from simply making the coaster run to exploring how particular variables affected success or failure.

Jason also expanded his boundaries. For instance, following one successful run, he continued to explore alternative solutions:

> [makes curve small and runs simulation] I think it's going to go off the track. [crashes]. Well, yeah, with that sharp of a curve, and it had that much speed going . . . I'm going to make [the] hills smaller, so maybe even with the sharper curve, it will stay on the tracks. [coaster makes it] I kinda figured that one [would work], 'cause . . . the first hill was not . . . so steep . . . [changes mass to 6000]. I'm pretty sure this one will stay on. With that many people on there, it will . . . make it slower and all. Yeah, and . . . maybe also because [the first hill] wasn't very steep.

During this interaction, he recognized that curvature was one factor that caused the coaster crash. However, rather than changing the curve to ensure success, he changed the hill sizes to explore the coaster's limits. Jason's intentions evolved from choosing the most likely solution to finding alternative solutions. With this pattern, learners perceived that data could be interpreted according to a previous rule theory, but instead took action to test the boundaries of their beliefs.

Pattern 7: Altering initial interpretations through assimilation.

This pattern represents the beginning of a primitive theory or model created from both system-generated and intuitive theories (Driver & Scanlon, 1988). For instance, Mary perceived that mass was related to coaster speed (and therefore success). In response to information about gravity, mass, and acceleration provided by an on-line consultant (e.g., "objects of different mass fall to Earth at the same rate"), she provided the following analysis:

> Oh! . . . The more mass, the harder [an object] falls. But that's not right, because they just told you why it was wrong . . . . In weightlessness, mass has no effect on falling speed . . . like when it goes fast enough down a hill, and it goes swing! It goes real fast . . . . But when rising [draws illustration], mass matters.

In this instance, she perceived a difference between her initial theory (mass impacts coaster speed) and the evidence presented by the system. However, she reconciled her belief by deriving a situation in which her expectation was valid (*"when rising,* mass matters"). In this case, Mary used information from the system to alter her theory rather than rejecting it or testing her interpretation using system resources. Assimilation, then, is used to qualify, or establish exceptions to, conflicting data in order to preserve an underlying theory (Piaget, 1976). The theory, however, has nonetheless been altered because of its limited predictive value.

Personal theories are often tenuous and easily abandoned in favor of alternative theories which better explain events (Holland et al., 1986). When an expectation was not confirmed by system feedback, learners often changed or amended interpretations in order to make them consistent with new data. For instance, Rick investigated the impact of engine horsepower and curve radius on acceleration:

> I think the medium curve is pretty much suitable for all of the horsepowers. The large and small [curves], well, I don't know. . . . If you put a 100-horsepower engine on a small curve, it's not going to work though. The 100-horsepower, for the small curve, is just too much for it to handle. [changes curve to small and runs simulation; coaster is successful]. I . . . I didn't think it would make it because of how high the horsepower was. But it may also depend on the mass. [increases mass to 6000 kg]. On 6000 kg, then I'm almost *certain* [italics added] that it won't make it around the small curve. [coaster is successful]. Hmm. Well, I'm not really sure what to say. I mean . . . I was almost positive that it wouldn't make it, but I don't know how it did. . . .

Rick was clearly surprised by the results of the simulations and immediately offered alternative explanations for why the horsepower did not appear to impact the success of the coaster. The result was to add to his horsepower theory the influence of mass and curve size. However, when he could no longer explain the inconsistencies, he abandoned his series of investigations and reset the coaster to its default settings. In a similar instance, Jason's comments and actions were sparked by inconsistencies between observed data and expectancies:

> I'm going to put more weight on there. So it's like a full cart, I guess. [runs simulation] It's going to go off that track. [crashes]. I guess you just can't have that much power on. I'm going to put a smaller engine on there . . . . So with a smaller engine, I think it will stay on the track. [crashes]. I think since it had so many people on it, . . . it makes a lot of force . . . with all the weight . . . . I'm going to try it with less people . . . . Maybe it will stay on. [crashes] . . . I guess . . . even with the smallest engine, all that weight on it, is . . . playing a big part in making it go off . . . . With an engine with no people on it, I don't think it would go off. Yeah, if it didn't have any people in the cart, it wouldn't go off. I'm going to try it with a little less people in it. [crashes] Now I know . . . now I think it's like . . . I think it's the *hills* [italics added] now. Cause even with less people on there . . . with the real steep hills, it's getting too much speed.

When expectations were not confirmed, Jason either created new expectancies, or amended previous ones, in ways that preserved his underlying assumptions. Even as perceived data continued to conflict with his assumptions, his beliefs about the importance of mass and horsepower were not altered. This was evidenced by an interaction that took place shortly afterwards, when he tried to determine why the coaster failed to ascend the third hill:

> It didn't even have enough power to make it up that real steep hill. So, I'll make [hill 1] steeper . . . [goes to energy loading] Well let me try something. [changes horsepower from 25 to 50] I think it might have more power now, and then I can leave it like that and it might go over. [coaster does not ascend hill 3] . . . Will, I think I'll not make [hill 1] the steepest . . . but make it a little bit steeper.

During assimilation, theories changed to become more consistent with current observations. Previous theories were not elaborated and did not evolve; entirely new theories were tendered even though they contradicted previous interpretations. Powerful, intuitive assumptions mediated both interpretations about the consequences of prior actions and decisions about future actions; they were not easily altered. It appears that, during this stage, learners do *not* address or evaluate their theories. Instead, they attempt to explain observations by abandoning current theories or proposing independent theories to solve specific problems. Their interpretations appear to be governed by incomplete understandings and competing theories, which are strengthened or weakened depending on their utility in predicting specific circumstances (Holland et al., 1986).

Pattern 8: Recognition of data as inconsistent with theory.

For this pattern, multiple theories are either strengthened or weakened, depending on how data are interpreted and evaluated. Learners continue to assimilate until data are perceived as conflicting with a theory. Learners may interpret observations consistently with a theory, systematically test it, and evaluate whether feedback confirms or refutes the theory. Over time, learners perceive conflicting evidence, offer explanations for discrepant events, systematically test their interpretations, and evaluate the consistency of the theory using system feedback.

In the present study, learners offered theories or reasons for the consequences of an event, held predicted variables constant, and intentionally tested them using system manipulation tools. On occasion, learners would seek to intentionally test a theory such as in Mary's case: "It would be better to have more people because you would have more speed. But then, again, let's look . . . . Have the lowest [mass of] people and the lowest motor [power], does it act the same way? [runs simulation]. Still goes almost as fast." In this instance, she attempted to validate her theory by systematically testing it.

Overall, learners did not typically appear to use system features to derive and test hypothetical problems or to derive counter examples to confirm or refute a theory. Jason, for instance, often used the system to test and revise his hypotheses in order to solve a problem; he did not, however, derive a hypothetical problem in order to confirm or refute his hypotheses which was not predictive of success:

> [sets hills] I'm not sure if it will even make it over the hill. [coaster stops at top of hill 3] . . . 'cause that first hill is like shorter than the third hill . . . [changes hill 1 to medium; stops at top of hill 3] Still didn't make it. Add more horsepower to it [increases horsepower from 25 to 50]. *Still* [italics added] didn't make it . . . . Change the weight on it [reduces mass from 6000 to 4000 kg]. I think it will make it over now. [stops at top of hill 3]. Yeeee . . . nope. [changes mass to 2000 kg.; still does not ascend hill 3] . . . Well, if I change the horsepower, it might make it over the hill. [changes horsepower to 100]. [stops at top of hill 3]. Still didn't do it. Change the . . . hills I guess.

After he lowered hill 3, the coaster ran successfully. However, despite evidence that could be used to question the validity of his horsepower theory, Jason did not overtly employ the system to confront his faulty assumption. That is, he did not test his belief using a counter example to determine if horsepower affected acceleration (e.g., design a track and hold all variables constant *except* for horsepower in order to test its influence). Interestingly, Jason successfully answered a question during the Radio Quiz Show about whether doubling the size of the motor was necessary when doubling the hill size. He was aware of the relationship between horsepower and acceleration at an abstract level, but failed to recognize that the information was counter to his operational theory about horsepower.

As theories became consolidated and refined, learners typically stated that the coaster crashed because the horsepower was set too high. They tested interpretations by holding other variables constant while decreasing the horsepower. When the coaster continued to crash, learners *could* have perceived that the theory was not predictive, and *could* have evaluated the event as being counter to their theory. Data from this study, however, indicated that learners seldom overtly evaluated the horsepower theory. Instead, they either ignored the new data, assimilated the data into the existing theory, or created an independent theory. Consequently, they failed to recognize instances of counterexamples and evolve their theories accordingly.

Perception of dissonance is necessary for "meta-conceptual awareness" (Vosniadou, 1992), that is, recognition that beliefs are limited. A sophisticated learner often perceives that a theory might be faulty, gradually recognizes instances of counter examples, and derives new problems to test theory's robustness systematically across diverse problems. The findings of this and other studies (see for example, Karmiloff-Smith & Inhelder, 1975), however, indicate that young learners do not spontaneously test faulty theories, although they may gradually recognize instances that are counter to them.

Most learners failed to use *ErgoMotion* to systematically construct and test counter examples. Jason, however, recognized counter examples that refuted his initial theory. This interaction followed a review of a video clip in which he stated, "Probably too much horsepower":

> See, I still don't think . . . . Like then I must have thought that the horsepower had something to do with it, but I don't now. I mean [the horsepower doesn't] do [anything] but, go up [the first hill]. . . . Like if you have a 100-horsepower engine . . . it will just go up [the first hill] twice as fast than with a 50-horsepower. It'll just take less time. I don't think it has [anything] to do with the speed on it now . . . . See then, I guess that I figured that . . . it was the horsepower and all, but now . . . I don't. Just thinking about it . . . it ain't got nothing to do with it.

Earlier in the interview, he expressed doubts about the horsepower theory on two occasions. As shown in Figure 5c, Jason began to evaluate the limitations of this theory. At the end of the interview, he explained why he changed his conclusion about the horsepower.

> . . . 'Cause I was just thinking back to . . . . Because even with a 25-horsepower engine, 'cause I had a 50 on there one time, and it still went off. So I changed it to a 25, and it still went off again. So I figured it probably didn't have nothing to do with it.

GENERAL DISCUSSION: THE RESILIENCE OF THEORIES-IN-ACTION

A prominent implication of this study is that learner theories are resistant to change. Learners created initial theories, but the theories did not appear to evolve significantly. Through interaction with the system, learners became more *aware* of their intuitive theories by using them to explain system events; they did not, however, recognize limitations in predictive value of these theories and attempt to refine them accordingly. Learners hold powerful personal theories that often dominate cognitive processes and actions with OELEs.

Piaget (1976) identified two critical processes of conceptual development: assimilation and accommodation. Children at varied ages and developmental stages use available intuitive frameworks to interpret events. The evolutionary shift to accommodation takes place only after learners have been repeatedly exposed to conflicting data regarding limitations in the usefulness of their conceptions (Ackermann, 1991). This study highlighted the strength of intuitive theories and their resilience to change—even in the face of conflicting data, limited usefulness, and alternative explanatory frameworks.

The enduring nature of misconceptions or intuitive ideas in science is a common finding among learners of all age levels (see, for example, Champagne, Gunstone, & Klopfer, 1985; Lewis & Linn, 1994). In this study, learners appeared to experience difficulty moving beyond simple assimilation for several reasons. Fundamentally, they failed to perceive and interpret data as being inconsistent with existing theories. Instead, learners tended either to (a) preserve the theory, using the data as an exception; (b) abandon the theory temporarily in favor of another, more explanatory theory, for the isolated incident; or (c) elaborate the theory by assimilating the conflicting data. Even when confronted with obvious conflicting evidence (e.g., clear expectations refuted by unambiguous feedback), learners failed to act on the perceived inconsistencies. Instead, they either changed theories temporarily, without acknowledging the previous theory used to drive the action, or discounted the data as an exception rather than attempting to explain it (see the protocol excerpts of Rick, Mary, & Jason in Pattern 7).

Research in science misconceptions indicates that fragmented or naive conceptions that typically underlie understanding often impede the development of canonical understanding (Champagne et al., 1985). Even in situations where learners interpret accurately, deep-rooted misconceptions resurface when solving novel or analog problems (Perkins & Simmons, 1988). In this case, simply telling learners the canonical rule may short-circuit the child's experience-based intuitive rules, as evident in the durability of science misconceptions in classroom settings. Likewise, presenting alternative views may be insufficient to alter deeply entrenched intuitive beliefs (diSessa & White, 1982; Vosniadou, 1992).

The durability of misconceptions depends upon the learner's ability to identify and consolidate personal beliefs, recognize their limitations, and gradually build upon them (Linn & Muilenburg, 1996; Vosniadou, 1992). The goal of OELEs is to provide authentic contexts for learners to identify their beliefs, test their validity, refine them in ways consistent with data, and gradually evolve alternative understandings. However, it appears that short-term learning via OELEs, despite the provision of manipulation tools and action-specific feedback, may be insufficient for conceptual change and theory evolution. The resilience of theories-in-action may require extended periods of time, multiple representations of data, conceptual perspectives, and varied problem contexts in order to facilitate their evolution (Cognition and Technology Group at Vanderbilt, 1992; Papert, 1993a; Spiro et al., 1991).

IMPLICATIONS FOR DESIGN OF OELES

In order for OELEs to support conceptual development, systems are needed that facilitate intentional reflection on, and evolution of, beliefs (Hawkins & Pea, 1987; Scardamalia, Bereiter, McLean, Swallow, & Woodruff, 1989). Insufficient metacognitive awareness leads to difficulties in recognizing counter examples and detecting biases in thinking (Karmiloff-Smith & Inhelder, 1975; Wilson & Brekke, 1994). OELEs need to enable opportunities for intentional reflection on beliefs, strategies, and intentions. Some OELEs have been designed to facilitate awareness of beliefs with opportunities to reflect metacognitively (Scardamalia et al., 1989), to formalize observations (Tobin & Dawson, 1992), and to develop hypotheses (Lewis et al., 1993). Opportunities for reflection have been embedded within the system and are supported via tools, feedback, and features.

This study also illustrated the tendency for naive learners to rely on dominant visual cues to guide their interpretations. This finding is consistent with expert-novice studies that illustrate the tendency for novices to focus on surface features rather than on the substantive aspects of problems (Chi, Glaser, & Rees, 1982). Consequently, it is essential that perceptual cues are linked with important information. In the present study, the dominant cues (video simulations) were perceived by learners as precisely reflecting information that the simulations did not represent. Haphazard use of perceptual cues is likely to promote misperceptions and misunderstandings. Accordingly, naive learners might benefit from constrained systems that reduce the richness of the cues presented (Petre, 1995). Animated graphics (vs. video simulations), amplication techniques, and adaptive feedback might be useful techniques for reducing potential errors in perception.

Another implication centers on how learners think and collect data during open-ended learning. It is widely assumed that learners can maneuver within the environment and make informed choices, even without complete understanding of prerequisite knowledge. This study indicated, however, that some learners continue to rely on, or prefer, externally-directed methods for learning. Open learning contexts, however, do not explicitly support or promote these approaches. Without experience-driven approaches, learners are unlikely to capitalize on the features provided by the system and build and evolve the cognitive skills engendered by and requisite to these environments.

CONCLUSION

Alternative approaches to traditional instruction have been long proposed. From Dewey's (1933; 1938) vision of school-based apprenticeships to Bruner's (1961) approaches to discovery learning, alternative views about the nature of understanding and ideal pedagogies have been debated. With recent developments in technology and student-centered learning, debates between constructivists and instructivists have re-emerged (Jonassen, 1991; Phillips, 1995). Instructivists argue that constructivist approaches lack systematic frameworks for design and assessment, and are therefore difficult to replicate and integrate into the curriculum (Dick, 1991). Constructivists, on the other hand, express concern regarding the inability of traditional approaches to support higher-order thinking and problem-solving skills (Kember & Murphy, 1990; National Science Teacher's Association, 1993; Papert, 1993a). Highly structured approaches may work well for teaching simple information and skills, but may fail to support reasoning, complex thinking, and the development of metacognitive skills (Kember & Murphy, 1990; Spiro et al. 1991).

Questions remain, however, regarding the effectiveness of constructivist environments in supporting higher-order thinking and problem-solving. Constructivist approaches have been plagued by an absence of empirically validated assumptions and associated pedagogical strategies. The present study, as well as others (see Atkins & Blisset, 1992; Hill, 1995) have identified problems in applying constructivist approaches to support understanding. Conversely, other studies have reported notable benefits of using student-centered environments to enhance learning (Cognition and Technology Group at Vanderbilt, 1992; Harel & Papert, 1991; Linn & Muilenburg, 1996; Scardamalia et al., 1989). These approaches promise to redefine the nature and goals of learning; the requisite design technology, however, remains distressingly incomplete.

The effectiveness of constructivist environments relies heavily on the quality of the learner's task management and decision-making processes (Perkins, 1991). Such environments tacitly presume that students are able to make effective judgments, or can be guided to make appropriate choices using advice or hints (Hannafin, Hall, Land, & Hill, 1994; Hannafin & Land, in press). Yet, studies of learner control and metacognition have consistently confirmed the limitations of learner decisions regarding what, when, and how to learn (Steinberg, 1977; 1989). These are important concerns, particularly in light of continued growth of educational applications of information technologies. Effective evaluation and management of open-ended activities and resources have become integral to success in the use of such systems.

Several issues remain regarding open-learning environments. Perhaps the most compelling issue pertains to the feasibility of student-centered, constructivist approaches in everyday teaching and learning. To some, direct instruction and traditional assessment appear antithetical to the goals of open-learning environments (Jonassen, 1991; Kember &

Murphy, 1990). Others, however, have suggested methods that reconcile traditional and constructivist pedagogies. In order to impact school curricula, the reciprocity between and among approaches may need to be exploited. Lebow (1993) described a series of ". . . principles for constructivist ISD" (p. 5) designed to imbue instructional designers with constructivist values. Perkins (1991) differentiated constructivist approaches that promote discovery *without* direct instruction (WIG—Without the Information Given) versus *following* direct instruction (BIG—Beyond the Information Given). Rieber's 1992 Newtonian physics microworld augmented direct instruction in basic skills with student-centered manipulations of a virtual space craft. Similarly, the Cognition and Technology Group at Vanderbilt (1992) identified a range of teaching strategies suitable for traditional classrooms through problem-centered applications of the Jasper series. Choi and Hannafin (in press) adapted situated learning concepts to the teaching and learning of mathematics. Clearly, there are many ways open-learning concepts can influence classroom teaching and learning.

Finally, advances in assessment of learning outcomes (both quantitative and qualitative) are warranted. The current study illustrated that learners *can* use this type of environment to extend and formalize their understanding of scientific notions; however, no measures of formal knowledge or skill development were gathered. It is conceivable that process-outcome tradeoffs are tacitly made when using open-learning systems; that is, traditional measures of effectiveness (scores on tests of formal knowledge) may suffer because of increased emphasis on improved learning process (understanding how to improve one's understanding). These tradeoffs may be considered worthwhile and justifiable, or unacceptable. Research is needed to better understand and assess the role of open-learning environments in improving teaching-learning processes as well as learning outcomes. □

Susan M. Land is an assistant professor of the Instructional Psychology and Technology program at the University of Oklahoma. Michael J. Hannafin is Director of the Learning and Performance Support Lab at the University of Georgia.

This manuscript is based on the doctoral dissertation by the first author conducted at The Florida State University. We wish to acknowledge Dr. Marcy P. Driscoll, Dr. Robert A. Reiser, and Dr. Richard K. Wagner for their cooperation and support as committee members, and George Dawson for providing use of ErgoMotion. The manuscript was prepared while the first author was working as a postdoctoral fellow at The University of Georgia's Learning and Performance Support Laboratory.

REFERENCES

Ackermann, E. (1991). From decontextualized to situated knowledge: Revisiting Piaget's water-level experiment. In I. Harel & S. Papert (Eds.), *Constructionism* (pp. 269–294). Norwood, NJ: Ablex Publishing Corporation.

Atkins, M., & Blissett, G. (1992). Interactive video and cognitive problem-solving skills. *Educational Technology, 32*(1), 44–50.

Bowen, C. (1992). *Student and teacher outcomes: Results from national field testing with IMS's ScienceVision materials.* Technical report #1; Interactive Media Science Project, Florida State University.

Brown, J.S., Collins, A., & Duguid, P. (1989). Situated cognition and the culture of learning. *Educational Researcher, 18*(1), 32–41.

Bruner, J. (1961). The act of discovery. *Harvard Educational Review, 31*(1), 21–32.

Carey, S. (1986). Cognitive science and science education. *American Psychologist, 41*(10), 1123–1130.

Champagne, A., Gunstone, R., & Klopfer, L. (1985). Instructional consequences of students' knowledge about physical phenomena. In L.H.T. West & A.L. Pines (Eds.), *Cognitive structure and conceptual change* (pp. 61–90). Orlando: Academic Press.

Chan, C., Burtis, P., Scardamalia, M., & Bereiter, C. (1992). Constructive activity in learning from text. *American Educational Research Journal, 29*(1), 97–118.

Chi, M., Glaser, R., & Rees, E. (1982). Expertise in problem solving. In R. Sternberg (Ed.), *Advances in the psychology of human intelligence* (Vol. 1, pp. 7–75). Hillsdale, NJ: Erlbaum.

Choi, J-I., & Hannafin, M.J. (in press). The effects of instructional context and reasoning complexity on mathematics problem solving. *Educational Technology Research and Development.*

Cognition and Technology Group at Vanderbilt. (1992). The Jasper experiment: An exploration of issues in learning and instructional design. *Educational Technology Research and Development, 40*(1), 65–80.

Dewey, J. (1933). *How we think.* Boston: Heath.

Dewey, J. (1938). *Experience and education.* New York: Collier Macmillan.

Dick, W. (1991). An instructional designer's view of constructivism. *Educational Technology, 31*(5), 41–44.

diSessa, A., & White, B. (1982). Learning physics from a dynaturtle. *Byte, 7,* 324.

Driscoll, M.P. (1995). Paradigms for research in instructional systems. In G. Anglin (Ed.), *Instructional technology: Past, present, and future (2nd ed.)* (pp. 322327). Englewood, CO: Libraries Unlimited, Inc.

Driver, & Scanlon. (1988). Conceptual change in science. *Journal of Computer-Assisted Learning (5),* 25–36.

Edwards, L. (1995). The design and analysis of a mathematical microworld. *Journal of Educational Computing Research, 12*(1), 77–94.

Ericsson, K.A., & Simon, H.A. (1992). *Protocol analysis: Verbal reports as data.* Cambridge: The MIT Press.

Guba, E.G., & Lincoln, Y. (1982). Epistemological and methodological bases of naturalistic inquiry. *ECTJ, 30*(4), 233–252.

Hannafin, M.J. (1992). Emerging technologies, ISD, and learning environments: Critical perspectives. *Educational Technology Research and Development, 40*(1), 49–63.

Hannafin, M.J., Hall, C., Land, S.M., & Hill, J.R. (1994). Learning in an open-ended environment: Assumptions, methods, and implications. *Educational Technology, 34*(8), 48–55.

Hannafin, M.J., & Land, S.M. (in press). The foundations and assumptions of technology-enhanced student-centered learning environments. *Instructional Science.*

Harel, I., & Papert, S. (1991). Software design as a learning environment. In I. Harel & S. Papert (Eds.), *Constructionism* (pp. 41–84.) Norwood, NJ: Ablex.

Hawkins, J., & Pea, R. (1987). Tools for bridging the cultures of everyday and scientific thinking. *Journal of Research in Science Teaching, 24*(4), 291–307.

Hashweh, M. (1988). Descriptive studies of student's conceptions in science. *Journal of Research in Science Teaching, 25*(2), 121–134.

Hill, J. (1995). *Cognitive strategies and the use of a hypermedia information system: An exploratory study.* Unpublished doctoral dissertation, Florida State University.

Holland, J., Holyoak, K., Nisbett, R., & Thargard, P. (1986). *Induction: Processes of inference, learning, and discovery.* Cambridge, MA: MIT Press.

Jacob, E. (1987). Qualitative research traditions: A review. *Review of Educational Research, 57*(1), 1–50.

Jonassen, D. (1984). The mediation of experience and educational technology: A philosophical analysis. *Educational Technology Research and Development, 32*(3), 153–167.

Jonassen, D. (1991). Objectivism versus constructivism: Do we need a new philosophical paradigm? *Educational Technology Research and Development, 39*(3), 5–14.

Karmiloff-Smith, A., & Inhelder, B. (1975). If you want to get ahead, get a theory. *Cognition, 3*(3), 195–212.

Kember, D., & Murphy, D. (1990). Alternative new directions for instructional design. *Educational Technology, 30*(8), 42–47.

Kozma, R.B. (1987). The implications of cognitive psychology for computer-based learning tools. *Educational Technology, 27*(11), 20–25.

Land, S.M., & Hannafin, M.J. (1996). A conceptual framework for the development of theories-in-action with open-ended learning environments. *Educational Technology Research and Development, 44*(3), 37–53.

Lebow, D. (1993). Constructivistic values for instructional systems design: Five principles toward a new mindset. *Educational Technology Research and Development, 41*(3), 4–16.

Lewis, E., & Linn, M. (1994). Heat energy and temperature concepts of adolescents, adults, and experts: Implications for curricular improvements. *Journal of Research in Science Teaching, 31*(6), 657–677.

Lewis, E., Stern, J., & Linn, M. (1993). The effect of computer simulations on introductory thermodynamics understanding. *Educational Technology, 33*(1), 45–58.

Lincoln, Y., & Guba, E. (1985). *Naturalistic inquiry.* Newbury Park, CA: Sage.

Linn, M., & Muilenburg, L. (1996). Creating lifelong science learners: What models form a firm foundation? *Educational Researcher, 25*(5), 18–24.

Litchfield, B., & Mattson, S. (1989). The interactive media science project: An inquiry-based multimedia science curriculum. *Journal of Computers in Mathematics and Science Teaching, 9*(1), 37–43.

Mayer, R.E. (1984). Aids to text comprehension. *Educational Psychologist, 19,* 30–42.

Mayer, R.E. (1989). Models for understanding. *Review of Educational Research, 59,* 43–64.

Merriam, S. (1988). *Case study research in education: A qualitative approach.* San Francisco: Jossey-Bass.

Miles, M.B., & Huberman, A.M. (1984). *Qualitative data analysis: A sourcebook of new methods.* Newbury Park, CA: Sage.

National Science Teachers' Association. (1993). *NSTA standards for science teacher preparation: An NSTA position statement.* Washington, DC: National Science Teachers' Association.

Papert, S. (1993a). *The children's machine: Rethinking school in the age of the computer.* New York: Basic Books, Inc.

Papert, S. (1993b). *Mindstorms* (2nd ed.). New York: Basic Books, Inc.

Pea, R.D., (1993). Practices of distributed intelligence and designs for education. In G. Salomon's (Ed.), *Distributed intelligence* (pp. 47–87). New York:

Cambridge.
Perkins, D. (1991). Technology meets constructivism: Do they make a marriage? *Educational Technology, 31*(5), 18–23.
Perkins, D., & Simmons, R. (1988). Patterns of misunderstanding: An integrative model for science, math, and programming. *Review of Educational Research, 58*, 303–326.
Petre, M. (1995). Readership skills and graphical programming. *Communication of the ACM, 38*(6), 33–43.
Phillips, D.C. (1995). The good, the bad, and the ugly: The many faces of constructivism. *Educational Researcher, 24*(7), 5–12.
Piaget, J. (1970). *The child's conception of movement and speed*. New York: Ballantine.
Piaget, J. (1976)., *The grasp of consciousness*. Cambridge, MA: Harvard University Press.
Rieber, L.P. (1992). Computer-based microworlds: A bridge between constructivism and direct instruction. *Educational Technology Research and Development, 40*(1), 93–106.
Robinson, R.S. (1995). Qualitative research—A case for case studies. In G. Anglin (Ed.), *Instructional technology: Past, present and future* (2nd ed.). (pp. 330–337). Englewood, CO: Libraries Unlimited, Inc.
Roth, W.M., & Roychoudhury, A. (1993). The development of science process skills in authentic contexts. *Journal of Research in Science Teaching, 30*(2), 127–152.
Salomon, G. (1986). Information technologies: What you see is not (always) what you get. *Educational Psychologist, 20*, 207–216.
Salomon, G., Globerson, T., & Guterman, E. (1989). The computer as a zone of proximal development: Internalizing reading-related metacognitions from a reading partner. *Journal of Educational Psychology, 81*(4), 620–627.
Scardamalia, M., Bereiter, C., McLean, R., Swallow, J., & Woodruff, E. (1989). Computer-supported intentional learning environments. *Journal of Educational Computing Research, 5*(1), 51–68.
Schön, D.A. (1983). *The reflective practitioner: How professionals think in action*. New York: Basic Books.
Spiro, R., Feltovich, P., Jacobson, M., & Coulson, R. (1991). Cognitive flexibility, constructivism, and hypertext: Random access instruction for advanced knowledge acquisition in ill-structured domains. *Educational Technology, 31*(5), 24–33.
Steinberg, E. (1977). Review of student control in computer-assisted instruction. *Journal of Computer-Based Instruction, 3*, 84–90.
Steinberg, E. (1989). Cognition and learner control: A literature review, 1977–1988. *Journal of Computer-Based Instruction, 16*, 117–121.
Strauss, A., & Corbin, J. (1990). *Basics of qualitative research: Grounded theory procedures and techniques*. Newbury Park, CA: Sage Publications.
Tobin, K., & Dawson, G. (1992). Constraints to curriculum reform: Teachers and the myths of schooling. *Educational Technology Research and Development, 40*(1), 64–92.
Twigger, D., Byard, M., Draper, S., Driver, R., Hartley, R., Hennessey, S., Mallen, C., Mohamed, R., O'Malley, C., O'Shea, T., Scanlon, E. (1991). The 'Conceptual change in science' project. *Journal of Computer-Assisted Learning, 7*, 144–155.
Vosniadou, S., & Brewer, W. (1987). Theories of knowledge restructuring in development. Review of *Educational Research, 57*(1), 51–67.
Vosniadou, S. (1992). Knowledge acquisition and conceptual change. *Applied Psychology: An International Review, 41*(4), 347–357.
Wilson, T., & Brekke, N. (1994). Mental contamination and mental correction: Unwanted influences on judgments and evaluations. *Psychological Bulletin, 116*(1), 117–142.
Yin, R. (1994). *Case study research* (2nd ed.). Newbury Park, CA: Sage Publications.